

Original Paper

Improving Suicidal Ideation Detection in Social Media Posts: Topic Modeling and Synthetic Data Augmentation Approach

Hamideh Ghanadian¹, BSc, MSc, PhD; Isar Nejadgholi², BSc, MSc, PhD; Hussein Al Osman¹, BSc, MSc, PhD

¹School of Electrical Engineering and Computer Science, University of Ottawa, Ottawa, ON, Canada

²National Research Council Canada, Ottawa, ON, Canada

Corresponding Author:

Hamideh Ghanadian, BSc, MSc, PhD
School of Electrical Engineering and Computer Science
University of Ottawa
75 Laurier Ave E
Ottawa, ON, K1N 6N5
Canada
Phone: 1 6134000702
Email: hghanadian36@gmail.com

Abstract

Background: In an era dominated by social media conversations, it is pivotal to comprehend how suicide, a critical public health issue, is discussed online. Discussions around suicide often highlight a range of topics, such as mental health challenges, relationship conflicts, and financial distress. However, certain sensitive issues, like those affecting marginalized communities, may be underrepresented in these discussions. This underrepresentation is a critical issue to investigate because it is mainly associated with underserved demographics (eg, racial and sexual minorities), and models trained on such data will underperform on such topics.

Objective: The objective of this study was to bridge the gap between established psychology literature on suicidal ideation and social media data by analyzing the topics discussed online. Additionally, by generating synthetic data, we aimed to ensure that datasets used for training classifiers have high coverage of critical risk factors to address and adequately represent underrepresented or misrepresented topics. This approach enhances both the quality and diversity of the data used for detecting suicidal ideation in social media conversations.

Methods: We first performed unsupervised topic modeling to analyze suicide-related data from social media and identify the most frequently discussed topics within the dataset. Next, we conducted a scoping review of established psychology literature to identify core risk factors associated with suicide. Using these identified risk factors, we then performed guided topic modeling on the social media dataset to evaluate the presence and coverage of these factors. After identifying topic biases and gaps in the dataset, we explored the use of generative large language models to create topic-diverse synthetic data for augmentation. Finally, the synthetic dataset was evaluated for readability, complexity, topic diversity, and utility in training machine learning classifiers compared to real-world datasets.

Results: Our study found that several critical suicide-related topics, particularly those concerning marginalized communities and racism, were significantly underrepresented in the real-world social media data. The introduction of synthetic data, generated using GPT-3.5 Turbo, and the augmented dataset improved topic diversity. The synthetic dataset showed levels of readability and complexity comparable to those of real data. Furthermore, the incorporation of the augmented dataset in fine-tuning classifiers enhanced their ability to detect suicidal ideation, with the F_1 -score improving from 0.87 to 0.91 on the University of Maryland Reddit Suicidality Dataset test subset and from 0.70 to 0.90 on the synthetic test subset, demonstrating its utility in improving model accuracy for suicidal narrative detection.

Conclusions: Our results demonstrate that synthetic datasets can be useful to obtain an enriched understanding of online suicide discussions as well as build more accurate machine learning models for suicidal narrative detection on social media.

(JMIR Form Res 2025;9:e63272) doi: [10.2196/63272](https://doi.org/10.2196/63272)

KEYWORDS

suicidal ideation detection; large language models; synthetic data; topic modeling; social media

Introduction

Suicide is a pressing global public health issue with far-reaching consequences for individuals, families, and communities. The World Health Organization [1] has highlighted the alarming increase in suicide rates in recent years, emphasizing the urgent need for effective prevention strategies [2]. Traditionally, identifying individuals at risk of suicide has relied on clinical assessments and crisis hotlines. However, the widespread adoption of social media has opened new avenues for early detection and intervention [3].

Natural language processing (NLP) techniques have emerged as a promising tool for suicide detection, leveraging machine learning to analyze textual data shared on social media platforms [4-6]. Social media datasets have become invaluable in the study of suicidal ideation. As more people express their thoughts and emotions online, these datasets offer a unique glimpse into individuals' digital lives, providing rich data for research and mental health support [7]. Researchers use these datasets to analyze text, identifying patterns and linguistic cues associated with suicidal ideation [8-10].

However, while social media provides a wealth of information, it is not without its limitations. For instance, social media platforms tend to attract a younger demographic, which may skew the data and make them less representative of older populations. Additionally, the open nature of social media may encourage users to share certain aspects of their experiences while discouraging the disclosure of more personal or sensitive factors [11]. These biases can have significant implications for machine learning models trained on social media data. If the data are not representative of all demographics or fail to capture less frequently discussed factors, the models may struggle to generalize effectively. For example, a model trained on data that overrepresent certain themes or demographics may perform poorly when encountering posts from underrepresented groups or those addressing less common topics. This could lead to false negatives, where the model fails to identify at-risk individuals, or biased outputs, where the model perpetuates stereotypes or stigmatization present in the training data.

To address these limitations, it is crucial to complement social media datasets with information from other reliable sources. Within psychology, extensive research has been conducted to understand the underlying psychological, social, and environmental factors contributing to suicidal thoughts and behaviors. Several investigations have explored how psychological factors, including depression, anxiety, a sense of hopelessness, and feelings of low self-worth, influence the emergence of suicidal thoughts [12-14]. These studies have investigated the strong association between suicidal thoughts and conditions like depression [15,16], bipolar disorder [17], borderline personality disorder [18], and substance abuse [19,20]. The studies used a combination of quantitative and

qualitative methods to explore the factors contributing to suicide [21-24].

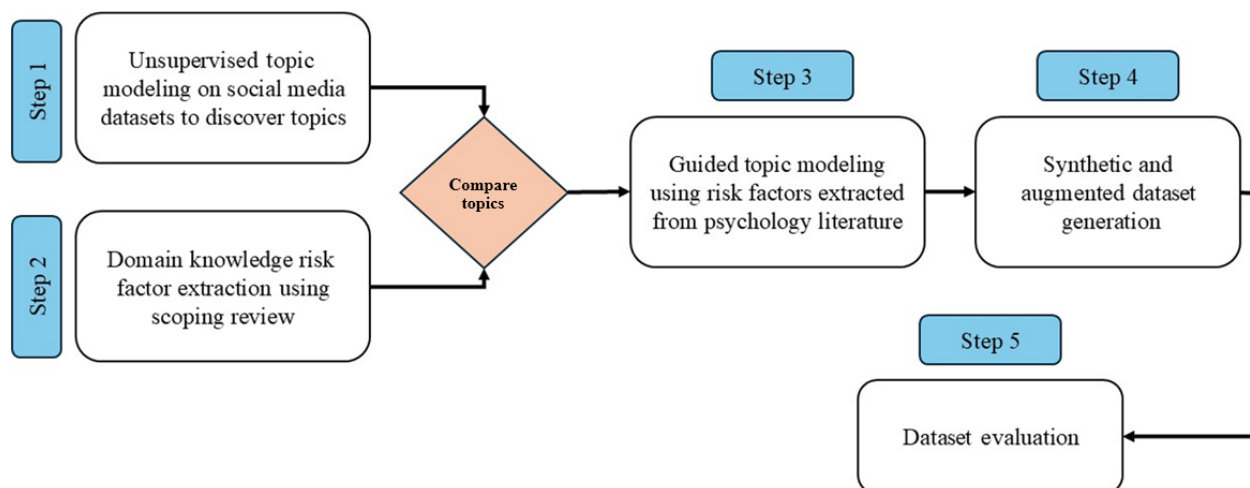
Our objective in this study is to identify gaps between the risk factors represented in social media data and those established in psychology literature. We hypothesize that social media data do not fully capture empirically established factors related to suicidal ideation, particularly those that may be underrepresented due to demographic or disclosure biases. To examine this, we conducted a comprehensive analysis of suicide-related social media datasets using topic modeling techniques to identify themes and topics [25]. We then compared the extracted themes with factors outlined in psychology literature to locate any significant gaps. When such gaps were identified, we explored the potential of augmenting real-world data with synthetic data generated by advanced language models like GPT-3.5 Turbo to improve the representation of underreported factors. The use of synthetic data has gained traction in recent years, particularly with the advent of generative models that can produce high-quality, realistic data [26,27]. This study presents a novel approach for identifying and mitigating topic gaps in suicidal ideation detection models, aiming to improve their generalizability and fairness.

Methods

Study Methodology

In this subsection, we elaborate on our study methodology. Figure 1 illustrates how the study methodology was developed. Our approach included the following steps:

- Step 1 (unsupervised topic modeling): We performed unsupervised topic modeling to discover the topics and risk factors mostly discussed on social media.
- Step 2 (domain knowledge extraction): We extracted relevant social risk factors from psychology literature to ground the content assessment of datasets in these factors.
- Step 3 (guided topic modeling): We compared topics extracted from social media and the literature. We shifted toward supervised guided topic modeling on social media using discovered topics from the literature to identify underrepresented and missing risk factors.
- Step 4 (synthetic and augmented dataset): We extended and annotated the existing synthetic datasets by incorporating additional risk factors that were missing from existing datasets. Moreover, we created an augmented dataset by combining synthetic data with real social media data to enhance its generalizability and topic coverage.
- Step 5 (dataset evaluation): To evaluate the utility of synthetic data, we analyzed both real and synthetic datasets by assessing the complexity, readability, and diversity of the text within each dataset. Additionally, we trained state-of-the-art classifiers using real-world, synthetic, and augmented datasets. Subsequently, the performance of these classifiers was evaluated by testing them on both real-world and synthetic test sets.

Figure 1. Overview of the multistep methodology used in this study to assess topic gaps in suicidal ideation detection from Reddit social media posts.

Unsupervised BERTopic

In this subsection, we present the methodology for conducting topic modeling using BERTopic [28], a state-of-the-art deep learning approach for discovering topics in text data. Our objective was to assess the quality, diversity, and coverage of datasets collected from social media in relation to suicidal ideation.

BERTopic leverages transformer-based language models as embedding models, combined with clustering methods for topic extraction [29]. BERTopic integrates transformer-based techniques with term frequency–inverse document frequency (TF-IDF) to create compact, interpretable clusters, preserving the most relevant terms in topic descriptions. This approach leverages deep learning and is mostly used with the sentence transformers embedding model, which supports document embedding extraction in more than 50 languages [30]. BERTopic’s topic modeling procedure involves 3 main stages: document embeddings, document clustering, and topic representation.

Text Embedding

Text embedding refers to the vector representation of text within a multidimensional space where textual contents conveying similar meanings exhibit similar embeddings. In this project, we used the “SentenceTransformers” Python framework for state-of-the-art sentence and text embeddings [31]. Although there are many models for text embeddings, we used the sentence transformers “all-MiniLM-L6-v2” model as it has been shown to be one of the best-performing models within the BERTopic framework [32].

Topic Extraction

In this step, similar documents or sentences are grouped based on their content. It is a method of organizing large amounts of textual information into meaningful categories or clusters, providing a high-level overview of the information contained within. Before clustering the embeddings, a dimensionality reduction is implemented, as embeddings are often high in dimensionality. In this work, we used the UMAP (Uniform Manifold Approximation and Projection) algorithm to reduce

the dimensionality of the embeddings because it can capture both the local and global structures of high-dimensional data in lower-dimensional space [33]. It has also been proven that for short text clustering, UMAP demonstrates superior results [34,35]. The hyperparameter space involved in UMAP is manually inspected, and based on the performance of the model and presented topics, the best parameters are selected. The number of neighbors, the number of components, and the minimum distance of each component were selected as 15, 5, and 0, respectively.

Following the dimensionality reduction of our input embeddings, we needed to cluster them into groups of similar embeddings to extract our topics. The method used in this paper is HDBSCAN (Hierarchical Density-Based Spatial Clustering of Applications with Noise), introduced by Campello et al [36]. This method is based on the density clustering method that finds clusters of different shapes and identifies outliers where possible. Similar to UMAP, the parameters of this model are manually inspected, and the proper parameters are chosen. There is no automated method for determining values for HDBSCAN. The parameters should be set manually based on domain knowledge and understanding of the dataset. Hence, we selected 10 and 5 as the minimum cluster size and sample number in each cluster, respectively.

Keyword Extraction for Topics

In this step, class-based term frequency–inverse document frequency (C-TF-IDF) scores are used to identify a set of keywords that represent the topic for a better interpretation of the topic’s content. TF-IDF is a technique used to extract features from text documents, which is achieved by combining 2 components: term frequency and inverse document frequency. Term frequency represents the simple word count within a document, treating each word count as a feature, and it is calculated by dividing the number of times the term occurs in the document by the total number of terms in the document. Inverse document frequency gauges the informativeness of specific words by measuring their frequency within a document relative to their frequency across all other documents. C-TF-IDF is similar to TF-IDF but is adopted for multiple classes by joining all documents per class. Thus, each class is converted

to a single document instead of a set of documents. After calculating the C-TF-IDF scores for all words in each topic, words with the highest scores are chosen as keywords associated with that topic.

Social and Psychological Knowledge Extraction

We conducted a scoping review to offer a current and thorough synthesis of psychology studies, aiming to identify topics, themes, and risk factors related to the sensitive and complex issue of suicidal ideation. Scoping reviews serve as a method to assess the scope of literature on a particular subject, providing insights into the available research and offering a broad overview of its focus [37]. Additionally, they highlight the types of evidence that guide practice in the field and examine how the research has been conducted [38]. Our protocol was developed using the scoping review methodological framework proposed by Arksey and O'Malley [39] and further refined by Peters et al [40].

Research Question

The central research question guiding this review was as follows: "What are the most frequently reported risk factors associated with suicidal ideation in the psychology and mental health literature?" By answering this question, the review seeks to provide a clearer understanding of the key factors that contribute to the emergence of suicidal thoughts, ultimately informing future research and interventions aimed at preventing suicide and supporting individuals at risk.

Search Strategy

We scoured prominent academic databases, such as PubMed, PsycArticles, ScienceDirect, and Google Scholar, employing a systematic approach. Our search strategy involved using identical keywords across all databases: "suicidal ideation" and "suicide risk factors."

Eligibility Criteria

To be eligible for inclusion, studies were required to be peer-reviewed review or systematic review publications that investigated risk factors associated with suicidal ideation. Eligible studies had to be published between January 2014 and August 2024, address all forms of suicidal behavior including ideation and attempts, and focus on the general population.

Studies were excluded if they focused on specific groups that could introduce additional factors into the analysis, were published in a language other than English, or were not peer-reviewed publications, such as book chapters.

Study Selection

All identified publications were initially screened for relevance based on abstract and title. Subsequently, the full text of selected publications was assessed for eligibility. Furthermore, the reference lists of eligible papers were used to identify additional studies.

This exploration allowed us to identify a wide array of relevant review papers, forming the foundation of our research. Subsequently, we reported the most common topics among all the selected research articles. Based on our analysis of the literature, several social and psychological factors were

consistently reported in relation to suicidal ideation in psychology. These topics have not been listed in a specific order of importance but represent the consistently reported themes in the literature reviewed.

Mental Health Disorders and Personality Traits

"Depression" is a well-documented and significant risk factor for suicide. The persistent feelings of sadness and emotional pain that characterize depression can lead individuals to contemplate or attempt suicide as a means of escape from their suffering. It is vital to recognize the signs of depression, offer support, and connect individuals to mental health professionals and resources for effective treatment and intervention [41-43].

"Anxiety" disorders are commonly associated with suicidal ideation. The chronic emotional distress and physical symptoms associated with severe anxiety can contribute to the development of suicidal thoughts [44].

"Posttraumatic stress disorder" (PTSD) is strongly associated with an increased risk of suicidal ideation. Individuals who have experienced traumatic events may struggle with the emotional aftermath, including intrusive memories, hyperarousal, and avoidance of reminders, which can lead to constant emotional distress and a sense of being overwhelmed. These constant feelings of traumatic memories can contribute to thoughts of suicide [45,46].

"Bipolar disorder," formerly called manic depression, is a mental health condition that causes extreme mood swings. These include emotional highs (also known as mania) and lows (also known as depression) [47]. Suicide attempts and completed suicide are significantly more common in patients with bipolar disorder when compared with the general population [47,48].

"Schizophrenia" is a severe mental disorder that disrupts both cognitive and social functioning, often resulting in the onset of additional health conditions [49]. Schizophrenia is strongly linked to an increased risk of suicidal ideation. The distress caused by its symptoms, feelings of isolation, and perceived loss of control over one's mind can contribute to a deep sense of hopelessness. Additionally, the stigma and social withdrawal often associated with schizophrenia may exacerbate these feelings, further increasing the risk of suicide [50,51].

"Borderline personality disorder" is a prevalent mental health condition linked to elevated suicide rates, significant functional impairment, frequent co-occurrence with other mental disorders, and extensive treatment needs. Long-term outcome studies of patients with borderline personality disorder have documented a high rate of suicide completion [52,53].

The expression and experience of "anger" have been reported as influential factors in suicidal ideation. Unresolved anger and intense emotional turmoil can drive individuals toward suicidal thoughts and actions. Anger, when left unmanaged, can escalate distress and lead to impulsive decisions with dire consequences. Recognizing and managing anger are crucial facets of suicide detection [41,54].

"Perfectionism," marked by excessively high standards and self-criticism, has been identified as a psychological factor related to suicidal ideation. The relentless pursuit of unattainable

standards can lead to feelings of inadequacy and despair, increasing the risk of suicidal ideation. Recognizing the need for balance and self-compassion is pivotal in addressing this risk factor [41].

Feelings of “hopelessness,” characterized by a pervasive sense of despair and an inability to envision a better future, can be a potent predictor of suicidal behavior. Those burdened by overwhelming hopelessness may see suicide as the only means of escape from their emotional suffering [41,42,55].

Substance Abuse

Alcohol and drug misuse is a significant risk factor for suicidal ideation and behavior [56]. The connection between substance abuse and suicide is complex, as substances like drugs and alcohol can impair judgment and exacerbate underlying emotional distress. Individuals who struggle with addiction may turn to substances as a means of coping with psychological pain, and when combined with impaired decision-making, this can increase the likelihood of suicidal thoughts and actions [57-59].

Sociodemographic Status

Prolonged “unemployment” can erode self-esteem, create financial difficulties, and contribute to feelings of hopelessness, increasing the risk of suicide. Government support and job assistance programs can help mitigate this risk [55]. “Financial hardships” can trigger intense stress, making individuals vulnerable to suicide. Economic support and resources are instrumental in addressing this risk factor [44,60].

“Education pressure,” including exams and expectations, can lead to emotional turmoil and an increased risk of suicidal ideation, particularly among students. Educational institutions must provide resources for coping with academic stress [61,62].

“Sexual minority” individuals, such as those who identify as lesbian, gay, bisexual, transgender, queer (LGBTQ+), often face unique stressors related to their sexual orientation or gender identity [63]. Discrimination, prejudice, and stigma can lead to feelings of isolation, rejection, and psychological distress. Research consistently shows that sexual minority individuals are at a higher risk for suicidal ideation and attempts compared to their heterosexual counterparts [64-67].

Abuse

“Bullying,” including physical, verbal, or cyber bullying, has consistently emerged as a significant topic related to suicidal ideation. The experience of bullying can lead to social isolation, low self-esteem, and emotional distress, contributing to the development of suicidal thoughts [44,68-70].

“Sexual abuse” is a recognized risk factor for suicide, which includes any sexual activity that occurs without consent, also referred to as sexual assault or sexual violence [71]. Dissociation is a common response to sexual abuse, and higher levels of dissociation have been associated with self-harm, suicidal thoughts, and suicide attempts [72,73].

Family-Related Issues

“Family-related stressors,” such as conflict, dysfunctional dynamics, and poor communication, can significantly impact an individual’s emotional well-being and contribute to suicidal

thoughts. Strengthening family relationships and providing support to those affected are essential in mitigating this risk factor [43,55].

Difficulties in “relationships,” including conflicts, breakups, and marital dissatisfaction, have been reported as significant topics in relation to suicidal ideation. Relationship problems can contribute to emotional distress and feelings of hopelessness, leading to thoughts of suicide [55].

The death of family members or friends has been reported as a risk factor associated with suicidal ideation. Grief, feelings of loneliness, and a sense of being unable to cope with the loss can increase the risk of suicidal thoughts [74].

Racism

Studies have consistently highlighted the significant impact of racial discrimination on suicidal ideation. Experiencing racism and racial prejudice can increase the risk of suicidal thoughts [75-77].

Immigration

The process of immigration, with its cultural adjustments, isolation, and uncertainty, can intensify stress and emotional distress, increasing the risk of suicide among immigrants. Providing support and resources tailored to the immigrant experience is essential [78,79].

Dementia

Dementia, particularly in its advanced stages, can lead to significant cognitive and emotional challenges. Individuals with dementia may experience confusion, memory loss, and personality changes, which can be distressing for both them and their caregivers. The experience of losing one’s cognitive abilities and identity can contribute to feelings of hopelessness and despair, leading to thoughts of suicide [80-82].

Chronic Physical Problems

Living with chronic physical health conditions can be emotionally taxing, and individuals facing such challenges may be more susceptible to suicidal ideation. Chronic pain, disability, and limitations in physical functioning can erode one’s quality of life and lead to a sense of hopelessness [83]. Coping with the constant demands of managing a chronic condition can also contribute to emotional distress [84,85].

Guided BERTopic

In this research, we began by applying unsupervised BERTopic to the social media datasets to identify key topics discussed within them. Next, we conducted a scoping review to examine established suicidal risk factors. We then compared the topics from the social media analysis with risk factors extracted from psychology literature. During this process, we observed that the effectiveness of topic modeling techniques in capturing domain-specific terms may be limited. To address this, we used guided topic modeling to ensure that certain specialized terms are detected and appropriately represented in the topics.

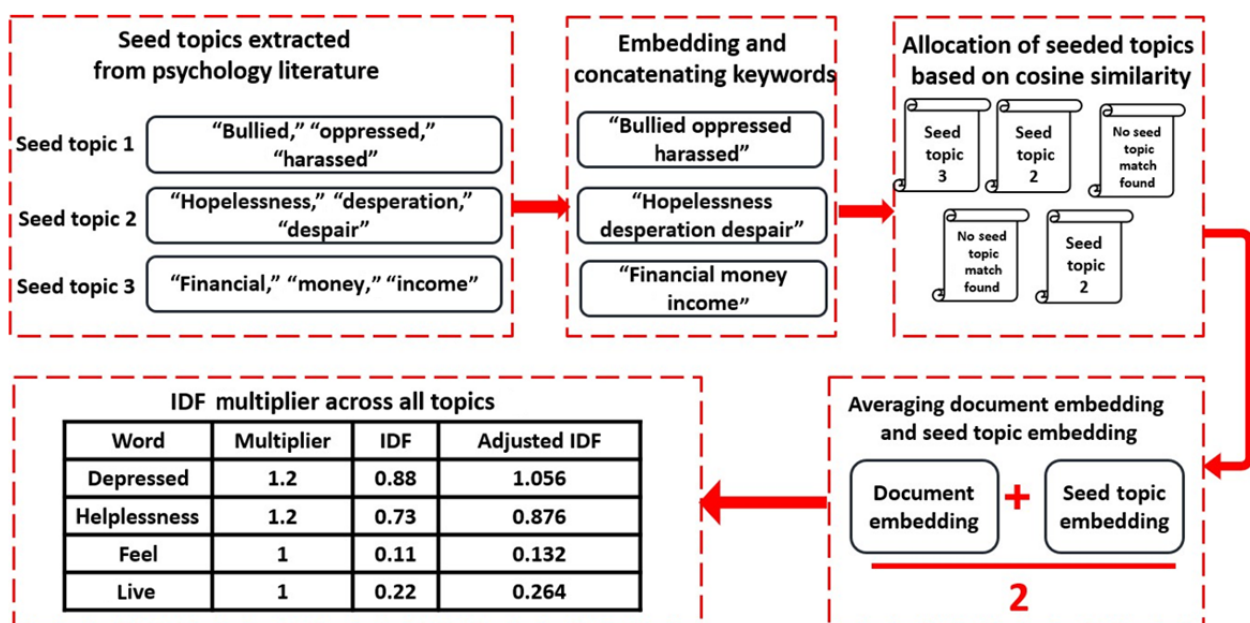
Guided topic modeling (supervised topic modeling) is an extension of traditional topic modeling that incorporates external information or guidance to influence the topic discovery process.

In this project, we employed guided BERTopic [86], which introduces external information in the form of seed words to guide the algorithm in discovering topics that align with the specified guidance. This guidance helps to improve the relevance and coherence of the identified topics. Here, we used discovered suicidal risk factors from psychology literature in the Social and Psychological Knowledge Extraction section as categories to guide the topic modeling process. Each category comes with sets of seed words that are suggested using “Meriam-Webster Dictionary” [87] as the most related keywords for each category. This deliberate approach allowed us to align the resulting topics with known psychological factors that contribute to suicide risk, creating a more focused and domain-informed representation.

Guided BERTopic involves 2 primary steps. First, the BERTopic algorithm generates embeddings for each seeded topic by concatenating them and passing them through the document embedder. As shown in Figure 2, these embeddings are compared to the existing document embeddings using cosine

similarity and are then assigned a label. If a document is most similar to a seeded topic, it receives that topic’s label; otherwise, if it is most similar to the average document embedding, it will be categorized as an outlier (–1 label). UMAP then applies these labels in a semisupervised manner, guiding the dimensionality reduction process to emphasize the distinctions between seeded topics and potentially identify outliers, thereby steering the topic creation more effectively toward the seeded topics. Second, all words in the seed topic list are assigned to a multiplier with a value greater than 1. These multipliers are applied to increase the inverse document frequency values of the words across all topics by boosting the likelihood of a seeded topic word appearing in a topic. After having generated our topics using C-TF-IDF, we employed the *KeyBERTInspired* extraction technique that leverages BERT embeddings and simple cosine similarity to find keywords and key phrases that are most similar to a document. Then, we selected keywords with the highest C-TF-IDF score as representative seed topics for the guided topic modeling.

Figure 2. Architecture of guided BERTopic using seed terms derived from psychology literature. Illustration of how seed words based on established suicide risk factors from the literature were incorporated into the guided BERTopic algorithm to steer topic discovery in Reddit social media posts for suicidal ideation detection. IDF: inverse document frequency.



Synthetic Data Generation

Synthetic data generation provides a practical solution for addressing data availability limitations by creating artificially generated data that closely resemble real-world data. Ghanadian et al [26] employed 3 generative large language models, namely GPT-3.5 Turbo, Flan-T5, and Llama2, to generate a synthetic dataset related to suicide. Their findings indicated that GPT-3.5 Turbo outperformed other generative models in creating synthetic data, that is, a classifier trained on a dataset generated by GPT-3.5 Turbo achieved higher *F*-scores when tested on the real-world and synthetic test sets. In our research, we used the dataset presented in the study by Ghanadian et al [26], along with domain knowledge-based risk factors we extracted, to generate a new dataset using GPT-3.5 Turbo. Moreover, we augmented 30% of the real dataset with a new synthetic dataset

to report the practicality of the generated data for suicidal ideation detection.

Dataset Analysis

For textual datasets, assessing the diversity of semantics and the sentence structure of textual content is crucial, even more so when dealing with synthetic datasets. To measure these qualities, we used 3 sets of metrics: complexity, readability, and entropy. Complexity refers to the intricacy and sophistication of the language used in a text, encompassing factors such as sentence structure, vocabulary richness, and syntactic intricacies. Readability pertains to the ease with which a text can be comprehended by its intended audience, considering elements such as sentence length, word difficulty, and overall coherence. Understanding complexity and readability in synthetic datasets aids in ensuring that the generated text

aligns with linguistic patterns observed in real-world data. Moreover, these parameters facilitate an assessment of the synthetic dataset, specifically regarding the incorporation of suitable language complexities. This evaluation allows us to examine if synthetic data replicate language patterns akin to those found in genuine, human-generated content. Furthermore, entropy is a metric that measures the unpredictability of a text. It assesses the information content or disorder present in the dataset. In simpler terms, entropy in text datasets gauges how diverse or varied the words or characters are within the dataset. High entropy indicates a higher degree of unpredictability,

suggesting a wider range of different words or characters used in the text. Conversely, low entropy implies a more predictable or ordered text with fewer variations in the words or characters used.

To measure the readability of text, we used the Flesch reading ease test [88], which quantifies readability based on sentence length and the number of syllables per word. As a benchmark, a high score indicates that the text is easily understood by an average 11-year-old, while a low score indicates that the text is best understood by university graduates. Table 1 presents the definition criteria for the Flesch reading ease test score.

Table 1. Flesch reading ease test score definition criteria.

Score	Difficulty
90-100	Very easy
80-89	Easy
70-79	Fairly easy
60-69	Standard
50-59	Fairly difficult
30-49	Difficult
0-29	Very confusing

Additionally, we used the type-token ratio [89] to assess the complexity of a text using lexical diversity measures. The basic idea behind that measure is that if the text is more complex, the author uses a more varied vocabulary, so there is a larger number of unique words [90].

Another selected metric was Shannon entropy [91], which is calculated based on the frequency of occurrence of different characters, words, or other linguistic units within the text. In word-based analysis, higher entropy suggests a wider range of vocabulary, showing greater linguistic diversity [92]. Calculation of Shannon entropy involves summing the probabilities of each word occurrence in the text, weighted by the logarithm of the inverse of these probabilities. The Shannon entropy H for a set of words with probabilities $p_1, p_2, \dots, p_n$ is calculated as follows:

$$H = - \sum_{i=1}^n p_i \cdot \log_2(p_i) \quad (1)$$

In this equation, H represents the calculated entropy value for the given set of words, and p_i represents the probability of the i th word occurring in the text. The sum extends over all unique words. By computing Shannon entropy in text analysis, one can gain insights into the richness, diversity, and complexity of the language used within the text dataset.

Datasets

In this section, we review the specifications of the datasets assessed in this work.

University of Maryland Reddit Suicidality Dataset

We used the University of Maryland Reddit Suicidality Dataset (UMD) [93,94] collected from Reddit. Reddit is an online website and forum for anonymous discussion on a wide variety of topics. The UMD is a collection of Reddit posts and

comments created by individuals who expressed suicidal thoughts or behaviors. The dataset contains over 100,000 posts and comments collected from various subreddits, including those related to mental health and suicide prevention, such as *Depression* [95] and *SuicideWatch* [96] subreddits. The data were collected over a period of several years and include the content of posts and comments, as well as the location and timing of the posts. This dataset contains annotations at the user level, using a 4-point scale to indicate the severity of suicide risk: (1) *no risk*, (2) *low risk*, (3) *moderate risk*, and (4) *high risk*. The goal of this annotation is to assess the risk level of individuals through an examination of their online activities. This task necessitates minimal data, with users generally contributing only a limited number of posts on SuicideWatch. Among the 993 labeled users, 496 made at least one post on the SuicideWatch subreddit. The remaining 497 users served as control subjects. Since the provided labels were user-level labels, we aggregated all the posts of each user into a single data point, through the concatenation of all the posts made by a particular user. Using a binary classification approach similar to that by Ghanadian et al [26], we applied binarization to the UMD. In accordance with the 4 class definitions, the categories labeled as “*no risk*” and “*low risk*” were categorized as nonsuicidal, while those labeled as “*moderate risk*” and “*high risk*” were considered suicidal. A total of 490 anonymous posts with binary labels were employed in this paper.

The UMD has been repeatedly used by researchers to develop and test NLP algorithms and machine learning models in order to identify and analyze patterns in online communication related to suicide risk [97]. Ji et al [98] proposed a method for improving text representation by incorporating sentiment scores based on lexicon analysis and latent topics. Additionally, they introduced the use of relation networks for the detection of suicidal ideation and mental disorders, leveraging relevant risk

indicators. In another paper, Ji et al [99] used 2 pretrained masked language models, MentalBERT and MentalRoBERTa, specifically designed to support machine learning in the mental health care research field. The authors assessed these domain-specific models along with various pretrained language models on multiple mental disorder detection benchmarks. The results showed that using language representations pretrained in the mental health domain can enhance the performance of mental health detection tasks, highlighting the potential benefits of these models for the mental health care research community.

Knowledge Aware Assessment Dataset

Gaur et al [100] developed an annotated gold standard dataset of 500 Reddit users out of 2181 potentially suicidal users, using their content from mental health-related subreddits within the time frame of 2005 to 2016. The dataset consists of 5 different categories of suicidality, including suicidal ideation, suicidal behavior, actual attempt, suicide indicator, and supportive.

Suicidal ideation refers to thoughts of suicide, which may involve concerns related to suicide risk factors, such as job loss or the end of a significant relationship. Suicidal behavior is defined as actions that carry a higher risk, such as self-harm (either current or historical), active planning to commit suicide, or a history of institutionalization for mental health reasons. An actual attempt encompasses any deliberate action that could potentially lead to intentional death. This includes, but is not limited to, instances where an individual sought help, reconsidered their decision, or publicly expressed thoughts of suicide. The suicide indicator category serves as a classification method to distinguish individuals who use at-risk language from those who are actively experiencing general or acute symptoms. Often, users converse in supportive conversations and share their personal histories while using language from the clinical lexicon. The supportive category pertains to individuals engaging in discussions without expressing any history of being at risk, either in the past or at present.

2021 Reddit Dataset

In addition to the existing datasets, we collected a new dataset of suicidal social media posts from the Reddit platform using the Reddit application programming interface [101]. Specifically, we focused on the “SuicideWatch” subreddit to gather posts related to suicide and analyzed the topics discussed within this subreddit.

The initial data collection was conducted on September 11, 2021, with the goal of gathering 2500 posts published between May 1, 2021, and September 1, 2021. Subsequently, we conducted extensive text preprocessing, which included removing links, eliminating duplicates, handling special characters, removing stop words, filtering out irrelevant and noninformative posts, performing lemmatization, and conducting spellchecking. After these preprocessing steps, our dataset consisted of 2052 unlabeled posts from the “SuicideWatch” subreddit, which we used for the purpose of topic modeling in this study.

Synthetic Dataset

Ghanadian et al [26] generated a synthetic dataset to enhance the performance of state-of-the-art suicide detection approaches by augmenting real-world datasets. They harnessed the capabilities of 3 generative large language models, namely, GPT-3.5 Turbo, Flan-T5, and Llama 2, to generate synthetic data for the detection of suicidal ideation.

In this paper, we generated a dataset comprising 748 suicide-related posts. As discussed in the Social and Psychological Knowledge Extraction section, our updated suicidal risk factors and topics, derived from an exhaustive literature search, have led to an extension of the synthetic dataset initially created by Ghanadian et al [26]. We found 5 more risk factors associated with suicidal ideation in the literature. We prompted GPT-3.5 Turbo to generate both suicidal and nonsuicidal instances to add to the existing dataset. This dataset is binary, categorized into suicidal and nonsuicidal classes, with annotations independently provided by 2 expert human annotators. A notable 90% of the labels, initially generated by GPT-3.5, were agreed upon by the human annotators. However, for the remaining 10% of the data, the labels were altered based on the decision of the annotators. In cases where both annotators agreed on a label, that label was retained. Conversely, when disagreements arose, the annotators engaged in discussions to ultimately reach a consensus on the appropriate label.

Augmented Dataset

Data augmentation involves enriching a dataset by introducing variations to its existing instances or generating entirely new instances. This process is designed to enhance the diversity and quality of the dataset, which, in turn, can lead to improved model performance and generalization. Ghanadian et al [26] reported that when synthetic data were augmented with 30% of the UMD training set, the fine-tuned model outperformed the model trained with the full UMD. This ratio represents the minimum amount of augmentation required for the ALBERT model to surpass the performance results of the model trained solely on the UMD. Hence, we augmented 30% of the synthetic dataset with the UMD to achieve a balance between diversity and quality in the training dataset.

The augmented dataset was used to fine-tune the pretrained state-of-the-art models and then was evaluated on 2 separate testing sets. The first testing set was 20% of the UMD before any training. The second testing set was generated and annotated by Ghanadian et al [26]. They used several synthetic datasets to create the testing set for their evaluation.

Ethical Considerations

This study involved the analysis of suicidal posts from social media, which is a sensitive and ethically complex task. We obtained ethics approval for the secondary use of data from the Research Ethics Board at the University of Ottawa (approval number: H-02-23-8967). This approval confirms that our research complies with the ethical guidelines for working with human-derived data and protects the identity of individuals whose posts are analyzed. The data used in this study are from the UMD, which was accessed with authorization from its creators. This dataset was approved by the University of

Maryland's Institutional Review Board. The dataset consists of publicly available social media posts collected from Reddit, where users are anonymous by default. To further protect user privacy, Reddit usernames in the dataset have been replaced with numeric identifiers [102]. Since this study involves the secondary analysis of publicly available and anonymized social media data, informed consent from individual users was not required.

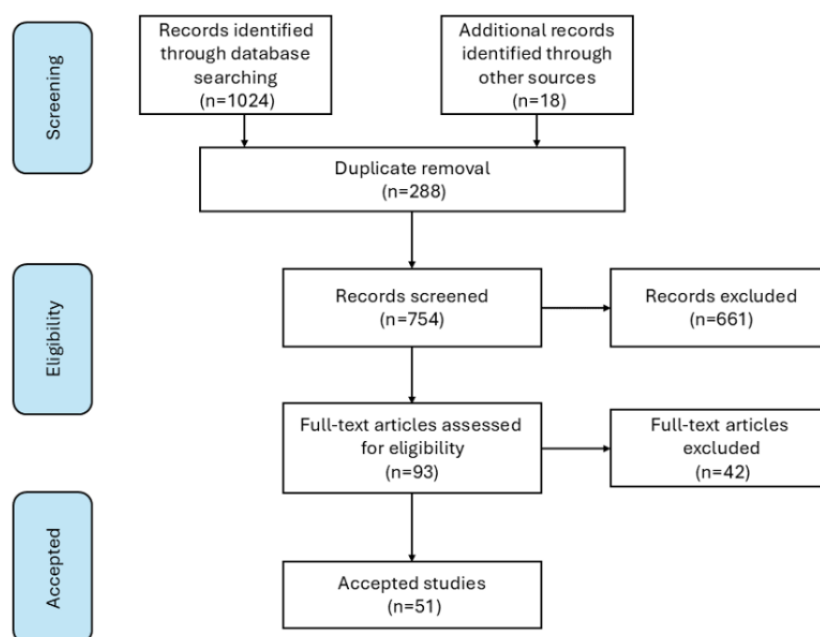
Results

Overview

We present the results according to this project's main research questions. First, we present the discovered topics in 3 real

datasets collected from social media, including the UMD, Knowledge Aware Assessment dataset, and 2021 Reddit dataset uncovered by unsupervised BERTopic. Second, we present the results of a scoping review and the reference table for each risk factor. Figure 3 presents the details of our scoping review process. Third, we present the results of topic discovery using guided BERTopic and a comparison between unsupervised and guided BERTopic. Finally, we provide an insightful breakdown, demonstrating the distribution of each topic within our synthetic dataset and the augmented dataset.

Figure 3. Scoping review workflow for extracting suicide risk factors from psychology literature.



To delve deeper into our investigation, we report the performance of the fine-tuned model on these synthetic and augmented datasets, offering a comprehensive comparison between the topic-diverse synthetic dataset and real dataset.

Unsupervised Topic Modeling

In this section, we assess the topic diversity in all datasets using basic BERTopic. Table 2 reports the most occurring topics and keywords in the selected datasets using basic BERTopic. Some

topics are common across all 3 datasets, while others are not discussed. For example, the topic of *education pressure* is discussed in the UMD and 2021 SuicideWatch datasets but is not found in the Knowledge Aware Assessment dataset. The output of topic modeling consisted of clusters of keywords, each associated with a probability of their relevance to the cluster. The title of each topic was chosen based on the highest probability keywords within the cluster.

Table 2. Distribution of suicide-related psychological and social risk factors identified through unsupervised BERTopic modeling in Reddit datasets.

Topics and risk factors extracted from psychology	Dataset		
	UMD ^a (SW ^b subreddit) (n=490), n	Knowledge Aware Assessment dataset (n=500), n	2021 SW dataset (n=2050), n
Mental health disorders			
Depression	98	78	756
Anxiety	45	73	244
PTSD ^c	0	0	4
Sociodemographic status			
Unemployment	18	5	0
Financial crisis	0	21	0
Education pressure	15	0	28
Abuse			
Being bullied	5	0	6
Family domain			
Family issues	50	14	34
Relationship problems	17	21	30
Personality and psychological traits			
Hopelessness	9	0	8
Racism	0	0	17
Substance abuse	4	0	0
Chronic physical problems	0	1	3

^aUMD: University of Maryland Reddit Suicidality Dataset.

^bSW: SuicideWatch.

^cPTSD: posttraumatic stress disorder.

Scoping Review Knowledge Extraction

In our scoping review of psychology literature, we initially identified 1042 articles related to suicide. After applying the inclusion and exclusion criteria outlined in Figure 3, a total of 51 studies were retained for analysis. Table 3 provides a list of references we investigated to extract underlying risk factors of

suicidal ideation. This table organizes all the studies reporting the identified risk factors. Some of these risk factors fall under broader categories, allowing for a more structured understanding. In the Social and Psychological Knowledge Extraction section, we have provided a description of each extracted risk factor and how it plays a role in suicidal ideation.

Table 3. List of risk factors for suicidal ideation extracted through a scoping review of 51 psychology and mental health studies.

Category	Studies
Mental health disorders	
Depression	[12,41-43,103-111]
Anxiety	[44,106-108,110,112-114]
Bipolar	[12,17,103,109-111]
Schizophrenia	[12,103,105,107,109,110,113]
Borderline	[12,106,110,115,116]
PTSD ^a	[45,46,107]
Sociodemographic status	
Unemployment	[12,55,107-109]
Education pressure	[61,62,109,111]
Financial crisis	[44,60,107,108,111,114]
Sexual minority stigma	[63-67,107,111]
Abuse	
Being bullied	[44,68-70]
Sexual abuse	[107,109,111,117,118]
Family domain	
Death of loved ones	[74,108,109]
Family conflicts	[43,55,110]
Relationship problems	[55,109,110]
Personality and psychological traits	
Hopelessness	[12,41,42,55,108,119]
Anger	[41,54,107,108]
Perfectionism	[41,107,109]
Chronic physical pain	[83-85]
Dementia	[80-82]
Racism	[75-77]
Immigration	[12,78,79,109,111]
Substance abuse	[56-59,110,111,114]

^aPTSD: posttraumatic stress disorder.

Guided Topic Modeling

In unsupervised topic modeling, we investigated the underlying topics within each social media dataset. A comparison between the extracted topics in the Unsupervised Topic Modeling and Scoping Review Knowledge Extraction sections revealed that many topics reported in psychology literature were not discovered in social media using unsupervised BERTopic. The absence of these topics was evident only when compared to the risk factors in psychology literature, and without this comparison, these important gaps in the discussion might have been overlooked.

To address this, we employed guided topic modeling, which focuses on specific risk factors of interest. This approach ensures that important but less frequently mentioned topics are identified and included in the analysis. Hence, the topics from psychology were used as seed topics for the discovery of the topics in these datasets. Table 4 presents the list of seed words used in guided topic modeling to extract topics from the UMD. We conducted seed topic extractions separately for each of the 3 social media datasets. It is important to note that this list of words does not need to be exhaustive and only serves as a hint about the topic for the topic modeling algorithm.

Table 4. List of manually curated seed words representing 23 risk factor categories used to guide topic modeling of suicide-related Reddit posts, grounded in terms extracted from psychology studies and verified using the Merriam-Webster Dictionary.

Category	Seed words
Depression	Depressed, sadness, and mentally ill
Anxiety	Anxious, phobia, and stress
Schizophrenia	Delusion
Bipolar	Manic and temperamental
Borderline	Petulant and impulsive
PTSD ^a	War, memory, and accident
Sexual abuse	Assault and rape
Being bullied	Bullying, oppress, and alone
Family issues	Family, parents, mom, and dad
Relationship problems	Wife, husband, partner, girlfriend, and boyfriend
Death of loved ones	Loss, grief, and mourn
Anger	Outrage and annoyed
Perfectionism	Perfection and expectations
Hopelessness	Despair
Unemployment	Job, work, and poverty
Financial crisis	Money and income
Education pressure	College, school, and overwhelmed
Sexual minority stigma	LGBTQ+ ^b and identity
Racism	Discrimination, justice, bias, and hate
Substance abuse	Alcohol, drug, and opioid
Chronic physical pain	Constant, hurt, and escape
Immigration	Moving, loneliness, and culture
Dementia	Alzheimer

^aPTSD: posttraumatic stress disorder.

^bLGBTQ+: lesbian, gay, bisexual, transgender, queer.

Real Dataset Topic Verification

Here, we aim to understand the distribution of topics in real data using guided topic modeling. Three real datasets collected from social media were investigated for suicide-related risk factors and topics. Table 5 presents the suicide topics in each real dataset along with the number of posts for each topic. Since we were interested in the distribution of these topics in relation to suicidal thoughts in labeled datasets (UMD and Knowledge Aware suicidality), we only considered the suicidal classes for

topic modeling and evaluation. The results in Table 5 show that while social media provides a vast and dynamic platform for individuals to express their thoughts and experiences, it may not always comprehensively reflect the nuanced and scientifically established suicide-related topics discussed in academic psychology literature. The conversational nature of social media often includes a wide range of personal narratives, opinions, and language that may or may not align with the structured and research-driven topics found in psychology literature.

Table 5. Distribution of suicidal risk factors extracted using guided BERTopic in real datasets.

Topics and risk factors extracted from psychology	Dataset		
	UMD ^a (SW ^b subreddit) (n=490), n	Knowledge Aware Assessment dataset (n=500), n	2021 SW dataset (n=2050), n
Mental health disorders			
Depression	115	79	806
Anxiety	52	80	297
Bipolar	5	2	2
Schizophrenia	0	0	0
Borderline	0	2	0
PTSD ^c	5	0	4
Sociodemographic status			
Unemployment	30	25	0
Financial crisis	0	30	0
Education pressure	30	0	33
Sexual minority stigma	0	0	0
Abuse			
Being bullied	8	0	13
Sexual abuse	2	0	7
Family domain			
Death of loved ones	0	0	0
Family issues	55	14	55
Relationship problems	25	26	38
Personality and psychological traits			
Anger	0	0	0
Perfectionism	0	0	0
Hopelessness	9	0	17
Racism	0	0	36
Substance abuse	7	0	0
Immigration	0	0	0
Chronic physical problems	0	2	3
Dementia	0	0	0

^aUMD: University of Maryland Reddit Suicidality Dataset.

^bSW: SuicideWatch.

^cPTSD: posttraumatic stress disorder.

Although social media can offer valuable insights into real-world expressions of mental health concerns, researchers need to carefully interpret and validate social media data to ensure their reliability and relevance to the broader body of psychology literature on suicide. Underrepresentation of certain topics in social media data, specifically stigmatized topics, such as conversations around sexual minorities and racism, can lead to models that underperform in cases where users break the stigma and talk about these issues.

Topic Verification on Synthetic and Augmented Datasets

We employed guided topic modeling to verify if this method reveals the suicide topics and risk factors in the synthetic and augmented datasets. Note that these topics were used to generate the synthetic data. However, the number of topics discovered by the guided topic modeling did not sum up to the total number of posts, which was 908 for the synthetic dataset and 1055 for the augmented dataset. This discrepancy arose because some posts were associated with multiple topics and represented more than one risk factor. Table 6 displays the suicide topics within each synthetic and augmented dataset, along with the respective

number of posts for each topic. We observed that topic modeling showed a relatively equal distribution of topics in the synthetic dataset. Table 6 illustrates how effectively guided BERTopic extracted the topics within the documents. Furthermore, these

results demonstrate the significance of the generation of topic-diverse synthetic and augmented datasets for various research and applications within the domain of suicide-related studies.

Table 6. Topic coverage in synthetic and augmented suicidal ideation datasets using guided BERTopic.

Topics and risk factors extracted from psychology	Dataset	
	Synthetic dataset (n=908), n	Augmented dataset (n=1055), n
Mental health disorders		
Depression	62	173
Anxiety	46	68
Bipolar	19	20
Schizophrenia	23	23
Borderline	23	23
PTSD ^a	22	21
Sociodemographic status		
Unemployment	20	35
Financial crisis	21	39
Education pressure	21	20
Sexual minority stigma	41	42
Abuse		
Being bullied	39	39
Sexual abuse	18	20
Family domain		
Death of loved ones	40	41
Family issues	19	20
Relationship problems	40	43
Personality and psychological traits		
Anger	39	38
Perfectionism	48	48
Hopelessness	36	44
Racism	39	39
Immigration	20	18
Substance abuse	40	46
Chronic physical problems	56	61
Dementia	39	48

^aPTSD: posttraumatic stress disorder.

Dataset Analysis and Evaluation

In this subsection, we first analyze the quality of each dataset based on 3 indicators introduced in the Dataset Analysis section. The comparison between synthetic and nonsynthetic datasets (UMD, Knowledge Aware, and 2021 Reddit) presented in Table 7 reveals distinct patterns in terms of complexity, readability, and Shannon entropy. The synthetic dataset and augmented dataset exhibited relatively high complexity values of 72.77 and 70.27, respectively, which were comparable to that of the

2021 Reddit dataset (72.87) but surpassed those of the UMD and Knowledge Aware dataset, indicating that synthetic data are linguistically or structurally more complex. In terms of content diversity, measured by Shannon entropy, all datasets showed similar means, but the synthetic dataset was significantly more uniform, with very low deviation ($\sigma=0.05$), compared to the nonsynthetic datasets. Based on the results presented in Table 7, synthetic datasets tend to be more complex and are more controlled and consistent, whereas nonsynthetic datasets provide a broader range of readability and content diversity.

Table 7. Linguistic characteristics of real, synthetic, and augmented datasets for suicidal ideation detection.

Dataset	Complexity (type-token ratio)		Readability (Flesch score)		Shannon entropy	
	μ	σ	μ	σ	μ	σ
UMD ^a	61.18	16.15	82.49	10.87	4.31	0.17
Knowledge Aware dataset	49.04	19.53	82.51	15.27	4.17	0.75
2021 Reddit dataset	72.87	20.13	75.76	48.02	4.27	0.30
Synthetic dataset	72.69	18.40	75.80	10.34	4.27	0.05
Augmented dataset	70.26	17.18	77.38	10.80	4.28	0.05

^aUMD: University of Maryland Reddit Suicidality Dataset.

Moreover, [Table 8](#) indicates that the readability of the synthetic and augmented datasets was more challenging than that of the real datasets. Specifically, 36% of the synthetic dataset fell into the “easy” and “very easy” categories, while 67% of the UMD fell into these categories. In contrast, 33% of the UMD and 64% of the synthetic dataset fell into the “fairly easy,” “standard,” “fairly difficult,” and “difficult” categories. Furthermore, we

conducted a statistical *t* test with a significance level of .05 on the readability, complexity, and entropy metrics, comparing the synthetic dataset with each of the real datasets. Our findings indicated a significant difference in Shannon entropy between the synthetic and real datasets. However, no significant differences were observed in terms of readability and complexity between the real and synthetic datasets.

Table 8. Distribution of Flesch reading ease scores across all datasets.

Flesch reading ease interval	UMD ^a , n	Knowledge Aware dataset, n	2021 Reddit dataset, n	Synthetic dataset, n	Augmented dataset, n
Very confusing	2	0	10	0	0
Difficult	1	3	30	0	5
Fairly difficult	5	5	50	50	50
Standard	30	25	200	130	140
Fairly easy	100	140	400	270	300
Easy	200	240	600	170	270
Very easy	100	50	350	80	120

^aUMD: University of Maryland Reddit Suicidality Dataset.

Additionally, we created a binary classifier for detecting suicidal ideation using different datasets. For that, we fine-tuned ALBERT [120], a transformer-based model optimized for performance and speed, using the UMD and our synthetic and augmented datasets, to evaluate the effect of topics and risk factor inclusion on the performance of a pretrained model. To fine-tune these models, we used the Huggingface library [121]. The Huggingface library is an open-source library and data science platform that provides tools to build, train, and deploy machine learning models. We compared our classification results with a baseline ALBERT model fine-tuned on the UMD by Ghanadian et al [10]. We used the Trainer [122] class from Huggingface transformers for feature-complete training in PyTorch. The hyperparameters were selected based on the default values commonly used in similar studies. The final hyperparameters used in our experiments were as follows:

learning rate, $2e^{-5}$; batch size, 4; dropout rate, 0.1; and maximum sequence length, 512.

[Table 9](#) presents the performance results of fine-tuning the ALBERT model using the synthetic and augmented training datasets. The model fine-tuned on the augmented dataset outperformed the other 2 models, achieving F_1 -scores of 0.91 and 0.90 on the UMD and synthetic testing subsets, respectively. Achieving a high F_1 -score is important when evaluating classifiers, especially with imbalanced datasets. A high F_1 -score indicates that the model is both precise and effective at identifying at-risk cases. This is critical in sensitive domains like mental health, where failing to detect or incorrectly identifying individuals at risk can have serious real-world consequences.

Table 9. Performance metrics of suicidal ideation classifiers trained on real, synthetic, and augmented data.

Test set metrics	Nonsynthetic	Synthetic	
	UMD ^a dataset	ChatGPT dataset	Augmented dataset
UMD test subset			
Accuracy	0.87	0.72	0.88
F_1 -score	0.87	0.81	0.91
Synthetic test subset			
Accuracy	0.67	0.87	0.90
F_1 -score	0.70	0.86	0.90

^aUMD: University of Maryland Reddit Suicidality Dataset.

Discussion

This study investigated whether social media data adequately capture empirically established risk factors associated with suicidal ideation and whether synthetic data augmentation can improve the representation of underrepresented risk factors in suicide detection models. Our findings reveal that real-world social media datasets lack coverage of several critical risk factors, particularly those related to marginalized communities, financial crises, racism, and chronic health conditions. By incorporating insights from psychology literature and leveraging guided topic modeling, we identified these gaps and generated synthetic data to enhance topic diversity. Our results demonstrate that augmenting real-world datasets with topic-diverse synthetic data improves the performance of machine learning models in detecting suicidal ideation, as evidenced by an increase in the F_1 -score from 0.87 to 0.91 on the UMD test subset and from 0.70 to 0.90 on the synthetic test subset. These findings support our hypothesis that social media data alone do not fully represent the nuances of suicide risk factors and that synthetic data augmentation can lead to more accurate and fair suicidal ideation detection models.

Traditional data collection methods, specifically self-reports, are subject to various kinds of biases, including social desirability, recall, and self-perception biases. While the use of naturalistic data collected from social media mitigates some of the self-report biases and incorporates contextual information, it, unfortunately, introduces other types of biases, mainly selection bias, platform-induced behavior, and public image curation bias. Many demographics are underrepresented on social media, and even if present, they might shy away from expressing their real self. On the other hand, traditional methods are more controlled, and as we have shown in our literature review, larger numbers of topics and demographics have been covered under those studies. For that reason, we compared the social media datasets to risk factors collected in traditional studies to identify underrepresented risk factors.

This study assessed real-world datasets from social media for their coverage of suicidal ideation topics and risk factors. Additionally, it reviewed psychology literature to identify expert-validated risk factors, suicidal language, and terminology. Integrating this knowledge into NLP models can enhance their contextual awareness in identifying and understanding suicidal

ideation in social media posts. Leveraging insights from psychology also supports the development of ethically responsible artificial intelligence systems for addressing sensitive mental health issues.

Unsupervised topic modeling and a scoping review of psychology literature provided 2 sets of suicide topics and risk factors. Table 2 summarizes 13 suicide topics identified across 3 social media datasets, while Table 3 lists 23 risk factors extracted from the literature review. These findings offer valuable insights into the context of suicidal ideation. However, the comparison reveals a significant limitation in social media datasets, which is the absence of critical topics essential for addressing suicidal ideation. This gap could create a barrier to the development of robust NLP models for analyzing suicide-related content.

To address the limitations of unsupervised topic modeling, given the risk factors discovered in our scoping review, we performed guided topic modeling on 3 social media datasets (Table 5) for providing a more comprehensive overview of the suicide topics and risk factors present in the data. The results indicate that certain topics missed during unsupervised topic modeling were identified through guided topic modeling. This issue arises when less frequently discussed topics are overshadowed by more dominant ones, causing them to be overlooked by unsupervised methods. In contrast, guided topic modeling can specifically target and extract these less prominent yet critical topics.

Furthermore, we observed that there was a discrepancy in the distribution of topic representations across the datasets. As an example, let us consider the UMD in Table 5, where the topic “anxiety” appears 10.4 times more than the topic “PTSD.” Such disparities in topic representations could lead to an inherent bias within the models. Biases can occur when certain topics are overrepresented or underrepresented. These biases will potentially impact the effectiveness and fairness of NLP models, as they may disproportionately emphasize or neglect certain aspects of suicidal ideation. Therefore, addressing these data limitations and imbalances is crucial to ensure the development of NLP models that provide accurate and equitable insights into this critical issue.

Moreover, we observed that suicidal narratives related to dementia, sexual minority stigmas, immigration, death of loved ones, perfectionism, and anger were never discussed in these

datasets, and topics of being bullied, PTSD, substance abuse, and chronic physical problems were rarely mentioned. Financial crises and racism, which are 2 common and important risk factors of suicide, were only discussed in 1 of the datasets, with a relatively low number of examples. The most represented topics in these datasets were depression and anxiety. This observation is not surprising since many other risk factors lead to mental pressure. In social media conversations, users mostly talk about depression and anxiety, which are surface-level symptoms of what they are experiencing and not the root causes that led to these feelings.

In this study, we harnessed the innovative approach of synthetic dataset creation as a means to enhance the fairness and accuracy of NLP models in the context of detecting suicidal ideation. Using the extracted risk factors from psychology, we constructed a synthetic dataset that comprehensively represents the entire spectrum of risk factors associated with suicidal ideation. To leverage the strengths of both real and synthetic data, we augmented 30% of the UMD by incorporating our synthetic dataset. Table 6 reports the distribution of psychological topics within our synthetic and augmented datasets. We applied guided topic modeling on the synthetic and augmented datasets primarily as a sanity check to show that guided topic modeling performs as expected and, therefore, to analyze the content of datasets according to expected topics. In other words, our goal was to verify whether all relevant topics and risk factors were included in the dataset and could be identified by a cluster- and transformer-based model.

Understanding complexity and readability in synthetic datasets helps in ensuring that the generated text aligns with linguistic patterns observed in real-world data. Moreover, these parameters facilitate an assessment of the synthetic dataset, specifically regarding the incorporation of suitable language complexities. This evaluation allows us to examine whether synthetic data replicates language patterns akin to those found in genuine, human-generated content.

Shannon entropy serves as a quantitative measure of diversity, reflecting the range of vocabulary in a dataset. Our study's finding of a lower Shannon entropy in synthetic datasets despite higher complexity prompts a nuanced discussion. This discrepancy indicates that, despite intricate language patterns, synthetic datasets might lack the diverse lexical richness found in real datasets. Thus, the relationship between diversity and Shannon entropy suggests that achieving linguistic complexity does not guarantee a broad vocabulary range. Hence, augmenting a real dataset with synthetic data can leverage the advantages of both datasets, incorporating the linguistic complexity characteristic of synthetic datasets and the broad range of diversity inherent in real datasets. Moreover, the relationship between diversity and complexity in datasets reveals a fascinating interplay. While complexity often indicates intricate language structures, the presence of a diverse range of expressions and ideas enhances the overall diversity of the dataset. However, as seen in Table 7, a higher complexity in synthetic datasets does not necessarily translate to a higher diversity, as reflected by a lower Shannon entropy. This suggests that complexity might be influenced more by the intricacy of language patterns than by a broad lexical spectrum.

In order to guarantee the quality of the augmented and synthetic datasets, we fine-tuned the ALBERT model, as a binary classifier, using the aforementioned datasets. Following this fine-tuning, we proceeded to rigorously evaluate the model's performance on 2 distinct testing subsets. As depicted in Table 9, the results underscore an interesting trend. The model fine-tuned on the UMD exhibited a higher performance when evaluated on an in-domain testing subset but showed a lower performance when tested on an out-of-domain testing subset. A similar pattern emerged when the model was fine-tuned on the ChatGPT synthetic dataset. However, an intriguing twist arose with the augmented dataset. This dataset notably enhanced the model's performance across both the in-domain and out-of-domain testing subsets. This observation implies that the synergistic inclusion of both real-world and synthetically generated data can yield a more diverse NLP model. This research insight illuminates the potential advantages of a hybrid approach, emphasizing the importance of leveraging the complementary strengths of both real and synthetic datasets to improve the overall performance and adaptability of NLP models in the critical domain of suicidal ideation detection.

Our study has some limitations that should be acknowledged. First, high-quality annotated datasets collected from social media are scarce, so this work exclusively used the Reddit dataset. While valuable information on this topic is shared on other social media platforms, such as X and Facebook, to the best of our knowledge, there is no publicly available large annotated dataset that includes such data. Creating new datasets involves both data collection and a careful annotation process performed by multiple experts, making it an expensive undertaking. Second, due to the limitation of data availability and the fact that the classifier was trained solely on Reddit data, it may not perform as effectively on datasets from other social media platforms. Future work should incorporate data from platforms like X to provide broader insights and improve generalizability.

This study highlights the value of integrating domain knowledge from psychology with computational techniques to improve suicidal ideation detection in social media. By examining 3 real-world datasets, we observed that several well-established risk factors, such as chronic illness, racism, immigration stress, and identity-based stigma, were either absent or rarely discussed. To address these topic gaps, we applied guided topic modeling informed by psychology literature and constructed a synthetic dataset with broader thematic representation. Our evaluations showed that this synthetic data, when combined with real data, enhanced topic diversity and preserved linguistic quality. The classifier fine-tuned on the augmented dataset significantly outperformed models trained solely on real or synthetic data, improving the F_1 -score to 0.91 on the UMD and 0.90 on the synthetic test set. These results suggest that synthetic augmentation not only fills in content gaps but also leads to more effective and inclusive detection models.

The findings of this study underscore the importance of integrating psychological insights into NLP models to improve the detection of suicidal ideation on social media. By addressing gaps in topic coverage and leveraging synthetic data augmentation, this work contributes to the development of more

robust and ethical artificial intelligence tools for mental health applications. Future research should continue refining these approaches by expanding dataset sources and enhancing model

interpretability to ensure that technology is both effective and fair in handling sensitive mental health issues.

Acknowledgments

This research was conducted with the support of the University of Ottawa and the Natural Sciences and Engineering Research Council of Canada through the Discovery Grant program. We sincerely thank the anonymous reviewers for their insightful feedback, which helped improve the quality of this work. We also extend our gratitude to the creators of the University of Maryland Reddit Suicidality Dataset for providing access to the data, as well as to the researchers whose contributions to suicide risk assessment have informed and enriched our study.

Data Availability

The generated synthetic dataset and the code used in this study are publicly available on our GitHub repository [123]. The other datasets used in this research, including the University of Maryland Reddit Suicidality Dataset (UMD), are not publicly available and require permission from the creators of the dataset for access. More information on obtaining the UMD can be found on the UMD website [102]. Researchers interested in accessing the UMD should contact the dataset creators directly for permission and further instructions. By making these resources accessible, we aim to promote transparency, reproducibility, and further research on suicidal ideation detection.

Conflicts of Interest

None declared.

Multimedia Appendix 1

PRISMA-ScR (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) checklist.

[PDF File (Adobe PDF File), 77 KB-Multimedia Appendix 1]

References

1. Suicide. World Health Organization. URL: <https://www.who.int/news-room/fact-sheets/detail/suicide> [accessed 2025-05-19]
2. O'Connor RC, Nock MK. The psychology of suicidal behaviour. *The Lancet Psychiatry*. Jun 2014;1(1):73-85. [doi: [10.1016/s2215-0366\(14\)70222-6](https://doi.org/10.1016/s2215-0366(14)70222-6)]
3. Ghosal S, Jain A. Depression and suicide risk detection on social media using fastText embedding and XGBoost classifier. *Procedia Computer Sci*. 2023;218:1631-1639. [doi: [10.1016/j.procs.2023.01.141](https://doi.org/10.1016/j.procs.2023.01.141)]
4. Sawhney R, Joshi H, Gandhi S, Shah RR. Towards ordinal suicide ideation detection on social media. In: *Proceedings of the 14th ACM International Conference on Web Search and Data Mining*. 2021. Presented at: WSDM '21; March 8-12, 2021; Virtual Event, Israel. [doi: [10.1145/3437963.3441805](https://doi.org/10.1145/3437963.3441805)]
5. Fernandes AC, Dutta R, Velupillai S, Sanyal J, Stewart R, Chandran D. Identifying suicide ideation and suicidal attempts in a psychiatric clinical research database using natural language processing. *Sci Rep*. May 09, 2018;8(1):7426. [doi: [10.1038/s41598-018-25773-2](https://doi.org/10.1038/s41598-018-25773-2)] [Medline: [29743531](https://pubmed.ncbi.nlm.nih.gov/29743531/)]
6. Bejan CA, Ripperger M, Wilimitis D, Ahmed R, Kang J, Robinson K, et al. Improving ascertainment of suicidal ideation and suicide attempt with natural language processing. *Sci Rep*. Sep 07, 2022;12(1):15146. [doi: [10.1038/s41598-022-19358-3](https://doi.org/10.1038/s41598-022-19358-3)] [Medline: [36071081](https://pubmed.ncbi.nlm.nih.gov/36071081/)]
7. Buddhitha P, Inkpen D. Multi-task learning to detect suicide ideation and mental disorders among social media users. *Front Res Metr Anal*. Apr 17, 2023;8:1152535. [FREE Full text] [doi: [10.3389/frma.2023.1152535](https://doi.org/10.3389/frma.2023.1152535)] [Medline: [37138946](https://pubmed.ncbi.nlm.nih.gov/37138946/)]
8. Boonyarat P, Liew DJ, Chang Y. Leveraging enhanced BERT models for detecting suicidal ideation in Thai social media content amidst COVID-19. *Information Processing & Management*. Jul 2024;61(4):103706. [doi: [10.1016/j.ipm.2024.103706](https://doi.org/10.1016/j.ipm.2024.103706)]
9. Singh LG, Mao J, Mutalik R, Middleton SE. Extracting and Summarizing Evidence of Suicidal Ideation in Social Media Contents Using Large Language Models. In: *Proceedings of the 9th Workshop on Computational Linguistics and Clinical Psychology*. 2024. Presented at: CLPsych 2024; March 2024; St. Julians, Malta.
10. Ghanadian H, Nejadgholi I, Al Osman H. ChatGPT for suicide risk assessment on social media: quantitative evaluation of model performance, potentials and limitations. *arXiv*. Preprint posted online on June 15, 2023. [FREE Full text] [doi: [10.18653/v1/2023.wassa-1.16](https://doi.org/10.18653/v1/2023.wassa-1.16)]
11. Skaik R, Inkpen D. Suicide ideation estimators within Canadian provinces using machine learning tools on social media text. *J Adv Inf Technol*. 2021;12(4):357-362. [doi: [10.12720/jait.12.4.357-362](https://doi.org/10.12720/jait.12.4.357-362)]
12. Franklin JC, Ribeiro JD, Fox KR, Bentley KH, Kleiman EM, Huang X, et al. Risk factors for suicidal thoughts and behaviors: a meta-analysis of 50 years of research. *Psychol Bull*. Feb 2017;143(2):187-232. [doi: [10.1037/bul0000084](https://doi.org/10.1037/bul0000084)] [Medline: [27841450](https://pubmed.ncbi.nlm.nih.gov/27841450/)]

13. Bentley KH, Franklin JC, Ribeiro JD, Kleiman EM, Fox KR, Nock MK. Anxiety and its disorders as risk factors for suicidal thoughts and behaviors: a meta-analytic review. *Clin Psychol Rev*. Feb 2016;43:30-46. [FREE Full text] [doi: [10.1016/j.cpr.2015.11.008](https://doi.org/10.1016/j.cpr.2015.11.008)] [Medline: [26688478](https://pubmed.ncbi.nlm.nih.gov/26688478/)]
14. Bayliss LT, Christensen S, Lamont-Mills A, du Plessis C. Suicide capability within the ideation-to-action framework: a systematic scoping review. *PLoS One*. 2022;17(10):e0276070. [FREE Full text] [doi: [10.1371/journal.pone.0276070](https://doi.org/10.1371/journal.pone.0276070)] [Medline: [36301944](https://pubmed.ncbi.nlm.nih.gov/36301944/)]
15. Orsolini L, Latini R, Pompili M, Serafini G, Volpe U, Vellante F, et al. Understanding the complex of suicide in depression: from research to clinics. *Psychiatry Investig*. Mar 2020;17(3):207-221. [FREE Full text] [doi: [10.30773/pi.2019.0171](https://doi.org/10.30773/pi.2019.0171)] [Medline: [32209966](https://pubmed.ncbi.nlm.nih.gov/32209966/)]
16. Kalin NH. Insights into suicide and depression. *Am J Psychiatry*. Oct 01, 2020;177(10):877-880. [doi: [10.1176/appi.ajp.2020.20081207](https://doi.org/10.1176/appi.ajp.2020.20081207)] [Medline: [32998546](https://pubmed.ncbi.nlm.nih.gov/32998546/)]
17. Costa LDS, Alencar AP, Nascimento Neto PJ, dos Santos M, da Silva CGL, Pinheiro SDFL, et al. Risk factors for suicide in bipolar disorder: a systematic review. *J Affect Disord*. Jan 01, 2015;170:237-254. [doi: [10.1016/j.jad.2014.09.003](https://doi.org/10.1016/j.jad.2014.09.003)] [Medline: [25261630](https://pubmed.ncbi.nlm.nih.gov/25261630/)]
18. Paris J. Suicidality in borderline personality disorder. *Medicina (Kaunas)*. May 28, 2019;55(6):223. [FREE Full text] [doi: [10.3390/medicina55060223](https://doi.org/10.3390/medicina55060223)] [Medline: [31142033](https://pubmed.ncbi.nlm.nih.gov/31142033/)]
19. Lee KH, Jun JS, Kim YJ, Roh S, Moon SS, Bukonda N, et al. Mental health, substance abuse, and suicide among homeless adults. *J Evid Inf Soc Work*. Jul 05, 2017;14(4):229-242. [doi: [10.1080/23761407.2017.1316221](https://doi.org/10.1080/23761407.2017.1316221)] [Medline: [28678621](https://pubmed.ncbi.nlm.nih.gov/28678621/)]
20. Homan S, Gabi M, Klee N, Bachmann S, Moser A, Duri' M, et al. Linguistic features of suicidal thoughts and behaviors: a systematic review. *Clin Psychol Rev*. Jul 2022;95:102161. [FREE Full text] [doi: [10.1016/j.cpr.2022.102161](https://doi.org/10.1016/j.cpr.2022.102161)] [Medline: [35636131](https://pubmed.ncbi.nlm.nih.gov/35636131/)]
21. Arensman E, Larkin C, McCarthy J, Leitao S, Corcoran P, Williamson E, et al. Psychosocial, psychiatric and work-related risk factors associated with suicide in Ireland: optimised methodological approach of a case-control psychological autopsy study. *BMC Psychiatry*. Sep 06, 2019;19(1):275. [FREE Full text] [doi: [10.1186/s12888-019-2249-6](https://doi.org/10.1186/s12888-019-2249-6)] [Medline: [31492119](https://pubmed.ncbi.nlm.nih.gov/31492119/)]
22. Brockie T, Kahn-John M, Mata Lopez L, Bell E, Brockie T, Brockie T, et al. A mixed-methods study protocol on factors contributing to suicide clusters among Native American youth in a northern plains reservation. *Front Public Health*. Jan 8, 2023;11:1281109. [FREE Full text] [doi: [10.3389/fpubh.2023.1281109](https://doi.org/10.3389/fpubh.2023.1281109)] [Medline: [38259800](https://pubmed.ncbi.nlm.nih.gov/38259800/)]
23. Grattidge L, Hoang H, Mond J, Lees D, Visentin D, Auckland S. Exploring community-based suicide prevention in the context of rural Australia: a qualitative study. *Int J Environ Res Public Health*. Feb 01, 2023;20(3):2644. [FREE Full text] [doi: [10.3390/ijerph20032644](https://doi.org/10.3390/ijerph20032644)] [Medline: [36768008](https://pubmed.ncbi.nlm.nih.gov/36768008/)]
24. Liu L, Pollock NJ, Contreras G, Tonmyr L, Thompson W. Pandemic-related impacts and suicidal ideation among adults in Canada: a population-based cross-sectional study. *Health Promot Chronic Dis Prev Can*. Mar 15, 2023;43(3):105-118. [FREE Full text] [doi: [10.24095/hpcdp.43.3.01](https://doi.org/10.24095/hpcdp.43.3.01)] [Medline: [36630582](https://pubmed.ncbi.nlm.nih.gov/36630582/)]
25. Kumar M, Dredze M, Coppersmith G, De Choudhury M. Detecting Changes in Suicide Content Manifested in Social Media Following Celebrity Suicides. In: HT '15: Proceedings of the 26th ACM Conference on Hypertext & Social Media. 2015. Presented at: 26th ACM Conference on Hypertext & Social Media; September 1-4, 2015; Guzelyurt, Northern Cyprus. [doi: [10.1145/2700171.2791026](https://doi.org/10.1145/2700171.2791026)]
26. Ghanadian H, Nejadgholi I, Osman HA. Socially aware synthetic data generation for suicidal ideation detection using large language models. *IEEE Access*. 2024;12:14350-14363. [doi: [10.1109/access.2024.3358206](https://doi.org/10.1109/access.2024.3358206)]
27. Li Z, Zhu H, Lu Z, Yin M. Synthetic data generation with large language models for text classification: potential and limitations. *arXiv*. Preprint posted online on October 11, 2023. [FREE Full text] [doi: [10.18653/v1/2023.emnlp-main.647](https://doi.org/10.18653/v1/2023.emnlp-main.647)]
28. BERTopic. GitHub. URL: <https://maartengr.github.io/BERTopic/index.html> [accessed 2025-05-19]
29. Maarten G. BERTopic: neural topic modeling with a class-based TF-IDF procedure. *arXiv*. Preprint posted online on March 11, 2022. [FREE Full text]
30. Egger R, Yu J. A topic modeling comparison between LDA, NMF, Top2Vec, and BERTopic to demystify Twitter posts. *Front Sociol*. May 6, 2022;7:886498. [FREE Full text] [doi: [10.3389/fsoc.2022.886498](https://doi.org/10.3389/fsoc.2022.886498)] [Medline: [35602001](https://pubmed.ncbi.nlm.nih.gov/35602001/)]
31. Reimers N, Gurevych I. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In: Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 2019. Presented at: 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing; November 2019; Hong Kong, China. [doi: [10.18653/v1/d19-1410](https://doi.org/10.18653/v1/d19-1410)]
32. Pretrained Models. SBERT. URL: https://www.sbert.net/docs/sentence_transformer/pretrained_models.html [accessed 2025-05-19]
33. McInnes L, Healy J, Melville J. UMAP: Uniform Manifold Approximation and Projection for Dimension Reduction. *arXiv*. Preprint posted online on February 9, 2018. [FREE Full text]
34. Asyaky MS, Mandala R. Improving the Performance of HDBSCAN on Short Text Clustering by Using Word Embedding and UMAP. 2021. Presented at: 8th International Conference on Advanced Informatics: Concepts, Theory and Applications (ICAICTA); September 29-30, 2021; Bandung, Indonesia.

35. Oskolkov N. Dimensionality reduction. In: Egger R, editor. *Applied Data Science in Tourism*. Tourism on the Verge. Cham. Springer; 2022:151-167.
36. Campello RJGB, Moulavi D, Sander J. Density-based clustering based on hierarchical density estimates. In: Pei J, Tseng VS, Cao L, Motoda H, Xu G, editors. *Advances in Knowledge Discovery and Data Mining*. PAKDD 2013. Lecture Notes in Computer Science, vol 7819. Berlin, Heidelberg. Springer; 2013:160-172.
37. Munn Z, Peters MDJ, Stern C, Tufanaru C, McArthur A, Aromataris E. Systematic review or scoping review? Guidance for authors when choosing between a systematic or scoping review approach. *BMC Med Res Methodol*. Nov 19, 2018;18(1):143. [FREE Full text] [doi: [10.1186/s12874-018-0611-x](https://doi.org/10.1186/s12874-018-0611-x)] [Medline: [30453902](https://pubmed.ncbi.nlm.nih.gov/30453902/)]
38. Armstrong R, Hall BJ, Doyle J, Waters E. Cochrane Update. 'Scoping the scope' of a cochrane review. *J Public Health (Oxf)*. Mar 23, 2011;33(1):147-150. [doi: [10.1093/pubmed/fdr015](https://doi.org/10.1093/pubmed/fdr015)] [Medline: [21345890](https://pubmed.ncbi.nlm.nih.gov/21345890/)]
39. Arksey H, O'Malley L. Scoping studies: towards a methodological framework. *Int J Soc Res Methodology*. Feb 2005;8(1):19-32. [doi: [10.1080/1364557032000119616](https://doi.org/10.1080/1364557032000119616)]
40. Peters MDJ, Godfrey CM, Khalil H, McInerney P, Parker D, Soares CB. Guidance for conducting systematic scoping reviews. *Int J Evid Based Healthc*. Sep 2015;13(3):141-146. [doi: [10.1097/XEB.000000000000050](https://doi.org/10.1097/XEB.000000000000050)] [Medline: [26134548](https://pubmed.ncbi.nlm.nih.gov/26134548/)]
41. Boergers J, Spirito A, Donaldson D. Reasons for adolescent suicide attempts: associations with psychological functioning. *J Am Acad Child Adolesc Psychiatry*. Dec 1998;37(12):1287-1293. [doi: [10.1097/00004583-199812000-00012](https://doi.org/10.1097/00004583-199812000-00012)] [Medline: [9847501](https://pubmed.ncbi.nlm.nih.gov/9847501/)]
42. Klonsky ED, May AM, Saffer BY. Suicide, suicide attempts, and suicidal ideation. *Annu Rev Clin Psychol*. Mar 28, 2016;12(1):307-330. [doi: [10.1146/annurev-clinpsy-021815-093204](https://doi.org/10.1146/annurev-clinpsy-021815-093204)] [Medline: [26772209](https://pubmed.ncbi.nlm.nih.gov/26772209/)]
43. Vilhjalmsdottir R, Kristjansdottir G, Sveinbjarnardottir E. Factors associated with suicide ideation in adults. *Soc Psychiatry Psychiatr Epidemiol*. Mar 25, 1998;33(3):97-103. [doi: [10.1007/s001270050028](https://doi.org/10.1007/s001270050028)] [Medline: [9540383](https://pubmed.ncbi.nlm.nih.gov/9540383/)]
44. Lázaro-Pérez C, Munuera Gómez P, Martínez-López JA, Gómez-Galán J. Predictive factors of suicidal ideation in Spanish university students: a health, preventive, social, and cultural approach. *J Clin Med*. Feb 02, 2023;12(3):1207. [doi: [10.3390/jcm12031207](https://doi.org/10.3390/jcm12031207)] [Medline: [36769853](https://pubmed.ncbi.nlm.nih.gov/36769853/)]
45. Florez IA, Allbaugh LJ, Harris CE, Schwartz AC, Kaslow NJ. Suicidal ideation and hopelessness in PTSD: spiritual well-being mediates outcomes over time. *Anxiety Stress Coping*. Jan 28, 2018;31(1):46-58. [doi: [10.1080/10615806.2017.1369260](https://doi.org/10.1080/10615806.2017.1369260)] [Medline: [28846030](https://pubmed.ncbi.nlm.nih.gov/28846030/)]
46. Noor N, Pao C, Dragomir-Davis M, Tran J, Arbona C. PTSD symptoms and suicidal ideation in US female firefighters. *Occup Med (Lond)*. Dec 31, 2019;69(8-9):577-585. [doi: [10.1093/occmed/kqz057](https://doi.org/10.1093/occmed/kqz057)] [Medline: [31064010](https://pubmed.ncbi.nlm.nih.gov/31064010/)]
47. Goldstein TR, Ha W, Axelson DA, Goldstein BI, Liao F, Gill MK, et al. Predictors of prospectively examined suicide attempts among youth with bipolar disorder. *Arch Gen Psychiatry*. Nov 01, 2012;69(11):1113-1122. [FREE Full text] [doi: [10.1001/archgenpsychiatry.2012.650](https://doi.org/10.1001/archgenpsychiatry.2012.650)] [Medline: [22752079](https://pubmed.ncbi.nlm.nih.gov/22752079/)]
48. Goodwin FK, Jamison KR. *Manic-Depressive Illness: Bipolar Disorders and Recurrent Depression*. Oxford, England. Oxford University Press; 2007.
49. Schultz SH, North SW, Shields CG. Schizophrenia: a review. *Am Fam Physician*. Jun 15, 2007;75(12):1821-1829. [FREE Full text] [Medline: [17619525](https://pubmed.ncbi.nlm.nih.gov/17619525/)]
50. Hawton K, Sutton L, Haw C, Sinclair J, Deeks JJ. Schizophrenia and suicide: systematic review of risk factors. *Br J Psychiatry*. Jul 02, 2005;187(1):9-20. [doi: [10.1192/bjp.187.1.9](https://doi.org/10.1192/bjp.187.1.9)] [Medline: [15994566](https://pubmed.ncbi.nlm.nih.gov/15994566/)]
51. Sher L, Kahn RS. Suicide in schizophrenia: an educational overview. *Medicina (Kaunas)*. Jul 10, 2019;55(7):361. [FREE Full text] [doi: [10.3390/medicina55070361](https://doi.org/10.3390/medicina55070361)] [Medline: [31295938](https://pubmed.ncbi.nlm.nih.gov/31295938/)]
52. Paris J. Chronic suicidality among patients with borderline personality disorder. *Psychiatr Serv*. Jun 2002;53(6):738-742. [doi: [10.1176/appi.ps.53.6.738](https://doi.org/10.1176/appi.ps.53.6.738)] [Medline: [12045312](https://pubmed.ncbi.nlm.nih.gov/12045312/)]
53. Brodsky BS, Malone KM, Ellis SP, Dulit RA, Mann JJ. Characteristics of borderline personality disorder associated with suicidal behavior. *Am J Psychiatry*. Dec 1997;154(12):1715-1719. [doi: [10.1176/ajp.154.12.1715](https://doi.org/10.1176/ajp.154.12.1715)] [Medline: [9396951](https://pubmed.ncbi.nlm.nih.gov/9396951/)]
54. Jang J, Park J, Oh K, Lee K, Kim MS, Yoon M, et al. Predictors of suicidal ideation in a community sample: roles of anger, self-esteem, and depression. *Psychiatry Res*. Apr 30, 2014;216(1):74-81. [doi: [10.1016/j.psychres.2013.12.054](https://doi.org/10.1016/j.psychres.2013.12.054)] [Medline: [24507544](https://pubmed.ncbi.nlm.nih.gov/24507544/)]
55. Lee J, Lee M, Liao S, Chang C, Sung S, Chiang H, et al. Prevalence of suicidal ideation and associated risk factors in the general population. *Journal of the Formosan Medical Association*. Feb 2010;109(2):138-147. [doi: [10.1016/s0929-6646\(10\)60034-4](https://doi.org/10.1016/s0929-6646(10)60034-4)]
56. Landberg J. Alcohol and suicide in eastern Europe. *Drug Alcohol Rev*. Jul 29, 2008;27(4):361-373. [doi: [10.1080/09595230802093778](https://doi.org/10.1080/09595230802093778)] [Medline: [18584385](https://pubmed.ncbi.nlm.nih.gov/18584385/)]
57. Mino A, Bousquet A, Broers B. Substance abuse and drug-related death, suicidal ideation, and suicide: a review. *Crisis*. Jan 1999;20(1):28-35. [doi: [10.1027//0227-5910.20.1.28](https://doi.org/10.1027//0227-5910.20.1.28)] [Medline: [10365504](https://pubmed.ncbi.nlm.nih.gov/10365504/)]
58. Rizk MM, Galfalvy H, Miller JM, Milak M, Parsey R, Grunebaum M, et al. Characteristics of depressed suicide attempters with remitted substance use disorders. *J Psychiatr Res*. May 2021;137:572-578. [FREE Full text] [doi: [10.1016/j.jpsychires.2020.10.041](https://doi.org/10.1016/j.jpsychires.2020.10.041)] [Medline: [33158553](https://pubmed.ncbi.nlm.nih.gov/33158553/)]

59. Andersson HW, Mosti MP, Nordfjærn T. Suicidal ideation among inpatients with substance use disorders: Prevalence, correlates and gender differences. *Psychiatry Res.* Nov 2022;317:114848. [FREE Full text] [doi: [10.1016/j.psychres.2022.114848](https://doi.org/10.1016/j.psychres.2022.114848)] [Medline: [36116184](https://pubmed.ncbi.nlm.nih.gov/36116184/)]
60. Bryan CJ, Bryan AO. Financial strain, suicidal thoughts, and suicidal behavior among US military personnel in the National Guard. *Crisis.* Nov 2019;40(6):437-445. [doi: [10.1027/0227-5910/a000592](https://doi.org/10.1027/0227-5910/a000592)] [Medline: [31030554](https://pubmed.ncbi.nlm.nih.gov/31030554/)]
61. Farabaugh A, Bitran S, Nyer M, Holt DJ, Pedrelli P, Shyu I, et al. Depression and suicidal ideation in college students. *Psychopathology.* May 22, 2012;45(4):228-234. [doi: [10.1159/000331598](https://doi.org/10.1159/000331598)] [Medline: [22627683](https://pubmed.ncbi.nlm.nih.gov/22627683/)]
62. Okechukwu FO, Ogba KTU, Nwufu JI, Ogba MO, Onyekachi BN, Nwanosike CI, et al. Academic stress and suicidal ideation: moderating roles of coping style and resilience. *BMC Psychiatry.* Aug 12, 2022;22(1):546. [doi: [10.1186/s12888-022-04063-2](https://doi.org/10.1186/s12888-022-04063-2)] [Medline: [35962365](https://pubmed.ncbi.nlm.nih.gov/35962365/)]
63. Hatchel T, Polanin JR, Espelage DL. Suicidal thoughts and behaviors among LGBTQ youth: meta-analyses and a systematic review. *Archives of Suicide Research.* Oct 10, 2019;25(1):1-37. [doi: [10.1080/13811118.2019.1663329](https://doi.org/10.1080/13811118.2019.1663329)]
64. Kaufman EA, Meddaoui B, Seymour NE, Victor SE. The roles of minority stress and thwarted belongingness in suicidal ideation among cisgender and transgender/nonbinary LGBTQ+ individuals. *Arch Suicide Res.* Oct 10, 2023;27(4):1296-1311. [doi: [10.1080/13811118.2022.2127385](https://doi.org/10.1080/13811118.2022.2127385)] [Medline: [36214309](https://pubmed.ncbi.nlm.nih.gov/36214309/)]
65. Sutter M, Perrin PB. Discrimination, mental health, and suicidal ideation among LGBTQ people of color. *J Couns Psychol.* Jan 2016;63(1):98-105. [doi: [10.1037/cou0000126](https://doi.org/10.1037/cou0000126)] [Medline: [26751158](https://pubmed.ncbi.nlm.nih.gov/26751158/)]
66. Rhoades H, Rusow JA, Bond D, Lanteigne A, Fulginiti A, Goldbach JT. Homelessness, mental health and suicidality among LGBTQ youth accessing crisis services. *Child Psychiatry Hum Dev.* Aug 10, 2018;49(4):643-651. [doi: [10.1007/s10578-018-0780-1](https://doi.org/10.1007/s10578-018-0780-1)] [Medline: [29322361](https://pubmed.ncbi.nlm.nih.gov/29322361/)]
67. de Lange J, Baams L, van Bergen DD, Bos HM, Bosker RJ. Minority stress and suicidal ideation and suicide attempts among LGBT adolescents and young adults: a meta-analysis. *LGBT Health.* Jun 01, 2022;9(4):222-237. [doi: [10.1089/lgbt.2021.0106](https://doi.org/10.1089/lgbt.2021.0106)] [Medline: [35319281](https://pubmed.ncbi.nlm.nih.gov/35319281/)]
68. Luo Z, Wang J, Zhou Y, Mao Q, Lang B, Xu S. Workplace bullying and suicidal ideation and behaviour: a systematic review and meta-analysis. *Public Health.* Sep 2023;222:166-174. [doi: [10.1016/j.puhe.2023.07.007](https://doi.org/10.1016/j.puhe.2023.07.007)] [Medline: [37544128](https://pubmed.ncbi.nlm.nih.gov/37544128/)]
69. Husky MM, Bitfoi A, Carta MG, Goelitz D, Koç C, Lesinskiene S, et al. Bullying involvement and suicidal ideation in elementary school children across Europe. *J Affect Disord.* Feb 15, 2022;299:281-286. [doi: [10.1016/j.jad.2021.12.023](https://doi.org/10.1016/j.jad.2021.12.023)] [Medline: [34915081](https://pubmed.ncbi.nlm.nih.gov/34915081/)]
70. Zaborskis A, Ilionsky G, Tesler R, Heinz A. The association between cyberbullying, school bullying, and suicidality among adolescents. *Crisis.* Mar 2019;40(2):100-114. [doi: [10.1027/0227-5910/a000536](https://doi.org/10.1027/0227-5910/a000536)] [Medline: [30109963](https://pubmed.ncbi.nlm.nih.gov/30109963/)]
71. Finkelhor D. Sexual abuse: a sociological perspective. *Child Abuse Negl.* Jan 1982;6(1):95-102. [doi: [10.1016/0145-2134\(82\)90055-2](https://doi.org/10.1016/0145-2134(82)90055-2)] [Medline: [6892290](https://pubmed.ncbi.nlm.nih.gov/6892290/)]
72. Brokke SS, Bertelsen TB, Landrø NI, Haaland VO. The effect of sexual abuse and dissociation on suicide attempt. *BMC Psychiatry.* Jan 10, 2022;22(1):29. [FREE Full text] [doi: [10.1186/s12888-021-03662-9](https://doi.org/10.1186/s12888-021-03662-9)] [Medline: [35012509](https://pubmed.ncbi.nlm.nih.gov/35012509/)]
73. Lindert J, von Ehrenstein OS, Grashow R, Gal G, Braehler E, Weisskopf MG. Sexual and physical abuse in childhood is associated with depression and anxiety over the life course: systematic review and meta-analysis. *Int J Public Health.* Apr 12, 2014;59(2):359-372. [doi: [10.1007/s00038-013-0519-5](https://doi.org/10.1007/s00038-013-0519-5)] [Medline: [24122075](https://pubmed.ncbi.nlm.nih.gov/24122075/)]
74. Peteet JR, Maytal G, Rokni H. Unimaginable loss: contingent suicidal ideation in family members of oncology patients. *Psychosomatics.* Mar 23, 2010;51(2):166-170. [doi: [10.1176/appi.psy.51.2.166](https://doi.org/10.1176/appi.psy.51.2.166)] [Medline: [20332292](https://pubmed.ncbi.nlm.nih.gov/20332292/)]
75. Keum BT, Wong MJ, Salim-Eissa R. Gendered racial microaggressions, internalized racism, and suicidal ideation among emerging adult Asian American women. *Int J Soc Psychiatry.* Mar 2023;69(2):342-350. [FREE Full text] [doi: [10.1177/00207640221089536](https://doi.org/10.1177/00207640221089536)] [Medline: [35411802](https://pubmed.ncbi.nlm.nih.gov/35411802/)]
76. Robinson WL, Whipple CR, Jason LA, Flack CE. African American adolescent suicidal ideation and behavior: the role of racism and prevention. *J Community Psychol.* Jul 2021;49(5):1282-1295. [FREE Full text] [doi: [10.1002/jcop.22543](https://doi.org/10.1002/jcop.22543)] [Medline: [33675671](https://pubmed.ncbi.nlm.nih.gov/33675671/)]
77. Keum BT, Wong MJ. COVID-19 anti-Asian racism, perceived burdensomeness, thwarted belongingness, and suicidal ideation among Asian American Emerging Adults. *Int Rev Psychiatry.* 2023;35(3-4):302-309. [FREE Full text] [doi: [10.1080/09540261.2023.2182186](https://doi.org/10.1080/09540261.2023.2182186)] [Medline: [37267028](https://pubmed.ncbi.nlm.nih.gov/37267028/)]
78. Ratkowska KA, De Leo D. Suicide in immigrants: an overview. *Open J Med Psychol.* 2013;02(03):124-133. [doi: [10.4236/ojmp.2013.23019](https://doi.org/10.4236/ojmp.2013.23019)]
79. Hovey JD. Acculturative stress, depression, and suicidal ideation in Mexican immigrants. *Cultur Divers Ethnic Minor Psychol.* May 2000;6(2):134-151. [doi: [10.1037/1099-9809.6.2.134](https://doi.org/10.1037/1099-9809.6.2.134)] [Medline: [10910528](https://pubmed.ncbi.nlm.nih.gov/10910528/)]
80. Naismith H, Howard R, Stewart R, Pitman A, Mueller C. Suicidal ideation in dementia: associations with neuropsychiatric symptoms and subtype diagnosis. *International Psychogeriatrics.* Apr 2022;34(4):399-406. [doi: [10.1017/s1041610222000126](https://doi.org/10.1017/s1041610222000126)]
81. Cui R, Maxfield M, Fiske A. Dementia-related anxiety and coping styles associated with suicidal ideation. *Aging Ment Health.* Nov 04, 2020;24(11):1912-1915. [doi: [10.1080/13607863.2019.1636205](https://doi.org/10.1080/13607863.2019.1636205)] [Medline: [31271051](https://pubmed.ncbi.nlm.nih.gov/31271051/)]
82. Armstrong MJ, Moore K, Jacobson CE, Bedenfield N, Patel B, Sullivan JL. Frequency of suicidal ideation and associated clinical features in Lewy body dementia. *Parkinsonism Relat Disord.* Sep 2021;90:33-37. [doi: [10.1016/j.parkreldis.2021.07.029](https://doi.org/10.1016/j.parkreldis.2021.07.029)] [Medline: [34352608](https://pubmed.ncbi.nlm.nih.gov/34352608/)]

83. Fässberg MM, Cheung G, Canetto SS, Erlangsen A, Lapierre S, Lindner R, et al. A systematic review of physical illness, functional disability, and suicidal behaviour among older adults. *Aging Ment Health*. Sep 18, 2016;20(2):166-194. [FREE Full text] [doi: [10.1080/13607863.2015.1083945](https://doi.org/10.1080/13607863.2015.1083945)] [Medline: [26381843](https://pubmed.ncbi.nlm.nih.gov/26381843/)]
84. Vasiliadis H, D'Aiuto C, Lamoureux-Lamarche C, Pitrou I, Gontijo Guerra S, Berbiche D. Pain, functional disability and mental disorders as potential mediators of the association between chronic physical conditions and suicidal ideation in community living older adults. *Aging Ment Health*. Apr 23, 2022;26(4):791-802. [doi: [10.1080/13607863.2021.1913478](https://doi.org/10.1080/13607863.2021.1913478)] [Medline: [33890523](https://pubmed.ncbi.nlm.nih.gov/33890523/)]
85. Racine M. Chronic pain and suicide risk: A comprehensive review. *Prog Neuropsychopharmacol Biol Psychiatry*. Dec 20, 2018;87(Pt B):269-280. [doi: [10.1016/j.pnpbp.2017.08.020](https://doi.org/10.1016/j.pnpbp.2017.08.020)] [Medline: [28847525](https://pubmed.ncbi.nlm.nih.gov/28847525/)]
86. Guided Topic Modeling. GitHub. URL: https://maartengr.github.io/BERTopic/getting_started/guided/guided.html [accessed 2025-05-19]
87. Merriam-Webster. URL: <https://www.merriam-webster.com/> [accessed 2025-05-19]
88. Flesch RF. Estimating the comprehension difficulty of magazine articles. *J General Psychol*. Jan 1943;28(1):63-80. [doi: [10.1080/00221309.1943.10545195](https://doi.org/10.1080/00221309.1943.10545195)]
89. Chotlos JW. IV. A statistical and comparative analysis of individual written language samples. *Psychological Monographs*. 1944;56(2):75-111. [doi: [10.1037/h0093511](https://doi.org/10.1037/h0093511)]
90. Richards B. Type/Token Ratios: what do they really tell us? *J Child Lang*. Jun 17, 1987;14(2):201-209. [doi: [10.1017/s0305000900012885](https://doi.org/10.1017/s0305000900012885)] [Medline: [3611238](https://pubmed.ncbi.nlm.nih.gov/3611238/)]
91. Shannon CE. A mathematical theory of communication. *Bell Syst Technical J*. 1948;27(3):379-423. [FREE Full text] [doi: [10.1002/j.1538-7305.1948.tb01338.x](https://doi.org/10.1002/j.1538-7305.1948.tb01338.x)]
92. Snow EL, Allen LK, Jacovina ME, Crossley SA, Perret CA, McNamara DS. Keys to detecting writing flexibility over time: entropy and natural language processing. *Learning Analytics*. Feb 18, 2016;2(3):40-54. [doi: [10.18608/jla.2015.23.4](https://doi.org/10.18608/jla.2015.23.4)]
93. Zirikly A, Resnik P, Uzuner O, Hollingshead K. CLPsych 2019 Shared Task: Predicting the Degree of Suicide Risk in Reddit Posts. In: *Proceedings of the Sixth Workshop on Computational Linguistics and Clinical Psychology*. 2019. Presented at: Sixth Workshop on Computational Linguistics and Clinical Psychology; June 2019; Minneapolis, MN.
94. Shing HC, Nair S, Zirikly A, Friedenberg M, Daumé H, Resnik P. Expert, Crowdsourced, and Machine Assessment of Suicide Risk via Online Postings. In: *Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic*. 2018. Presented at: Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic; June 2018; New Orleans, LA. [doi: [10.18653/v1/w18-0603](https://doi.org/10.18653/v1/w18-0603)]
95. Depression subreddit. Reddit. URL: <https://www.reddit.com/r/depression/> [accessed 2025-05-19]
96. SuicideWatch subreddit. Reddit. URL: <https://www.reddit.com/r/SuicideWatch/> [accessed 2025-05-19]
97. Walsh CG, Ribeiro JD, Franklin JC. Predicting risk of suicide attempts over time through machine learning. *Clinical Psychological Science*. Apr 11, 2017;5(3):457-469. [doi: [10.1177/2167702617691560](https://doi.org/10.1177/2167702617691560)]
98. Ji S, Li X, Huang Z, Cambria E. Suicidal ideation and mental disorder detection with attentive relation networks. *Neural Comput & Applic*. Jun 24, 2021;34(13):10309-10319. [doi: [10.1007/s00521-021-06208-y](https://doi.org/10.1007/s00521-021-06208-y)]
99. Ji S, Zhang T, Ansari L, Fu J, Tiwari P, Cambria E. MentalBERT: publicly available pretrained language models for mental healthcare. *arXiv*. Preprint posted online on October 29, 2021. [FREE Full text]
100. Gaur M, Alambo A, Sain JP, Kursuncu U, Thirunaryan K, Kavuluru R, et al. Knowledge-aware assessment of severity of suicide risk for early intervention. 2019. Presented at: WWW '19: The World Wide Web Conference; May 13-17, 2019; San Francisco, CA. [doi: [10.1145/3308558.3313698](https://doi.org/10.1145/3308558.3313698)]
101. API documentation. Reddit. URL: <https://www.reddit.com/dev/api/> [accessed 2025-05-19]
102. The University of Maryland Reddit Suicidality Dataset. GitHub. URL: https://psresnik.github.io/umd_reddit_suicidality_dataset.html [accessed 2025-05-19]
103. Giupponi G, Innamorati M, Baldessarini RJ, De Leo D, de Giovannelli F, Pycha R, et al. Factors associated with suicide: Case-control study in South Tyrol. *Compr Psychiatry*. Jan 2018;80:150-154. [FREE Full text] [doi: [10.1016/j.comppsy.2017.09.010](https://doi.org/10.1016/j.comppsy.2017.09.010)] [Medline: [29091781](https://pubmed.ncbi.nlm.nih.gov/29091781/)]
104. Lasserre AM, Marti-Soler H, Strippoli MF, Vaucher J, Glaus J, Vandeleur CL, et al. Clinical and course characteristics of depression and all-cause mortality: a prospective population-based study. *J Affect Disord*. Jan 01, 2016;189:17-24. [doi: [10.1016/j.jad.2015.09.010](https://doi.org/10.1016/j.jad.2015.09.010)] [Medline: [26402343](https://pubmed.ncbi.nlm.nih.gov/26402343/)]
105. Moitra M, Santomauro D, Degenhardt L, Collins PY, Whiteford H, Vos T, et al. Estimating the risk of suicide associated with mental disorders: a systematic review and meta-regression analysis. *J Psychiatr Res*. May 2021;137:242-249. [FREE Full text] [doi: [10.1016/j.jpsychires.2021.02.053](https://doi.org/10.1016/j.jpsychires.2021.02.053)] [Medline: [33714076](https://pubmed.ncbi.nlm.nih.gov/33714076/)]
106. Harris EC, Barraclough BM. Suicide as an outcome for mental disorders. A meta-analysis. *Br J Psychiatry*. Mar 1997;170:205-228. [doi: [10.1192/bjp.170.3.205](https://doi.org/10.1192/bjp.170.3.205)] [Medline: [9229027](https://pubmed.ncbi.nlm.nih.gov/9229027/)]
107. Langford VM. Risk factors for suicide in men. *Nurs Clin North Am*. Dec 2023;58(4):513-524. [doi: [10.1016/j.cnur.2023.06.010](https://doi.org/10.1016/j.cnur.2023.06.010)] [Medline: [37832996](https://pubmed.ncbi.nlm.nih.gov/37832996/)]
108. Favril L, Yu R, Geddes JR, Fazel S. Individual-level risk factors for suicide mortality in the general population: an umbrella review. *Lancet Public Health*. Nov 2023;8(11):e868-e877. [doi: [10.1016/s2468-2667\(23\)00207-4](https://doi.org/10.1016/s2468-2667(23)00207-4)]

109. Pemau A, Marin-Martin C, Diaz-Marsa M, de la Torre-Luque A, Ayad-Ahmed W, Gonzalez-Pinto A, et al. Risk factors for suicide reattempt: a systematic review and meta-analysis. *Psychol Med*. Apr 16, 2024;54(9):1897-1904. [doi: [10.1017/s0033291724000904](https://doi.org/10.1017/s0033291724000904)]
110. Grover C, Huber J, Brewer M, Basu A, Large M. Meta-analysis of clinical risk factors for suicide among people presenting to emergency departments and general hospitals with suicidal thoughts and behaviours. *Acta Psychiatr Scand*. Dec 30, 2023;148(6):491-524. [doi: [10.1111/acps.13620](https://doi.org/10.1111/acps.13620)] [Medline: [37904016](https://pubmed.ncbi.nlm.nih.gov/37904016/)]
111. Jha S, Chan G, Orji R. Identification of risk factors for suicide and insights for developing suicide prevention technologies: a systematic review and meta-analysis. *Hum Behav Emerging Technologies*. Mar 13, 2023;2023:1-18. [doi: [10.1155/2023/3923097](https://doi.org/10.1155/2023/3923097)]
112. Anderberg J, Bogren M, Mattisson C, Brådvik L. Long-term suicide risk in anxiety-The Lundby Study 1947-2011. *Arch Suicide Res*. Jul 02, 2016;20(3):463-475. [doi: [10.1080/13811118.2015.1057663](https://doi.org/10.1080/13811118.2015.1057663)] [Medline: [26954705](https://pubmed.ncbi.nlm.nih.gov/26954705/)]
113. Athey A, Overholser J, Bagge C, Dieter L, Vallender E, Stockmeier CA. Risk-taking behaviors and stressors differentially predict suicidal preparation, non-fatal suicide attempts, and suicide deaths. *Psychiatry Res*. Dec 2018;270:160-167. [FREE Full text] [doi: [10.1016/j.psychres.2018.09.032](https://doi.org/10.1016/j.psychres.2018.09.032)] [Medline: [30253320](https://pubmed.ncbi.nlm.nih.gov/30253320/)]
114. Page A, Morrell S, Hobbs C, Carter G, Dudley M, Duflou J, et al. Suicide in young adults: psychiatric and socio-economic factors from a case-control study. *BMC Psychiatry*. Mar 06, 2014;14:68. [FREE Full text] [doi: [10.1186/1471-244X-14-68](https://doi.org/10.1186/1471-244X-14-68)] [Medline: [24597482](https://pubmed.ncbi.nlm.nih.gov/24597482/)]
115. Lieb K, Zanarini MC, Schmahl C, Linehan MM, Bohus M. Borderline personality disorder. *Lancet*. 2004;364(9432):453-461. [doi: [10.1016/S0140-6736\(04\)16770-6](https://doi.org/10.1016/S0140-6736(04)16770-6)] [Medline: [15288745](https://pubmed.ncbi.nlm.nih.gov/15288745/)]
116. Zanarini M. Prediction of the 10-year course of borderline personality disorder. *Am J Psychiatry*. May 01, 2006;163(5):827. [doi: [10.1176/appi.ajp.163.5.827](https://doi.org/10.1176/appi.ajp.163.5.827)]
117. Braquehais MD, Oquendo MA, Baca-García E, Sher L. Is impulsivity a link between childhood abuse and suicide? *Compr Psychiatry*. Mar 2010;51(2):121-129. [doi: [10.1016/j.comppsy.2009.05.003](https://doi.org/10.1016/j.comppsy.2009.05.003)] [Medline: [20152291](https://pubmed.ncbi.nlm.nih.gov/20152291/)]
118. Devries KM, Mak JYT, Child JC, Falder G, Bacchus LJ, Astbury J, et al. Childhood sexual abuse and suicidal behavior: a meta-analysis. *Pediatrics*. May 2014;133(5):e1331-e1344. [doi: [10.1542/peds.2013-2166](https://doi.org/10.1542/peds.2013-2166)] [Medline: [24733879](https://pubmed.ncbi.nlm.nih.gov/24733879/)]
119. Wolfe KL, Nakonezny PA, Owen VJ, Rial KV, Moorehead AP, Kennard BD, et al. Hopelessness as a predictor of suicide ideation in depressed male and female adolescent youth. *Suicide Life Threat Behav*. Feb 21, 2019;49(1):253-263. [FREE Full text] [doi: [10.1111/sltb.12428](https://doi.org/10.1111/sltb.12428)] [Medline: [29267993](https://pubmed.ncbi.nlm.nih.gov/29267993/)]
120. ALBERT Base v2. Hugging Face. URL: <https://huggingface.co/albert/albert-base-v2> [accessed 2025-05-19]
121. Wolf T, Debut L, Sanh V, Chaumond J, Delangue C, Moi A, et al. HuggingFace's transformers: state-of-the-art natural language processing. arXiv. Preprint posted online on October 9, 2019. [FREE Full text] [doi: [10.18653/v1/2020.emnlp-demos.6](https://doi.org/10.18653/v1/2020.emnlp-demos.6)]
122. Trainer. Hugging Face. URL: https://huggingface.co/docs/transformers/main_classes/trainer [accessed 2025-05-19]
123. Addressing Topic Gaps to Improve Suicide Ideation Detection in Social Media Posts A Topic Modeling. GitHub. URL: <https://github.com/Hamideh-ghanadian/Addressing-Topic-Gaps-to-Improve-Suicide-Ideation-Detection-in-Social-Media-Posts-A-Topic-Modeling-> [accessed 2025-05-20]

Abbreviations

C-TF-IDF: class-based term frequency-inverse document frequency

HDBSCAN: Hierarchical Density-Based Spatial Clustering of Applications with Noise

NLP: natural language processing

PTSD: posttraumatic stress disorder

TF-IDF: term frequency-inverse document frequency

UMAP: Uniform Manifold Approximation and Projection

UMD: University of Maryland Reddit Suicidality Dataset

Edited by A Mavragani; submitted 14.06.24; peer-reviewed by C Entwistle, C Haag, B Gong; comments to author 15.07.24; revised version received 10.10.24; accepted 08.05.25; published 11.06.25

Please cite as:

Ghanadian H, Nejadgholi I, Al Osman H

Improving Suicidal Ideation Detection in Social Media Posts: Topic Modeling and Synthetic Data Augmentation Approach

JMIR Form Res 2025;9:e63272

URL: <https://formative.jmir.org/2025/1/e63272>

doi: [10.2196/63272](https://doi.org/10.2196/63272)

PMID:

©Hamideh Ghanadian, Isar Nejadgholi, Hussein Al Osman. Originally published in JMIR Formative Research (<https://formative.jmir.org>), 11.06.2025. This is an open-access article distributed under the terms of the Creative Commons Attribution License (<https://creativecommons.org/licenses/by/4.0/>), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work, first published in JMIR Formative Research, is properly cited. The complete bibliographic information, a link to the original publication on <https://formative.jmir.org>, as well as this copyright and license information must be included.