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The Topics of Depression on Social Networking Sites

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Abstract While depressive linguistic expressions have been extensively studied in traditional clinical contexts, there has been comparatively little attention devoted to modeling how both depressed and non-depressed individuals express their symptoms on social networking sites as a holistic thematic process. This study addresses this gap by examining how depression is expressed linguistically on social networking sites using various topic modeling techniques, including an innovative methodology based on LLMs. We use datasets in the Brazilian Portuguese language gathered from Instagram, Reddit, and X. Our evaluation reveals that while common themes related to depression emerge across different social networking sites, each platform's unique characteristics influence the thematic content. Reddit discussions focus on symptomatology, Instagram on travel and positive emotions, and Twitter on everyday life and media. The LLM-based approach produced more interpretable topics with a higher embedding-based coherence metric, whereas traditional methods often resulted in noisy and less internally coherent topics. This research contributes to a deeper understanding of the holistic online expressions of depression and highlights the potential of advanced topic modeling techniques to reveal subtle aspects of mental health discussions online.

Keywords: Topic Modeling, Machine Learning, LLM, Depression, Social Networking Sites

1 Introduction

Depression is a complex psychopathology characterized by prolonged sadness and diminished interest in most activities [Association *et al.*, 2014]. Its symptoms often include noticeable fluctuations in weight and disruptions in sleep patterns. The onset can be triggered by several factors: medication or substance abuse, illness, loss of loved ones, stressors, or genetic predispositions [Association *et al.*, 2014]. Often, the impacts on the lives of individuals render professional, financial, and personal issues that can even affect the people around them. The symptomatology of depression has been widely studied and documented in traditional clinical settings, mainly on psychiatric manuals, such as the Diagnostic and Statistical Manual of Mental Disorders [Association *et al.*, 2014]. However, little attention has been devoted to comprehensively modeling how both depressed and non-depressed individuals express their symptoms on Social Networking Sites (SNSs) as a thematic process. This gap is significant, especially considering how SNSs have become ubiquitous in our lives, serving as a primary outlet for many to share their thoughts and experiences with friends and acquaintances. Exploring new ways that symptoms might be expressed is not merely about identifying who is depressed but about uncovering the thematic patterns and structures that emerge during their interactions on SNSs.

Numerous studies have established associations between SNSs usage and mental health through longitudinal analyses of participants [Coyne *et al.*, 2020; Ostic *et al.*, 2021]. While analyzing participant behavior provides valuable insights, this approach is labor-intensive and limited in scalability due to the vast and dynamic nature of online interactions. The sheer volume of data and the diverse ways individuals express themselves online pose significant challenges that advanced computational methods can address. Additionally, each social networking site encourages specific modes of expression shaped by the platform's design and user culture. These platform-specific dynamics influence how symptoms of depression are manifested and perceived across different SNSs.

Previous research has employed machine learning techniques to predict mental health states using various modalities. For instance, analyses based on written or visual content have yielded promising results for screening mental health states [Mann *et al.*, 2020, 2022; Bucur *et al.*, 2023; Zárate *et al.*, 2024]. Other studies have explored classifying a fine-grained set of depressive signs directly from textual content [Yadav *et al.*, 2020, 2023; Milintsevich *et al.*, 2023; Mendes and Caseli, 2024], while additional work has investigated screening depressed individuals through the structure of SNSs by examining relationships such as friends, followers, and mentions [dos Santos *et al.*, 2024; Oliveira and Paraboni, 2024].

More aligned with our study, researchers have also found thematic markers on these platforms using topic modeling approaches [Resnik *et al.*, 2015; Andalibi *et al.*, 2017; Koltai *et al.*, 2021; Sik *et al.*, 2023; Timakum *et al.*, 2023; Issaka *et al.*, 2024]. However, these studies often emphasize broad correlations, neglecting a deeper exploration of the specific themes prevalent among depressed and non-depressed SNS users. Moreover, prior work has frequently been limited to a single social networking site [Resnik *et al.*, 2015; Andalibi *et al.*, 2017; Koltai *et al.*, 2021; Sik *et al.*, 2023; Timakum *et al.*, 2023; Issaka *et al.*, 2024; Oliveira and Paraboni, 2024; Mendes and Caseli, 2024], used topic modeling features solely for classifying users, or relied on just one topic modeling approach [Koltai *et al.*, 2021; Sik *et al.*, 2023; Timakum *et al.*, 2023; Issaka *et al.*, 2024]. In contrast, our study applies a diverse set of topic modeling techniques across several Brazilian Portuguese datasets, including Instagram, Reddit, and X (formerly known as Twitter), to uncover linguistic patterns associated with depression. Our analysis employs methods such as Latent Dirichlet Allocation (LDA) [Blei *et al.*, 2003], Noiseless LDA (NLDA) [Churchill and Singh, 2021], Topic-Noise Discriminator (TND) [Churchill and Singh, 2021], Contextualized Topic Model (CTM) [Bianchi *et al.*, 2021], BERTopic [Grootendorst, 2022], and a novel approach based on Large Language Models (LLMs). Through both quantitative and qualitative evaluations, we aim to assess the quality of the extracted topics and their relevance in understanding the symptomatic expressions of depression online.

To guide our investigation, we formulated three research questions that address both the comparative and methodological aspects of our study: (1) how do thematic expressions of depression differ across various social networking sites? This question aims to explore the influence of platform-specific dynamics on the portrayal of depressive symptoms; (2) how do these thematic expressions differ between depressed and non-depressed individuals on these platforms? This inquiry allows us to examine the nuanced variations in language and themes that may reflect differing mental health states; finally, (3) how effective are advanced topic modeling techniques — including our novel LLM-based approach — in uncovering and characterizing these thematic differences? These research questions provide a comprehensive framework for our analysis, highlighting the significance of both the diverse linguistic landscapes of social media and the innovative methodologies employed in our study.

Our contributions include (1) the creation and collection of datasets from different SNSs in the Brazilian Portuguese language; (2) creating a new LLM-based topic modeling methodology; (3) conducting a comparative analysis of different topic modeling techniques across distinct subsets of each dataset, focusing on both depressed and non-depressed individuals; (4) creating a methodology to qualitatively evaluate the topics and discuss the main findings. This multifaceted approach not only enhances our understanding of how depression is expressed online but also offers potential pathways for improving mental health interventions by providing a deeper understanding of the specific issues and concerns that individuals with depression are discussing online.

2 Related Works

Resnik *et al.* [2013] explored the intersection of neuroticism and depression among university students using traditional topic modeling techniques such as LDA and the Linguistic Inquiry Word Count (LIWC). Their objective was to categorize and group similar emotional expressions among individuals suffering from these mental health conditions, offering insights into the linguistic patterns associated with these pathologies. In a follow-up study, Resnik *et al.* [2015] extended their investigation to include data from X, employing the LDA technique to enhance the detection of depression in online environments. By relying on supervised LDA and informative priors, the authors were able to find several key topics, such as “business,” “college,” “dance,” “fat,” “friday,” “fuck,” “god,” among others when using the supervised anchor algorithm [Resnik *et al.*, 2015].

Timakum *et al.* [2023] applied LDA for topic modeling within a Reddit community focused on bipolar disorder. Through this approach, they developed a comprehensive database that facilitated an in-depth analysis of the themes and topics related to the disorder. This enabled the identification of key terms that were most relevant to the community' s discussions, shedding light on the linguistic markers associated with bipolar disorder. They relied on LDA with a fixed $k = 30$ and manually labeled the topics. Among all topics, they labeled the top 10 topics: “help and advice,” “bipolar disorder,” “social process,” “therapy,” “drugs,” “episode,” “emotion expression,” “friend,” “relaxation,” and “drug-side effect” [Timakum *et al.*, 2023].

Andalibi *et al.* [2017] investigated sensitive self-disclosures on Instagram through the use of the hashtag “#depression,” employing both visual and textual qualitative content analysis complemented by statistical methods. Their study revealed that Instagram serves as a significant outlet for individuals to share vulnerable, stigmatized experiences to appeals for emotional support. Importantly, the findings indicate that these sensitive disclosures are generally met with positive, supportive responses, suggesting that the platform not only facilitates the expression of difficult emotions but also fosters a sense of community and social support. It is important to note that their analysis did not employ topic modeling techniques; instead, they relied on qualitative content analysis methods and statistical approaches to interpret the themes within the data, and manually developed codes for images and captions.

In addition to the studies discussed above, Koltai *et al.* [2021] investigated the phenomenon of suicide on a corpus of Instagram posts. The authors argue that, although users express suicide ideation, it often represents a cry for help. They collected English data from January 16, 2016 to January 31, 2019. They filtered for posts containing hashtags such as “#depression,” “#depressed,” “#suicide,” “#anxiety,” among others. The filtered dataset contained more than four million posts. After running the LDA algorithm, the authors found 11 topics: “self-harm,” “memes,” “art/photography,” “fitness/diet,” “mental health awareness,” “illness and mental consequences,” “mental illness and recovery,” “poetry,” “religion,” among others.

Sik *et al.* [2023] analyzed nearly 70,000 depression-related posts from the English-speaking online forum (r/depression) using a combination of unsupervised LDA topic modeling and qualitative deep reading. Their study identified 13 distinct topics that encapsulate various narrative strategies, such as "health related challenge," "making sense of drugs," "making sense of psy-discourses," "challenges of intimacy," "challenges of family," "unconditional positive regard," "self-reinforcing praxes," "fitting illness narratives," "recovery helpers counselling," "challenges of social life," "echoes of self-blaming," "religious support," and "media representation of mental disorders".

Gao and Sazara [2023] conducted a large-scale review — based on topic modeling — of approximately 96,000 publications related to machine learning applied to mental health research to analyze emerging trends and relationships. In their comparative analysis of LDA, Top2Vec, BERTopic, and LDA-BERT techniques, they produced a comprehensive overview of the machine learning models currently employed in mental health research, particularly during the COVID-19 pandemic. Their work identified significant topics and trends emerging from the extensive literature [Gao and Sazara, 2023]. Notably, BERTopic achieved the best topic diversity and coherence metrics. The study revealed prevalent topics capturing pandemic-related anxiety with terms such as "pandemic," "anxiety," and "psychological" appearing together. It also identified a topic corresponding to one of the depressive symptoms — insomnia or hypersomnia — characterized by words like "sleep," "insomnia," and "sleep quality." Additional topics addressed the stigmatization of mental health and factors related to genetic predispositions [Gao and Sazara, 2023].

Issaka *et al.* [2024] analyzed comments from X posts related to mental health using LDA for topic modeling. Their study uncovered general themes — by aggregating topics — such as "rejecting or critiquing the glamorization of mental health", "monetization of mental health by corporate organization", "societal misconception of mental health", "role of traditional media and social media", "unfiltered realities of depression", and "we are not romanticizing." Moreover, the study highlighted the influential roles of both traditional and social media in shaping public perceptions, alongside unfiltered portrayals of depression that resist romanticization. Notably, "suicide" emerged as the most frequently occurring term, followed by "issue," "anxiety," and "depression." [Issaka *et al.*, 2024].

LLM-based approaches to mental health have mainly focused on explainability and interpretability, stressing the importance of understanding the reasons the automatic system labeled an SNS user as depressed or not [Yang *et al.*, 2023; Wang *et al.*, 2024]. More recently, MentaLLaMA have been proposed to provide a open-source foundation LLM, trained for analyzing mental health as a text generation task [Yang *et al.*, 2024]. Nonetheless, these models are not trained to uncover latent thematic discussions.

In contrast to the aforementioned research, where the goal was to understand the linguistic signals of mental health disorders, their reliance on either a single dataset or a single technique limited the generalizability of their findings, as their approach failed to capture the full spectrum of language usage across diverse online communities. On the other hand, studies relying on LLMs for mental health research have been using it mainly for explainability and classification. In our study, we apply multiple techniques — including a novel LLM-based technique — to various SNSs datasets to overcome these limitations and find holistic thematic discussions.

3 Methods

Our experimental pipeline consists of four key stages: (i) collecting the datasets, (ii) preprocessing them to ensure compatibility with available topic modeling implementations, (iii) training the models and optimizing their hyperparameters, and (iv) conducting both qualitative and quantitative analyses of the results. Each of these steps is detailed in the following sections.

3.1 Datasets

To collect data for the TwitterUFF and InstagramUFF datasets, we recruited students from the Fluminense Federal University (UFF) to complete a Google Forms questionnaire. This questionnaire gathered demographic details and included the Beck Depression Inventory-II (BDI-II) psychometric test, which assesses depressive symptoms based on a scoring system. Students were also asked for consent to access their X (formerly Twitter) and Instagram profiles. Based on their BDI-II scores, students were categorized into two groups: those with moderate to severe symptoms were labeled as "depressed" and identified as needing psychological treatment. Ethical approval for this study was granted by the university's Institutional Review Board (IRB) under the protocol number 89859418.1.0000.5243. Additional details on the dataset collection process can be found in Mann *et al.* [2020]. We also use another X dataset, the DepressBR dataset from dos Santos *et al.* [2020], where labels were assigned based on self-reported statements like "I'm depressed" on their profiles.

For the Reddit dataset, we employed a distinct methodology compared to InstagramUFF, TwitterUFF, and DepressBR, which focus on content generated by depressed and non-depressed individuals. Our goal was to capture the type of content that depressed individuals might produce through participation in community discussions. More specifically, we are interested in collecting posts containing specific words that are related to depression. Reddit's structure, characterized by initial posts ("submissions") and their subsequent replies, influenced the type of content we collected. Notably, submissions tend to be longer and serve as the focal point of discussions, while replies are often brief and do not significantly expand on the original post. Therefore, we only collected the primary submissions to capture the central themes around which discussions revolve.

Reddit features "subreddits," specialized communities focused on specific topics, where users can share content related to the community's theme. While English forums include dedicated spaces like *r/depression*, no similar Portuguese subreddits exist, leading us to utilize the popular *r/brasil* and *r/desabafos* for gathering data on depression. We identified relevant posts using keywords such as "suicide"

Table 1. Dataset statistics after preprocessing. D is the subset of the original dataset only containing posts from depressed individuals. N is the subset of the original dataset containing posts from non-depressed individuals. Note that Reddit contains only content related to depression.

Dataset	Number of Documents	Average Tokens per Post (std)
InstagramUFF (D)	2719	10 (± 16)
InstagramUFF (N)	1680	9 (± 15)
TwitterUFF (D)	27928	5 (± 3)
TwitterUFF (N)	78171	6 (± 3)
DepressBR (D)	261390	6 (± 5)
DepressBR (N)	299493	6 (± 5)
Reddit	3402	183 (± 188)

and "depression", collecting a total of 3402 posts from 2008 to 2021.

To enhance topic modeling, we employed lemmatization, removed new lines, accents, and stopwords while retaining personal pronouns, and focused on nouns, verbs, and adjectives for improved coherence. We limited our vocabulary to the 2000 most frequent words to address the variability in online language and removed any posts with no content after preprocessing.

After preprocessing the documents, the basic statistics for each document can be seen in Table 1. Note that we split each original dataset into two partitions, depressed (D) and non-depressed (N). We do that to understand the differences in latent topics that models will learn from content created from the perspective of depressed as opposed to non-depressed individuals. As the Reddit dataset contains user submissions including words related to mental health expressions, we understand that this dataset — with loss of generality — contains the textual content of individuals with mental health symptoms. Although one might argue that this dataset might contain data from individuals relating to the pain of relatives or simply discussing the symptoms, we expect that submissions of this nature are rare among individuals with mental health symptoms expressing concern.

3.2 Topic Models

This study examines the application of topic modeling techniques to SNSs content, which often features irregular grammar, slang, and noise words related to trends and events. These characteristics create sparse and noisy vocabularies that complicate the use of traditional text models, making standard methods like LDA less effective without extensive preprocessing. To address this, we use the TND model, which treats documents as mixtures of topics and noise by estimating the noise distribution, allowing it to filter out irrelevant words and generate more coherent topics. TND employs a beta distribution to distinguish between topic and noise words, and the NLDA model further refines this by integrating the noise distribution with LDA to enhance topic quality.

The limitation of such models is that they rely on the Bag-of-Words (BoW) assumption, which fails to capture syntactic and semantic relationships, as well as subword or morphological information. For example, in Portuguese, different representations of laughter like "kkk" and "kkkkkkkk" might be treated as distinct in BoW models. Modern LLMs offer contextual vector representations that address these limitations by potentially capturing morphology, semantics, syntax, word order, and polysemy. Specifically, the CTM utilizes BERT representations, which provide several advantages: (1) BERT's contextual nature allows for direct use of raw text data, preserving information; (2) the length of posts in our dataset is manageable within BERT's sequence limit; (3) BERT' s subword tokenization helps embed variations of words into coherent low-dimensional spaces, mitigating the noisy vocabulary issue.

Another embedding-based model is BERTopic. However, unlike LDA, TND, NLDA, and CTM, BERTopic drop the BoW assumption entirely and does not consider the documents as a mixture of topics, which is a mixture of words. Specifically, the author proposes a topic modeling technique based on four steps: (1) embed documents in d-dimensional space with a pretrained language model; (2) reduce the dimensionality of the document embeddings — to improve the performance and quality of clusters; (3) generate clusters from the document embeddings; (4) apply c-TF-IDF to extract the topics.

Although we could use any textual feature extractor, dimensionality reduction technique, or clusterization algorithm, we rely on the same techniques used in the original study: Sentence-BERT [Reimers and Gurevych, 2019] for extracting document embeddings, Uniform Manifold Approximation and Projection for Dimension Reduction (UMAP) for dimensionality reduction [McInnes *et al.*, 2018], and HDBSCAN [McInnes *et al.*, 2017] for clusterization. Finally, the c-TF-IDF is similar to the traditional TF-IDF but applied to the cluster of documents. In other words, clusters of documents are treated as a single document, where $c \in C$ is a document created by concatenating all documents from a cluster in $tf(t, c)$ from Equation 1. As such:

$$tf(t, c) = \frac{f_{t,c}}{\Sigma_{t' \in c} f_{t',c}} \tag{1}$$

$$icf(t, C) = log(1 + \frac{A}{|c \in C : t \in c|}) \tag{2}$$

$$\text{c-TF-IDF}(t, c, C) = tf(t, c) \cdot icf(t, C) \tag{3}$$

where A is the average number of words per cluster, and $|c \in C : t \in c|$ is the frequency of term t across all clusters. Hence, c-TF-IDF models the importance of words in clusters — all combined documents in the cluster — which will be used to select the topic-word distribution for each cluster of

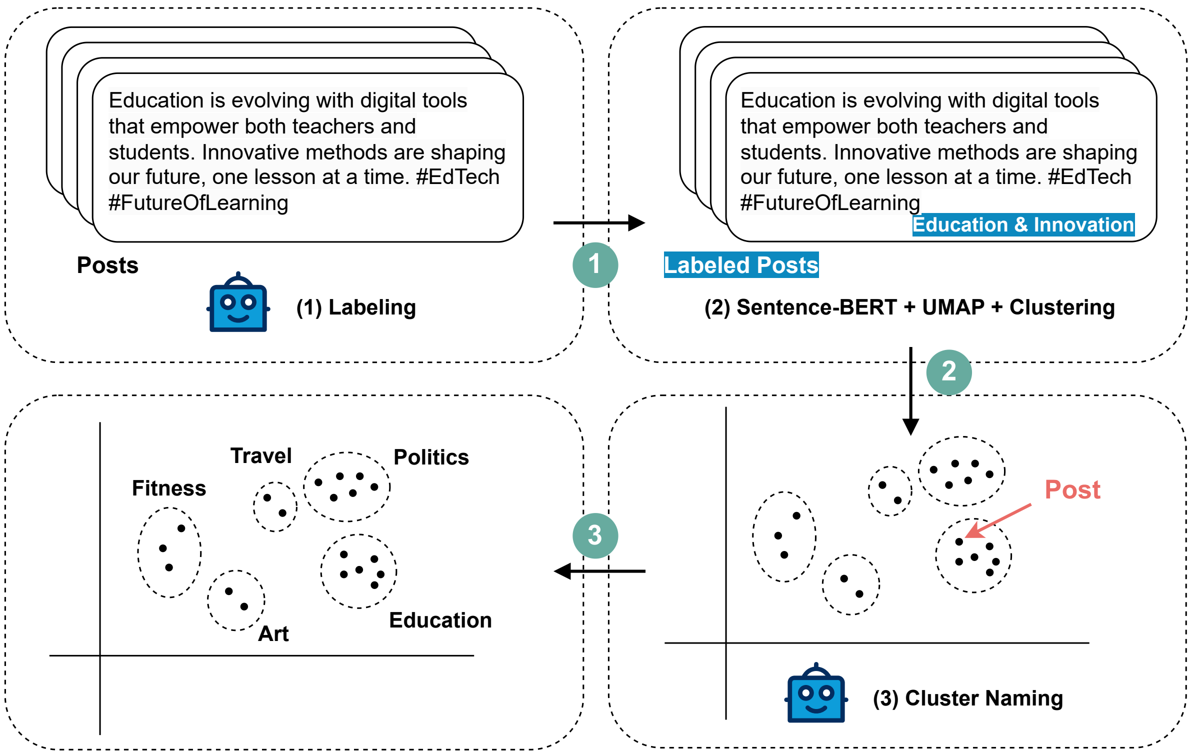

Figure 1. Overview of the proposed LLM-based topic modeling.

documents [Grootendorst, 2022]. In other words, BERTopic will select topic words using c-TF-IDF scores instead of a probability distribution. Based on this approach, different from the other topic models, BERTopic can attribute only one topic for each document — when the document is part of a cluster, the cluster itself is the topic, and the c-TF-IDF selects the relevant words for that cluster.

3.3 LLM-based Topic Modeling

Large Language Models (LLMs) have achieved state-of-the-art performance in a range of language generation tasks, yet they come in different architectures that each offer unique strengths. For instance, Masked Language Models (MLMs), such as BERT [Devlin *et al.*, 2019] and its successors [Liu *et al.*, 2019], are trained to predict randomly masked tokens within an input sequence. In contrast, sequence-to-sequence (seq2seq) models — exemplified by Flan-T5 [Chung *et al.*, 2024] — are designed to transform an input sequence into an output sequence, excelling in tasks such as summarization, translation, and question answering.

On the other hand, causal language models, which are trained in an autoregressive fashion, generate text one token at a time [Brown *et al.*, 2020]. This family of LLMs is particularly effective for tasks requiring fluent and coherent text completion without the need for gradient updates or fine-tuning. More importantly, causal language models are often trained with reinforcement learning from human feedback (RLHF), as exemplified by the ChatGPT-4 family [Achiam *et al.*, 2023]. Training with RLHF enables these models to function as interactive chatbots, capable of completing tasks in a conversational manner through textual prompt inputs. In our study, we employed such a model, leveraging prompt engineering — a technique that involves designing better prompts to improve the model's responses — to automatically label thousands of posts in a human-like manner. This chatbot-like capability was essential to our task, as it allowed us to achieve high-quality, context-aware labeling of thematic content across our datasets. For this paper henceforth, we use "LLMs" for referring to the family of models that enable chatbot-like interactions.

We developed a novel methodology using LLMs to generate topics, a technique that, to our knowledge, has not been explored in prior studies. Initially, we employed a prompt-based strategy to label the "theme" of each post individually, as illustrated by the first step in Figure 1 — see Appendix B for the complete prompt. Given the large volume of posts in some datasets, we implemented a cost-effective sampling approach due to the high cost associated with API calls of LLMs. For datasets with fewer than 1000 posts, we processed the entire dataset. For datasets with more than 2000 posts, we applied a random sampling technique, starting with 95% of the data and reducing the sample size by 5% for every additional 1000 posts, capping the sample at a minimum of 5% of the total dataset. For example, for the DepressBR (N) dataset in Table 1, we randomly sample 14974 posts. This method allowed us to balance API costs while ensuring a representative sample for topic generation. Next, we used Sentence-BERT to extract embeddings for each theme label, followed by dimensionality reduction via UMAP. We then applied clustering to group semantically similar theme labels, resulting in distinct topics — or clusters, as illustrated in step 2 in Figure 1. Finally, clusters were automatically named through another prompt, as detailed in step 3 in Figure 1 (see Appendix B for prompts). This fully automated methodology eliminates the need for manually naming latent topics, improving both efficiency and consistency over traditional methods. Furthermore, in a dynamic scenario where new data is frequently included, the automated nature of this methodology ensures that topics remain consistent and up-to-date without requiring continuous manual intervention. This adaptability is particularly advantageous for real-time applications, where the thematic landscape may evolve over time, such as understanding how individuals suffering with depression change the thematic discussion over time on online communities.

4 Experimental Evaluation

Implementation Details For training LDA and CTM, we rely on the OCTIS library[1] [Terragni *et al.*, 2021]. For TND and NLDA, and BERTopic, we use the implementation provided in the original articles [Churchill and Singh, 2021; Grootendorst, 2022]. For our proposed LLM-based methodology, we use the gpt-3.5-turbo-0125, gpt-4o-2024-05-13, and sabiazinho-3-2025-02-06[2] models.

4.1 Experimental Methods

For all models, we experiment with the range of $[3, 15]$ for K, the number of topics. For traditional models (non-LLM-based models), we execute several experiments with different hyperparameters. For LDA, TND, and NLDA, we fix the number of $\alpha = 50/k$ and $\beta = 0.1$ based on the evidence in the literature showing those values to return good topics [Griffiths and Steyvers, 2004]. Furthermore, for TND and NLDA, we set the skew (β_1) value as 25 and the maximum number of noise words as 200 and train for 1000 iterations; for NLDA, we consider ϕ in the range $[1, 2, 3, 4, 5]$. For CTM, we use a learning rate range of $[2*10^{-3}, 2*10^{-1}]$, and we conduct 20 iterations of optimization, wherein for each model iteration, we execute five trials for the same hyperparameter combination. We use HDBSCAN for clusterization with the minimum cluster size of 10, using the Euclidean metric and the Excess of Mass algorithm to find the most persistent clusters. For BERTopic and the LLM-based method, we rely on the UMAP to reduce the number of dimensions before clusterization: we set the size of the local neighborhood used for manifold approximation to 15; we set the dimension space to have size 10; the minimum distance between embedded points to 0; and the cosine metric to compute the distance in high dimensional space. For BERTopic, CTM, and the LLM-based methodology, we use sentence embeddings relying on multilingual BERT — we use multilingual embeddings given that we often find several posts in multiple languages, such as English and French.

4.2 Evaluation Metrics

We employ quantitative and qualitative evaluations. For the quantitative evaluation, we use the metrics Normalized Pointwise Mutual Information (NPMI), External Word Embeddings Topic Coherence (EWETC), and Inversed Rank-Biased Overlap (IRBO). For the qualitative evaluation (for non-LLM methods), we involved an expert in Psychology (one of the authors) who labeled and selected the most coherent and informative topics based on their professional judgment.

All quantitative metrics get the top N words from a topic $t \in T$ to calculate a score between all pairs of words. As such, every metric relies on calculating score metrics for a single pair of top words, and then we take the average between all pairs to measure the final score for a single topic [Röder *et al.*, 2015]. The score for the model is often the average of the scores for every topic.

For example, considering a single pair of distinct words w_i^t and w_j^t from topic $t \in T$, we need to find co-occurrence counts for those words in a corpus. We find the co-occurrence counts in a test corpus by relying on a sliding window of size 10 to evaluate the experiments. Thus, we collect the co-occurrences and calculate the Pointwise Mutual Information (PMI) according to Equation 4:

$$\text{PMI}(w_i^t, w_j^t) = log\frac{P(w_i^t, w_j^t) + \epsilon}{P(w_i^t) \cdot P(w_j^t)} \tag{4}$$

where the probabilities are measured by the evidence of words w_i^t and w_j^t on the test set. The small term ϵ is used to avoid the logarithm of zero. The final coherence metric for the topic T is the average PMI score across all distinct pairs of words in a topic T. The probability $P(w_i^t, w_j^t)$ refers to the occurrence of words w_i^t and w_j^t in the same window size — a sliding fixed size subset window of words. An extension of the PMI metric is the NPMI, by normalizing the value of PMI according to Equation 5. The score for the model is the average of the NPMI scores between all pairs of words from the topic for all topics.

$$\text{NPMI}(w_i^t, w_j^t) = \frac{PMI(w_i^t, w_j^t)}{-log(P(w_i^t, w_j^t))} \tag{5}$$

We also use another coherence metric based on word embeddings: EWETC. For the word embedding coherence metric, we first extract the word embeddings for all words in a topic $t \in T$. Next, we normalize the word embeddings using the L1 norm. Thus, we define the EWETC metric according to Equation 6:

$$\text{EWETC(t)} = \frac{1}{N(N-1)}\sum_{i=1}^{N}\sum_{j=1\ j\neq i}^{N}(1 - \text{sim}(E_{w_i^t}, E_{w_j^t})) \tag{6}$$

where E is a word embedding matrix, EWETC(t) is the coherence for a single topic $t \in T$, and "sim" is the cosine similarity between two word embeddings. A model's overall score is the average topic coherence of all topics.

Finally, the IRBO metric evaluates the diversity of topics. In other words, it is a quantitative metric of the different topics.

$$\text{IRBO}(T, l, p) = 1 - \frac{1}{\binom{N}{2}}\sum_{i=1}^{K}\sum_{j=i+1}^{K}\text{RBO}(T_i, T_j, l, p) \tag{7}$$

The IRBO is shown in Equation 7, where K is the number of topics, T_i and T_j are the i-th and j-th topics, respectively,

[1] https://github.com/MIND-Lab/OCTIS
[2] https://www.maritaca.ai

l is the parameter representing the top k words to consider, p is a weight given to each agreement with depth d, and $\binom{N}{2}$ is the number of unique pairs of topics. The RBO function compares the top l words of topics T_i and T_j. The InvertedRBO function evaluates the topics for a single model directly. An InvertedRBO value of 0 means that topics T_i and T_j $\forall i, j$ are identical, and a value of 1 means that topics T_i and T_j $\forall i, j$ are entirely different — share no words. More detailed information about this metric and default values can be found on [Webber *et al.*, 2010].

4.3 Results

The quantitative results were obtained by training each model with multiple hyperparameters; we trained 917 models. Table 2 shows the best performant models for each evaluation metric. To select one best model for each dataset, we qualitatively evaluate all 21 models in Table 2 and compare the best models in each metric. Through a manual evaluation, we create a list of terms to label the topics, such as "Politics", "Social Processes", or "Positive Emotions". Next, we label the topics with the terms, except for noisy topics (without any relevant themes associated), and select the best model based on (1) the number of labeled topics, and (2) the diversity of topics. For diversity, we consider that topics such as "Social Processes" and "Everyday Life" are widespread in SNSs. As a result, we prioritize models that uncover more unique and less predictable topics, such as "Food", which present opportunities for deeper exploration and could yield more meaningful and novel insights. This contrasts with more commonly found topics like "Social Processes" and "Everyday Life", which, while relevant, tend to dominate social media discourse. By focusing on these more distinctive themes, we aim to highlight models that demonstrate a broader capacity for identifying diverse and meaningful subject matter, offering a richer understanding of the underlying trends and conversations.

It is important to note that the Reddit dataset, collected through keyword-based queries rather than through BDI-II scores or self-reported data, inherently contains a higher level of noise. This difference in collection methodology means that the Reddit data may include a broader range of content, not all of which is directly related to the personal experiences or clinical symptomatology of depression. As such, while the Reddit dataset provides valuable insights into general discussions on depression, its noisier nature should be taken into account when interpreting the quantitative results and comparing them with those derived from the more clinically anchored datasets.

In Table 2, the best models among all metrics are underscored, and all topics for all models are listed in Appendix A. Note that, through a qualitative evaluation, five out of the seven models were chosen among the best models according to the NPMI metric. This could be explained by the fact that NPMI has been highly correlated with human evaluation among many other topic coherence metrics [Röder *et al.*, 2015]. Through the manual evaluation, we only selected one model according to the IRBO metric and one model according to the EWETC metric, both applied to Twitter datasets.

Note that the LDA baseline only obtained better performance scores for the TwitterUFF (N) dataset considering the EWETC metric. However, NLDA and TND, the models based on the noise distribution, had a superior performance in 14 out of 21 models, illustrating the importance of modeling noise as part of the topic modeling methodology in online content.

Table 2. Best models for each dataset according to NPMI, IRBO, and EWETC metrics. Lines highlighted in bold represent the best overall models for each dataset, taking into consideration a qualitative evaluation of the topics. WE is the EWETC metric.

Model	K	Dataset	NPMI	IRBO	WE
Best models for the **NPMI** metric					
NLDA	7	DeprBR (D)	0.048	1.000	0.588
CTM	6	DeprBR (N)	0.094	0.993	0.680
TND	15	InstaUFF (D)	0.157	0.832	0.597
TND	7	InstaUFF (N)	0.051	0.942	0.585
NLDA	10	Reddit	0.026	0.998	0.553
TND	4	TwitterUFF (D)	0.053	0.693	0.464
CTM	6	TwitterUFF (N)	0.084	1.000	0.680
Best models for the **IRBO** metric					
NLDA	7	DeprBR (D)	0.048	1.000	0.588
NLDA	13	DeprBR (N)	0.051	1.000	0.605
NLDA	5	InstaUFF (D)	0.099	1.000	0.573
NLDA	3	InstaUFF (N)	-0.095	1.000	0.591
NLDA	3	Reddit	0.007	1.000	0.675
NLDA	4	TwitterUFF (D)	0.049	1.000	0.553
CTM	6	TwitterUFF (N)	0.084	1.000	0.680
Best models for the **EWETC** metric					
NLDA	3	DeprBR (D)	0.031	1.000	0.710
TND	6	DeprBR (N)	0.023	0.187	0.707
BTOPIC	4	InstaUFF (D)	-0.163	0.899	0.666
NLDA	4	InstaUFF (N)	-0.335	1.000	0.687
BTOPIC	9	Reddit	-0.079	0.724	0.724
BTOPIC	3	TwitterUFF (D)	-0.149	0.879	0.691
LDA	4	TwitterUFF (N)	0.072	0.774	0.686

For the embedding-based models, CTM obtained better performance scores in three out of 21 models. Notably, CTM performed better in non-depressed Twitter datasets. As BERTopic trains on the raw datasets, the NPMI metric for BERTopic often falls behind, given that there is much more noise in the corpus — such as accents and the lack of lemmatization. However, it demonstrated superior performance in three out of 21 models, according to the EWETC metric. This is expected because documents are embedded in a multidimensional space based on BERT embeddings and clustered to find topic-related documents in the embedding space. As a result, words selected through c-TF-IDF are expected to be close in the embedding space generated by BERT, which is the model we use to calculate the EWETC metric. Another point related to the EWETC metric is that because of the way it is computed, it favors models that result in topics with very closely related words but with shallow diversity among them. Consequently, as can be observed in Appendix A, the models selected by the EWETC metric contain non-diverse topics with closely related words in single topics.

According to qualitative evaluation, the best models were analyzed and had their topics labeled according to their themes. Table 3 shows the qualitative labels present in the best model for each dataset. Refer to Appendix A for a more fine-grained classification of topics. Transition refers to words related to movement, such as physical or temporal movements — "go", "come", "now", "year". Everyday Life contains words related to daily behavior, such as "good morning", "sleep", "class", and "day". Media and Communication refer to hashtags or words related to pictures and video streaming. Social Processes was inspired by the LIWC category with the same name; this category has words related to family, humans (boy, girl, woman, man, he, and she), or the act of social relationships, such as "talking" (with someone), and "friends". Positive emotions contain words such as "wonderful" and "awesome". Negative emotions contain words such as "crisis", "anxiety" and "depression". Travel is, sometimes, also related to positive emotions, but topics labeled as "Travel" contain hashtags with tourism terms or names of known regions, such as "europe". Culture is related to art and drawing words — hashtags such as "inktober". Work contain words such as "job", "study", "money", and "pay". Politics contain words such as "fascism", "elenão"[3] and "fight". Food contains words such as "pizza", "cake" and "potato".

As can be observed from Table 3, the most common topics across all datasets are Social Processes, Transition, and Everyday Life. This is expected because SNSs are a common place to discuss daily activities and interact with other friends virtually. Interestingly, five Travel topics emerged in one single model for the InstagramUFF (D) dataset, which is, again, expected because of the nature of Instagram, where individuals tend to portray themselves with a social representation of happiness through material and immaterial components [De Paola *et al.*, 2020]. Moreover, Instagram users do not post spontaneously taken pictures; instead, they intentionally stage the most visually compelling representation of an exciting life [De Paola *et al.*, 2020], which includes traveling pictures. Notably, users of Instagram have been known for portraying a socially compelling life by taking pictures in groups with partners, family members, and friends. As found by previous research with the InstagramUFF dataset, depressed users tend to post photos with a higher standard deviation on the number of faces [Mann *et al.*, 2020]. Moreover, topic models on Instagram also found several words related to nature landscapes, such as "sea", "sun", "nature", "beach" and "summer". In the same direction as other studies in the literature, the results demonstrate that nature was often anchored with peace and "goodvibes" [De Paola *et al.*, 2020] emotions. Again, these terms were commonly used among depressed individuals. Another interesting result is that Instagram topics often favored words supporting pictures, such as commonly used hashtags "#tbt", "#summer", "#smile' ', which is related to meaning multiplication [Bateman, 2014], where captions and pictures are different mediums to create a new meaning or complement each other. Therefore, according to the Instagram topic model results, the emergent social representation in Instagram favors success, nature, traveling, and positive emotions. Despite these seemingly positive social representations, according to BDI-II metrics, these individuals exhibit moderate to severe depressive symptoms, highlighting a contrast between their public expressions and internal experiences. In contrast, related work by Andalibi *et al.* [2017] found that Instagram posts featuring food and beverage imagery, self-appearance cues, and relationship-related content intended for support tend to attract significantly more comments and likes. Notably, while their study (and that of Koltai *et al.* [2021]) explicitly collected posts tagged with "#depression," our research gathers all posts from university students who self-reported high intensity of depressive symptoms measured by BDI-II. Furthermore, the topics identified by Andalibi *et al.* [2017] — such as "coping/support mechanisms" and "medication" — differ from those uncovered in our analysis, which include unique themes like "travel," "media and communication," and "transition" (see Table 6). These discrepancies indicate that even when originating from the same SNS, very different samples, variations in samples and how they were originally collected and filtered, drive completely different aspects of thematic discussions.

Reddit is a theme-centric social networking site where users curate and produce content based on specific subjects. As a result, we expect individuals talking about depression to also talk about its symptoms, which include depressed mood and feelings of worthlessness — since the Reddit dataset contains two topics of negative emotions. Although there are two topics of Social Processes in Table 3, also common to other datasets, the meaning of this topic in the Reddit dataset is subtly different. In this case, individuals addressing depression, symptomatology, and everyday situations explicitly discuss social relationships. Latent discussions of relationships, whether romantic or not, might give insight into the importance of social relations for depressed individuals. In the related literature, social relationships have been demonstrated to predict longevity better than many other biological or economic factors [Santini *et al.*, 2015]. As we historically evolved to live in complex societies, it is realistic to argue that humans were optimized to be social animals by prioritizing social relations. Social support's role is vital as it is related to better physical and mental health [Thoits, 2011]. However, we note that in this scenario, the social relations could be divided into two groups: primary and secondary groups [Thoits, 2011]. The first is related to more spontaneous and intimate relationships, such as family members and close friends. The second group contains relationships mediated through formalisms and rules and less personal interactions. Reddit's anonymized nature also allows users to talk about intimate relationships keeping their anonymity. However, observing the topic words in Table 41 in the Appendix A, we can see that most words are related to the primary group, such as "father", "family", "home", "breakup", and "dating". When comparing words related to the primary group relations to other topics in Appendix A, DepressBR (N) was the only non-depressed dataset that contained words related to the primary group relations. Moreover, as indicated by Table 6, Reddit users frequently discuss a broad range of life topics, including student life, work, symptomatology, religion, therapy, medication, and mental health perception. The topics we identified in our dataset align closely with those reported in related literature, demonstrating con-

[3] Hashtag of the social movement against Jair Bolsonaro, former Brazilian President.

Table 3. Topic distribution per dataset considering the best selected models in Table 2.

Topic	InstagramUFF		TwitterUFF		DepressBR		Reddit
	D	N	D	N	D	N	D
Transition		1		1	1	1	
Everyday Life				1	1	1	
Media and Communication	2	1			1		
Social Processes	1			1	1	1	2
Positive Emotions	2	1				1	
Negative Emotions				1			2
Travel	5	1					
Culture		1					
Work							1
Politics			1			1	
Food			1				

sistency even across different languages and cultural contexts.

On the X datasets, among Media and Communication, Everyday Life, and Social Processes categories, topic models were able to find topics related to Politics. This also aligned with how individuals use X, such as venting personal frustrations, participating in political movements, or discussing the quality of various goods and services [Mikal *et al.*, 2016]. More specifically, both topics labeled as Politics considering datasets TwitterUFF (D) and DepressBR (N) contained the word "bolsonaro", but the TwitterUFF (D) dataset contained words of negative emotion, such as "hate", "to hate", and "no". Food is another topic linked to one of the Major Depressive Disorder (MDD) symptoms "significant weight loss or gain" [Association *et al.*, 2014]. The symptom involves a notable weight gain or loss for two weeks without commitment to any diet. Although the words in this topic refer to high-calorie foods such as "pizza", "cake" and "potato", the topic also has verbs such as "to want", "to eat", along with the personal pronoun "I", suggesting the user's active desire — thus the externalization of such desire — for calorie-rich foods. Additionally, as highlighted in Table 6 we found several similar topics as previous research, such as "social processes," "transition," "everyday life," and "negative emotions," despite the marked differences in how each dataset was collected and filtered. On the other hand, our topic models were able to find "positive emotions," "media and communication," and "culture" — this last one might be related to the student-nature of the dataset.

The aggregated topics for the depressed and non-depressed datasets can be observed in Table 4. Even though the data is aggregated, we stress that every social networking site has different goals, which inherently directs user behavior more in one direction than another. As such, it is natural to expect more Travel topics in Instagram data or Politics topics in Twitter data. It does not mean that five Travel topics in the depressed group against only one Travel topic in the non-depressed group mean that depressed individuals post more about Travel. From another viewpoint, Negative Emotions are more salient in the Reddit dataset, in which users explicitly talk about MDD symptomatology.

Table 4. Aggregated topics for depressed and non-depressed datasets.

Topic	Depressed	Non-depressed
Transition	1	3
Everyday Life	1	2
Media and Communication	3	1
Social Processes	4	2
Positive Emotions	2	2
Negative Emotions	2	1
Travel	5	1
Culture	0	1
Work	1	0
Politics	1	1
Food	1	0

Table 5. Best results for each dataset according to the EWETC metric using GPT.

Best models for the **EWETC** metric			
Model	K	Dataset	EWETC
GPT-3.5-Turbo	15	DepressBR (D)	0.868
GPT-4o	14	DepressBR (N)	0.871
GPT-4o	15	InstagramUFF (D)	0.846
GPT-4o	6	InstagramUFF (N)	0.856
GPT-4o	13	Reddit	0.910
GPT-4o	8	TwitterUFF (D)	0.867
GPT-4o	9	TwitterUFF (N)	0.877

4.4 LLM Results

For the LLM-based methodology, the best results according to the EWETC metric were achieved with the GPT-4o model, often showing higher values for K, except for the DepressBR (D) dataset where the GPT-3.5-turbo model performed better, as can be observed from Table 5. We do not use the NPMI metric to evaluate these models as it requires an exact match of theme strings (words or keywords within topics) found in the corpus, which was rarely observed. For instance, consider the theme "fight for workers' rights" in the topic "International Women's Day" in Table 28, we would need to find the co-occurrences of the said theme with another theme in the same topic, which does not appear in the corpus. This is expected because the NPMI metric processes themes as single-word entities. Additionally, the IRBO metric reached its maximum value for all models, as there were no repeated themes across different topics (clusters) since the themes often consisted of two or more words.

For the InstagramUFF (D) dataset, the LLM-based methodology successfully identified several topics aligned with the manually curated list, such as "gratitude" and "positive mindset' ' under the Positive Emotions category. It also captured the Travel theme through topics like "erasmus" and "first impressions from Portugal' ' . Interestingly, the Politics topic was further refined into distinct themes, such as "politics" and "democracy' ' . Moreover, the LLM-based approach uncovered new topics not identified by any of the best-performing traditional models, including, "cristianity", "religiosity", "culture' ' , and "personal image' ' .

Previous research has demonstrated a positive correlation between religious practices and improved subjective well-being [Jansen *et al.*, 2010; Garssen *et al.*, 2021]. For instance, a study involving 430 college students from a U.S. university, where most participants identified as Catholic or Protestant Christians, found that self-reported religiosity may serve as a protective factor against depression [Jansen *et al.*, 2010]. Moreover, they found that regardless of religious affiliation, attending church more frequently decreased the levels of depression [Jansen *et al.*, 2010; Garssen *et al.*, 2021]. Interestingly, unlike traditional methods, the LLM-based methodology detected traces of religiosity practices among the depressed students from University X. This finding suggests that these individuals might be engaging in religious practices as a potential coping mechanism to mitigate depressive symptoms. However, it has been demonstrated that the strength of the belief might influence how effective the protective factors are for depressive symptoms in young adulthood [Eliassen *et al.*, 2005; Jansen *et al.*, 2010]. Hence, moderate religiosity is found to be correlated with the highest level of depressive symptoms [Eliassen *et al.*, 2005], which might be the reason for the presence of the topic among the subset of depressed users in the InstragramX dataset.

Considering the InstagramUFF (N) dataset, we identified the "feelings", "love", and "enchantment" under the Positive Emotions category. We note that the "feelings" topic contains several types of feelings, such as "good feelings", "mixed feelings", "positive feelings", and "family feelings", which are inherently more complex than words such as "good", "happy", and "love" that appear in topics from traditional methods. The "love" topic presents the same variability with several kinds of love, such as "romance", "love for children", and "love for the city". This presents a richer diverse array of positive emotions than single words obtained with traditional methods. Furthermore, the LLM-based method obtained the topics "housing", containing themes related to several neighborhoods, and "pictures", containing themes related to types of pictures.

We observed from this analysis that in both InstagramUFF subsets the LLM-based methodology included all topics found by the best performant model for each metric into a single model. Furthermore, the topics found by the LLM-based methodology were better refined. For example, considering the InstagramUFF (D) dataset, the best NPMI model predominantly identifies only Travel and Positive Emotions, the best IRBO model focuses on Travel and Media & Communication, and the best EWETC highlighting Politics and Appearance. This demonstrates the superior breadth and depth of topics that LLM-based approaches can uncover, providing a more comprehensive understanding of the thematic discussions. While the traditional models obtained only a set of 7 unique topics among all best performant models for each metric (Tables 25– 27 in Appendix A), the LLM-based model obtained 15 orthogonal and unique set of topics.

Regarding the smaller LLM, Sabiazinho-3, although it consistently achieved lower EWETC metrics across all datasets, it uncovered a slightly different set of topics. Tables 31–33 present the topics identified by Sabiazinho-3 for the InstagramUFF (D) split, including "work," "peace," "love," and "entertainment." Notably, some topics detected by GPT-4o, such as "shows" and "politics," were labeled differently by Sabiazinho-3, appearing as "music" and "Brazilian politics," respectively. For the Instagram (N) dataset, Sabiazinho-3 (see Tables 39 and 40) revealed two topics related to "arts," one on "discrimination," and one on "travel" — a topic that GPT-4o did not detect, despite it being one of the most frequently identified by traditional methods. Furthermore, the topic "marielle franco," former Brazilian politician, highlighted students' involvement in political discourse about her murder. Table 6 stress the topics found by the LLM approaches, such as travel, student life, politics and religion — the last one not being found by Sabiazinho-3.

For the Reddit dataset, the LLM-based methodology provided a set of 13 unique and information-rich topics, while all traditional best performant models obtained a set of only 4 unique topics. While Social Processes and Work has not been explicitly found by the LLM-based methodology, there were a series of other orthogonal-themed topics. For example, topics such as "sexuality", "self-esteem and therapy", "mental health and suicide", "feelings and emotions" were identified. Notably, the topic "side effects and cost-benefit" addressed medication side effects and exercise benefits, a significant finding not captured by traditional methods.

The LLM-based approach also highlighted discussions on "bullying" and "education", linking these to educational contexts, whereas traditional methods only identified concerns about studying and working with less depth. Bullying involvement — both bullying others and being the victim of bullying — has beend studied to be correlated to higher risks of depression than adolescents not involved in any bullying practice [Klomek *et al.*, 2007; Moore *et al.*, 2017; Eyuboglu *et al.*, 2021]. Since the Reddit dataset might contain any social networking site user, it could be both the report from adolescents, or a worried parent, or even the report of a past traumatic event. Moreover, the topic "depression in different contexts", highlighted clear indications of depression within educational settings, which complements the "bullying" topic in the broader picture.

The "sexuality" topic also addressed concerns about "LGBTQ+" identity. Adolescents often need to hide their identity to avoid conflicts, such as bullying and stigmatization [Harrison, 2003]. A consequence of this behavior might be the isolation and the feeling of rejection which operates as another vulnerability factor for depression [Harrison, 2003]. The topic "sexual health", correlates with aspects of the BDI-II psychometric test that assesses loss of inter-

Table 6. Comparative summary of thematic topics in mental health-related discussions on SNSs. Each cell lists the study that identified the corresponding topic on the respective platform. (*) Mental Health Perception is how the SNS users and their audience perceive their mental health struggles. "ours (both)" means that LLM-based and non-LLM approaches found that specific topic for that SNS, while "ours (non-LLM)" found the topic only through the traditional approaches, and "ours (LLM)" found the topic only through the LLM-based approach.

Topic	**Instagram**	**X (Twitter)**	**Reddit**
Social Processes	ours (non-LLM) Andalibi *et al*. [2017]	ours (non-LLM) Issaka *et al*. [2024] Resnik *et al*. [2015]	ours (non-LLM) Timakum *et al*. [2023] Sik *et al*. [2023]
Transition	ours (non-LLM)	ours (non-LLM) Resnik *et al*. [2015]	—
Everyday Life	—	ours (non-LLM) Resnik *et al*. [2015]	—
Media and Communication	ours (non-LLM)	ours (non-LLM)	—
Work	ours (LLM)	—	ours (non-LLM)
Positive Emotions	ours (both) Andalibi *et al*. [2017]	ours (both)	Sik *et al*. [2023]
Negative Emotions	Andalibi *et al*. [2017] Koltai *et al*. [2021]	ours (both) Issaka *et al*. [2024] Resnik *et al*. [2015]	ours (non-LLM) Timakum *et al*. [2023] Sik *et al*. [2023]
Physical Symptoms	—	—	Sik *et al*. [2023] Timakum *et al*. [2023]
Coping/Support Mechanisms	Andalibi *et al*. [2017]	Issaka *et al*. [2024]	Timakum *et al*. [2023]
Treatment/Medical Concerns	—	—	Sik *et al*. [2023] Timakum *et al*. [2023]
Travel	ours (both)	—	—
Student Life	ours (LLM)	ours (LLM) Resnik *et al*. [2015]	ours (LLM) Sik *et al*. [2023]
Work	—	—	Sik *et al*. [2023]
Sleep Disturbance	—	Resnik *et al*. [2015]	Timakum *et al*. [2023]
Food	Andalibi *et al*. [2017]	ours (non-LLM) Resnik *et al*. [2015]	Timakum *et al*. [2023]
Religion	ours (LLM) Koltai *et al*. [2021]	Resnik *et al*. [2015]	Sik *et al*. [2023]
Politics	ours (LLM)	ours (both) Resnik *et al*. [2015]	ours (LLM)
Therapy	—	Issaka *et al*. [2024]	ours (LLM) Timakum *et al*. [2023] Sik *et al*. [2023]
Medication	Andalibi *et al*. [2017]	—	Timakum *et al*. [2023] Sik *et al*. [2023]
Mental Health Perception*	Andalibi *et al*. [2017] Koltai *et al*. [2021]	Issaka *et al*. [2024]	Sik *et al*. [2023]
Culture	ours (both) Koltai *et al*. [2021]	ours (LLM)	—
Fitness	Koltai *et al*. [2021]	Resnik *et al*. [2015]	—
Gaming	—	Resnik *et al*. [2015]	ours (LLM)

est in sex. The topic "sexual and psychological abuse" was also observed, in which the literature demonstrates that both types of abuses functions as a vulnerability factor for depression [Radell *et al.*, 2021]. The topic "emotional need" revealed skepticism towards existing mental health support systems. The topic "mental health and suicide" is related to one of the symptoms of MDD. Finally, the "excessive internet use" topic explored issues related to the excessive use of SNSs, gaming, and the internet in general; we note that addiction has significant implications to exacerbate mental disorder symptoms [Association *et al.*, 2014].

Sabiazinho-3 identified several common topics, including those related to mental health disclosures (e.g., "mental health," "mental disorder"), politics (e.g., "justice and rights," "economic crisis"), and issues concerning sexuality, education, and life. Notably, one topic labeled "envy" was found, although the associated terms did not strongly correspond to its label. Additionally, in the direction of the "work" topic, the model uncovered a topic named "quality of life at work," featuring terms that describe balancing work and life, as well as expressions of depression and anxiety in the work environment.

In the TwitterUFF (D) dataset, the LLM-based approach uncovered a diverse array of topics beyond the usual focus on "Everyday Life" and "Transition" seen in traditional methods. We identified topics such as "happiness", "feelings", "biodiversity", "memes", "brazilian culture", "mother", "interaction", and "healthy habits", presenting a richer and more varied set of orthogonal topics. For the TwitterUFF (N) dataset, we found the notable topics "dance", "entertainment", "feelings", "education", "professional dissatisfaction", and "television". Dance has been extensively investigated to be a highly effective treatment for depressive symptoms [Akandere and Demir, 2011; Karkou *et al.*, 2019]. Interestingly, the topic "feelings" appeared in both depressed and non-depressed subsets with very similar themes. However, the topic related to professional life concerns did not appear in the depressed subset, contrasting with findings from the Reddit dataset.

For the DepressBR (D) dataset, traditional methods (see Tables 7–9 in Appendix A) predominantly identified topics such as Transition, Everyday Life, Social Processes, and Media and Communication, resulting in only four unique topics across all models. Notably, the best-performing model according to the IRBO metric yielded topics that were largely non-informative. In contrast, the LLM-based methodology produced a much richer and more diverse array of topics. For example, the "emojis" topic suggests that users in this dataset may rely more heavily on emojis as a communication tool. The "solitude" topic, which is recognized as a significant vulnerability factor for depression [Association *et al.*, 2014], also emerged. Furthermore, the LLM-based results identified a "feelings" topic that included themes such as "feelings of weakness", "feelings of anger", and "feelings of inadequacy" which are consistent feelings among depressed individuals Busch [2009]; Zahn *et al.* [2015]. Both subsets contained the "social network" topic, but the depressed subset also included themes like "support network" and "pharmacy", whereas the non-depressed subset focused on social networking engagement, highlighting a clear distinction between the two groups.

In the context of X datasets, Sabiazinho-3 found a topic about the "lgbtq community," (Table 15) containing terms such as "lgbtqia+ pride," "lgbtq+ movement," "lgbtq+ acceptance," and "ban on lgbt language," thereby reflecting both concerns about the community and efforts to strengthen its bonds. Another noteworthy aspect is that Sabiazinho-3 was able to uncover topics in multiple languages although it is a model specialized in the Brazilian Portuguese language; for instance, it detected a topic labeled "케이팝" in Table 24 and the topic "happiness" in Table 31. Moreover, for the DepressBR (N) dataset, the model revealed distinct topics such as "literature," "education," and "productivity". In the context of depressed university students (TwitterUFF (D)), Sabiazinho-3 uncovered a "health" topic that reflects concerns about diseases and pregnancy, as well as a separate "virus" topic that delves further into issues of contamination; it also identified a "politics" topic. For non-depressed students (TwitterUFF (N)), the model detected topics including "philosophy," "politics" (topic already in english), "soccer," "education," and an entire topic comprising self-related terms — most notably, "self-acceptance."

Overall, the LLM-based methods provide a more diverse and enriched set of insights compared to traditional approaches, capturing subtle topics and themes that offer a deeper understanding of the complexities of manifestation of depressive symptoms on online communication. Traditional methods often produce unnamed topics with unrelated words, leading to vague and less informative topics. In contrast, LLM-based approaches generate themes that often consist of multiple words, allowing for a more precise and comprehensive description of the general topic — for example, a "feeling" topic containing the theme "feelings of anger". Traditional methods, relying on single-word themes, struggle to achieve this level of depth and specificity.

5 Discussion

Our study was guided by three central research questions: (1) How do thematic expressions of depression differ across various social networking sites? (2) How do these expressions vary between depressed and non-depressed individuals? (3) How effective are advanced topic modeling techniques — including our novel LLM-based approach — in uncovering and characterizing these thematic differences?

For the first question, our findings reveal distinct patterns across platforms. For example, Instagram predominantly features themes related to personal narratives, travel, and positive emotional displays, while Reddit tends to host more detailed discussions on mental health symptomatology, work–life balance, politics, economics, and medication, as well as explicit appeals for social support. These differences underscore the influence of collection and filtering methods; notably, our Reddit dataset — collected via keyword-based queries — exhibits a broader range of content compared to more clinically anchored datasets, such as InstagramUFF, where we collected the posting histories of students based on self-reported depressive symptoms. Moreover, Instagram datasets collected and filtered differently in previous studies [Andalibi *et al.*, 2017; Koltai *et al.*, 2021] yield a divergent set of topics. In contrast, discussions on X often gravitate toward everyday life aspects, positive and negative emotions expressions, social processes, memes, and politics, corroborating with earlier research [Resnik *et al.*, 2015; Mikal *et al.*, 2016; Issaka *et al.*, 2024]. Although subcultural topics may also emerge, their appearance is closely tied to the sample collected and the specific methodology employed (see "gaming" topic in Table 6).

For the second research question, our experimental evaluation revealed that distinguishing between depressed and non-depressed SNS users solely based on holistic thematic discussions is particularly challenging. Our experiments demonstrate a significant overlap in the topics discussed by both groups — common themes such as everyday life, social processes, and emotional expressions appear across the board. Even in cases where differences emerge, it is difficult to determine whether these distinctions arise from the specific characteristics of our sample or if they reflect broader patterns that generalize across diverse populations, cultures, and methodological approaches. Further research with varied datasets is required to assess the consistency and representativeness of these differences.

For the third research question, our advanced LLM-based methods demonstrate superior performance relative to traditional approaches. Although the smaller LLM, Sabiazinho-3, identifies a diverse array of orthogonal topics, its terms are sometimes less tightly correlated with the topic labels and may even appear in English and Korean — an issue not observed with GPT-4o, which consistently produces multi-word, coherent themes. Moreover, related works often yield topics with overlapping vocabulary, thereby limiting the depth and diversity of their findings. Overall, these results highlight that the choice of advanced topic modeling techniques plays a critical role in elucidating the complex, multi-faceted expressions of depression in online communication.

6 Challenges and Considerations

Language models, particularly LLMs, can indeed be influenced by having encountered similar data during their training phase. Since these models are trained on vast amounts of text data, they may have seen instances of the same or similar content before. However, LLMs do not remember specific data points or have direct access to their training data. Instead, they capture patterns, relationships, and structures within the text that allow them to generate plausible and contextually appropriate responses. Consequently, while the likelihood of a model encountering exact data points is low, it is possible for it to generate outputs that resemble content seen in training, especially for common or widely discussed topics. This phenomenon may become more apparent when working with highly specific or niche topics, where the model's responses are more dependent on the breadth and diversity of the training data. Although our datasets are not publicly available, it is possible that these models were trained on portions — or even the entirety — of their content. However, we apply these models to a task that they may not have been explicitly optimized for, suggesting that they might not have fully internalized the unique patterns present in our methodology. This approach helps mitigate the risk of dataset-specific biases influencing the models' predictions.

As for language independence, the methods employed by LLMs are generally robust across multiple languages, though their effectiveness may vary depending on the training corpus and the language itself. LLMs trained on multilingual corpora, such GPT-3.5-Turbo and GPT-4o, can handle a wide range of languages, but the quality of their performance is often higher for languages with abundant training data (e.g., English, Portuguese, Spanish). For languages with less representation in the training data, the model's performance may degrade, especially in tasks requiring deep contextual understanding. However, in terms of topic detection or identifying similar themes across languages, LLMs can often generalize reasonably well. This is particularly true for widely discussed topics or themes, which tend to be cross-linguistic. On the other hand, cultural, linguistic, or regional differences can influence the manifestation of topics in different languages, making it important to consider these nuances when analyzing cross-linguistic similarities. While some topics may appear across languages, they might be discussed or framed differently based on local contexts, idioms, or cultural norms. To further explore these nuances, we conducted experiments using a model specifically designed for Brazilian Portuguese — Sabiazinho-3 from Maritaca AI — to better capture the unique linguistic characteristics of this language.

7 Ethical Implications

The study of depression-related topics on SNSs presents significant ethical considerations that must be thoroughly examined to ensure responsible research practices. First and foremost, the collection and analysis of user-generated content raise concerns regarding privacy, informed consent, and the potential for harm. Even when data is publicly available, ethical guidelines dictate that researchers must carefully consider how such data is used, stored, and interpreted to minimize risks to individuals who may not have explicitly consented to their content being analyzed in this context. In our study, we have taken comprehensive measures to securely store and fully anonymize the data, ensuring that all personally identifiable information is removed and that the privacy of individuals is rigorously protected throughout the research process.

Additionally, in our study, we have approached the interpretation of depression-related discussions with great care to avoid reinforcing stigma or misrepresenting the lived experiences of individuals with mental disorders. We have been deliberate in our choice of language throughout our academic discussions and publications, aiming to promote awareness and understanding while minimizing the risk of perpetuating misconceptions. Moreover, we have taken special care with discussions about the holistic and generalist nature of topic modeling, to ensure that our analyses do not inadvertently mislabel or oversimplify the complex spectrum of human emotions and experiences discussed on SNSs.

A crucial ethical consideration is the potential impact of research findings on public policy and intervention strategies. While identifying trends in depression-related discourse can help shape mental health support services, misinterpretation or misuse of findings may lead to increased surveillance, discrimination, or stigmatization of vulnerable individuals. Researchers must engage with mental health professionals and policymakers to ensure that their work is applied in a manner that prioritizes well-being and ethical integrity.

Finally, researchers should consider how findings from studies on depression discourse can be effectively communicated to mental health professionals and support organizations. Collaboration with these stakeholders can help bridge the gap between computational insights and real-world applications, ensuring that research contributes meaningfully to improving mental health awareness and intervention efforts.

8 Conclusions

Identifying key topics discussed by depressed and non-depressed individuals on SNSs is crucial for understanding their online behavior. However, choosing the most suitable topic model for this task can be challenging. To address this, we evaluated six different topic modeling models: LDA, TND, NLDA, CTM, BERTopic, and our proposed LLM-based methodology on datasets containing posts from Instagram, Twitter, and Reddit in the Brazilian Portuguese language.

Our analysis revealed that while certain themes emerged consistently across SNSs, these themes are often influenced by the unique characteristics of each platform. For instance, Reddit discussions prominently featured themes related to the symptomatology of depression, reflecting its thematic focus. In contrast, Instagram topics were more related to travel and positive emotions, while Twitter discussions covered everyday life and media communication. The findings underscore that SNSs vary in their usage and focus, which affects the type of content shared. Users may prefer different platforms based on factors such as anonymity, thematic focus, or personal expression.

Our findings highlight the strengths of the LLM-based approach, which provided a richer and more diverse set of orthogonal topics compared to traditional methods, offering a unique and broad perspective on thematic discussions and linguistic patterns across SNSs. We expect this approach to help future research on understanding online behaviors and interactions, revealing a range of nuanced insights that traditional methods may not capture. The results underscore the value of employing advanced topic modeling techniques to gain a deeper appreciation of how individuals express themselves on SNSs, paving the way for more comprehensive analyses and future research in this field.

Future research should explore real-time monitoring of depression-related discourse to identify shifts in mental health trends. Developing adaptive algorithms that can detect emerging patterns in online discussions could provide valuable insights for early intervention. Furthermore, investigating the role of online community dynamics in shaping mental health discussions may offer a deeper understanding of how support networks function in digital spaces.

Another promising direction is the expansion of this research to different linguistic and cultural contexts. Understanding how depression is discussed in various social and demographic groups can lead to more inclusive and culturally sensitive mental health interventions. Strengthening collaborations between computational researchers, mental health professionals, and policymakers will be essential in translating research findings into practical applications that benefit individuals and society as a whole.

Declarations

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Authors' Contributions

P.M. conceptualized the study, developed the methodology and software, and wrote the original draft of the manuscript. M.U. conducted the experiments with the Large Language Models (LLMs) and performed the data analysis. E.H.M and A.P supervised the project. All authors contributed to the review and editing of the manuscript and approved the final version.

Competing interests

The authors declare that they have no competing interests.

Availability of data and materials

The data that support the findings of this study are available from the corresponding author upon reasonable request. However, a portion of the data is not publicly available due to ethical restrictions and to protect participant privacy.

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A Complete List of Topics

Table 7. NLDA model, DepressBR (D), best NPMI metric.

Transition	1	Everyday Life	3	4	Media and Com.	Social Processes
fazer	voce	bom	pessoa	ta	ver	ele
estar	todo	dia	vez	gente	gostar	ela
ano	poder	hoje	nunca	vc	video	falar
ainda	vida	casa	pensar	achar	foto	dar
bem	mundo	sair	tanto	ne	mano	ai
vir	amor	chegar	sentir	cara	demais	dizer
acabar	sim	dormir	chorar	eh	musica	amigo
semana	sobre	tomar	algum	tu	youtube	tar
esperar	porque	acordar	tao	nada	assistir	mae
voltar	precisar	amiga	conseguir	assim	eles	mandar

Table 8. NLDA model, DepressBR (D), best IRBO metric.

0	1	2	3	4	5	6
fazer	voce	bom	pessoa	ta	ver	ele
estar	todo	dia	vez	gente	gostar	ela
ano	poder	hoje	nunca	vc	video	falar
ainda	vida	casa	pensar	achar	foto	dar
bem	mundo	sair	tanto	ne	mano	ai
vir	amor	chegar	sentir	cara	demais	dizer
acabar	sim	dormir	chorar	eh	musica	amigo
semana	sobre	tomar	algum	tu	youtube	tar
esperar	porque	acordar	tao	nada	assistir	mae
voltar	precisar	amiga	conseguir	assim	eles	mandar

Table 9. NLDA model, DepressBR (D), best EWETC metric.

0	Everyday Life	2
pessoa	passar	tar
tudo	vir	eh
vida	chegar	tu
outro	dormir	ne
mundo	acabar	foto
sempre	tomar	mano
tempo	semana	demais
sobre	esperar	chorar
pai	acordar	chamar
precisar	dois	mandar

Table 10. GPT Model, DepressBR (D), Best EWETC Metric. (Part 1)

Equilíbrio	Flores	Emojis	Storytelling	Presença Online
tempo de disponibilidade	museus	emoji poop	drama de comunicação	tráfego de site
disponibilidade de tempo	saulo	smiley emojis	storytelling	google tradutor
traje casual	entre rios	emoji com risos	suspense	sunday service
hiatus	flores para adriana	emojis e expressões online	stories	google adwords
administração do tempo	santo antônio	expressões emojis	drama	google books
autenticidade e tranquilidade	alemanha	reação emoji	avatar	site
tempo de estudo	alianças	presença de emojis	american horror story season 6	app
gerenciamento do tempo	jason omara	emoji ʕ•ᴥ•ʔ	entertaining	roblox
tentativa de equilíbrio	flores	emoji frustração woman-facepalming	audição para fantasma da ópera	unfollow
tranquilidade	kamilla	emoticon emoji	toy story 4	referências a insultos online

Table 11. GPT Model, DepressBR (D), Best EWETC Metric. Anonymized (***). (Part 2)

Solidão	Música	Variedade	Redes Sociais	Debate
otaku	músicas muse imagine dragons e nickelback	discórdia	movimentos sociais	respeito democrático
colégio ***	wine sex	blues	variedade	debate
desafios na busca por um lar	fifth harmony	aquisição	rede de apoio	capitalismo
mal-entendido	carreira de selena	infidelidade	influenciadores sociais	debate social
animais de pelúcia	bandas de música	posicionamento dos senadores	farmácia	poliamor
solidão no condomínio	música	competitividade	causas sociais	debate online
denúncia anônima	soprano mezzo-soprano e contralto	contemplação	red bull	debates
susto	músicas da kat	assédio	saudações	violência política
sujidade	música hip hop	inscrições	seguidores	ranking de popularidade
sacrifício	show de jazz/rap	afecto	redação	violência policial

Table 12. GPT Model, DepressBR (D), Best EWETC Metric. (Part 3)

História	Vida Prossegue	Sentimentos	Conscientização	Festividades
história de o	razões para o zed estar fraco	expressão de sentimentos	verificação de identidade	festa em casa
história	escolha de outro clg	sentimento de confusão	mobilização	festa de tendel
dia do historiador	introversão	sentimentos de inadequação	conscientização para com o povo indígena	festinha de despedida
beijos durante as celebrações	frio	reserva de sentimentos	demonstração de afeto	festinha junina
ceilândia	critérios de nomeação	emoções e sentimentos	cultural impact	festa de neymar
pefabiodemelo	noite	sentimento de fraqueza	anulação de atos administrativos	festas de fim de ano
ceará	maçã	intensidade dos sentimentos	auto-mutilação	comemoração de festa
receitas para ceia	erro ortográfico	sentimento de raiva	construção de simulador	festas juninas
certeza	enganar quem te ama	emoções sentimentais	mobilização coletiva	festivais de comida
fascinação pela história	show de mágica	raiva contida	auto-ajuda	comemoração

Table 13. Sabiazinho-3 model, DepressBR (D), Best EWETC Metric. (Part 1)

Compartilhamento de ideias	Protesto	Disney	Musica
receitas de abóbora	revolta	disney	pop music
evolução de opiniões	protestocontrastf	disney+	funk music
gestão de equipe	protesto	finale	the masked singer
identificação de suspeitos	protestos	bad boys	rock music
expressões de surpresa	debate público	badlands	boy bands
incentivo ao suicídio	revolta com atendimento	história do time	band
compartilhamento de receitas	investigação policial	toy story	album sales
ser surpreendida	ministério público federal	badoo	indie music
compartilhamento de ideias	governo federal	bad guy	music stars
testes de convergência	ministério público	goodmorning	indie

Table 14. Sabiazinho-3 model, DepressBR (D), Best EWETC Metric. (Part 2)

Lar	Apresentação	Sentimentos	Melhoria
dallazen	apresentação pública	sentimento positivo	fuga da realidade
zé neto	apresentação ao vivo	sentimento de propósito	agonia
bauhaus	apresentação	sentimento positivo	chimpanzés
coleta de itens	sustentação vocal	emoções e sentimentos	chiste
japão	apresentação social	sentimento de gratidão	tinnitus
dor de garganta	aprovação	foco em sentimentos	fuga
lar	inovação	expressão de sentimentos	membros da sonserina
siga	localização	sentimento negativo	agorafobia
sia	empolgação	sentimento de felicidade	ruivas
zed	realização profissional	sentimento de companhia	movimento das mulheres

Table 15. Sabiazinho-3 model, DepressBR (D), Best EWETC Metric. (Part 3)

Pessoas	Educação	Comunidade lgbtq	Tecnologia
miles morales	educação e cultura	lgbtqiap+	diário online
março	falta de educação	movimento lgbtq+	digital aesthetics
marco	educação pública	casais lgbtq+	littleredbook
marina silva	erro de comunicação educacional	comunidade lgbtq	notebook
elias césar	educação política	movimento lgbt+	snapstories
maiara e maraísa	direitos sociais e educacionais	proibição de linguagem lgbt	gadgets
salvador	inclusión educativa	orgulho lgbtqia+	vantagem
marcos	educação infantil	apoio à comunidade lgbt	notebooks hp
pedro	education	apoio lgbtq+	interface design
getúlio vargas	educação financeira	aceitação lgbtq+	pandora

Table 16. CTM model, DepressBR (N), best NPMI metric.

Social Processes	1	Social Processes	3	4	Everyday Life
olho	the	voce	sonho	eu	dia
cabelo	you	ele	obrigar	querer	ir
cmg	it	fazer	real	pra	hoje
linda	is	gente	unico	ele	bom
kkk	in	vc	preciso	to	ver
ngm	my	poder	livro	ir	hora
puta	of	pessoa	dor	fazer	perfil
kkkkk	on	ela	ponto	falar	casa
kkkkkk	and	ta	pequeno	saber	dormir
kkkk	thi	falar	bolsonaro	pq	acordar

Table 17. NLDA model, DepressBR (N), best IRBO metric.

0	1	2	Everyday L.	Pos. Emo.	5	Soc. Proc.	7	Trans.	9	Politics	11	12
fazer	estar	vez	bom	sim	ai	ele	querer	ir	ta	todo	tudo	dar
coisa	ano	passar	dia	amo	mano	ela	saber	la	vc	grande	vida	hora
poder	bem	pensar	hoje	amor	tar	falar	gostar	chegar	achar	eles	nunca	acabar
gente	ainda	tanto	dormir	amar	foto	dizer	ninguem	tomar	pq	dever	sempre	agora
algum	dois	chorar	feliz	saudade	usar	cara	chamar	comer	eh	bolsonaro	nada	video
precisar	semana	mal	acordar	obrigar	pqp	mae	assim	voltar	ficar	familia	outro	mandar
qualquer	comecar	olhar	ouvir	lir	comprar	homem	comigo	cu	ne	historia	viver	perfil
trabalho	perder	fico	noite	gt	kkkk	pai	faco	assistir	mt	brasileiro	entender	certo
conseguir	ganhar	cada	aula	oi	onde	morrer	alguem	logo	tbm	povo	momento	twitter
lugar	jogo	rir	ontem	cabelo	meio	filho	conversar	show	oq	caso	vao	parar

Table 18. TND model, DepressBR (N), best EWETC metric.

0	1	2	3	4	5
eu	eu	eu	eu	ir	eu
ir	pra	pra	pra	eu	pra
pra	ele	ele	ele	pra	ele
ele	fazer	fazer	fazer	ele	algum
fazer	querer	querer	querer	fazer	ta
querer	ta	ta	ta	querer	fazer
nada	voce	voce	voce	ta	querer
ta	bom	bom	bom	voce	voce
voce	pessoa	pessoa	pessoa	bom	bom
bom	saber	saber	saber	dia	tentar

Table 19. GPT Model, DepressBR (N), Best EWETC Metric. (Part 1)

Campeonato	Atenção	Adoração de fãs	Opinião sobre sequências de filmes	Rodízio
fcseguindofcs	Níveis de atenção	Apatia em relação a shows	Fantástico	Mcimbra
Tata werneck	Atenção	Sinalização de defeito	Detona ralph 2	Muro de berlim
Fcseguindofc	Gestão da dor	Adoração de fã	Impressionante	Raoni
Coaching	Desespero por atenção	Adoração de fãs	Opinião sobre sequências de filmes	Molho de camarão
Cartola fc	Atenção no relacionamento	Expressão de empolgação	Filme animais fantásticos	Atacar demais lados da moeda
Coach	Desespero matutino	Apoio na pós-graduação	Horários de cinema	Fãs de mashirao ojiro
Liderança coach	Impacto na vida	Extração de siso	Woody e buzz lightyear	Lucas indo ao paredão
Fc my way	Bolsa de estudos	Interrupção de fala	Luto por cena de filme	Bispo de jinotega
Liderança no campeonato	Nise da silveira	Humilhação pública	Dormir durante o filme	Prefácio de livro do chesterton
liderança no campeonato	Declaração de voto	Crescimento em cidade pequena	Aversão ao cinema	Maluco dançar

Table 20. GPT Model, DepressBR (N), Best EWETC Metric. (Part 2)

Independência	Sentimentos pessoais	Maus-tratos aos animais	Redes sociais	Phishing
Independência	Sentimento de encantamento	Maus tratos infantis	Abuso verbal em redes sociais	Links de phishing
Inteligência e sagacidade	Sentimento pessoal	Maus-tratos a animais	Engajamento nas redes sociais	Phishing
Baile da independência	Sentimentos em relação a um jogo de futebol	Maus-tratos aos animais	Obsessão por redes sociais	Potencial de phishing
Proteção contra a negatividade	Expressão de sentimentos espontâneos	Maus-tratos a idosos	Desonestidade em redes sociais	Uso do google
Independência emocional	Sentimentos de impotência	Brincadeiras infantis	Identidade em redes sociais	Scam digital
Inteligência	Sentimentos de exclusividade	Brincadeiras	Interrupção nas redes sociais	Google adwords
Sonho de independência	Sentimentos negativos relacionados a uma pessoa	Maus-tratos aos animais	Identidade de usuário em redes sociais	Fraude/phishing
Espiritualidade	Crítica à banalização de sentimentos	Brincadeiras com idosos	Engajamento em redes sociais	Google assistente
Incoerência textual	Respeito aos sentimentos alheios	Bruxaria	Gerenciamento de redes sociais	Uso de photoshop
Incoerência	—	—	—	—

Table 21. GPT Model, DepressBR (N), Best EWETC Metric. (Part 3)

Engano	Governo	Humor	Uso de emoji
Engano	Candidatos ao governo	Humor matinal	Emoji na comunicação on-line
Arrobass falsas e enganosas	Impacto no governo	Humor sobre paternidade/maternidade	Uso de emojis loudly-crying-face
Propaganda enganosa	Polícia federal	Humor infantil	Emoji de susto
Engordar	Governo	Humor paterno	Reações de emojis
Retorno de alguém especial	Governo federal	Humor pet	Sinal de tristeza em emoji
Engano ou confusão	Governo temer	Sarcasmo	Emoji de rosto suado grinning-face-with-sweat
Engolir bracket	Figurino de policial	Idiota	Emojis de comida e bebida
Reconhecimento de alguém	Polícia	Nota de humor	Emojis e sentimentos positivos
Abraço especial	Governo francês	Humor e contradição	Reação emojificada
Abraço	Atividades do governo	Mudança de humor	Emoções através de emojis

Table 22. Sabiazinho-3 model, DepressBR (N), Best EWETC Metric. (Part 1)

Saudade	Compartilhamento	Páscoa	Awards
Frustração cotidiana	Representatividade	Talarico	Emmyawards
Alianças estratégicas	Compartilhar momentos especiais	Ovos de páscoa	Oscar 2023
Saudade da infância	Companheirismo	Narguilé	Oscar
Preferências de sabor	Compartilhamento	Páscoa	Emmy
Saudades do pai	Exemplo de saídaidiomararo	Ronco	Emmys
Combustíveis	Companhia	Temporada chuvosa	Oscars
Saudade	Compartilhamento excessivo	Salmo91	Emmy awards
Sazonalidade	Análise de tráfego	Nariz	Mtv hottest
Suicídio de profissionais da saúde	Aventura noturna	Palhaço	Mtv
Dicas de saúde	Comparativos	Paramore	Mtvhotest

Table 23. Sabiazinho-3 model, DepressBR (N), Best EWETC Metric. (Part 2)

Polícia	Educação	Facebook ads	Produtividade
Domestic violence	Educação e relacionamentos	Fastfood	Produtividade
Polícia federal	Financiamento educacional	Novo recurso facebook	Perturbação do sossego
Operação policial	Educação emocional	Visibilidade online	Cpi
Polícia federal	Frustração com a educação	Postura online	Perturbação sonora
Polícia surpresa	Sistema educacional	Gmail	Probabilidade
Invasão policial	Investir na educação básica	Pdf	Perturbação humana
Polícia	Educação a distância	Sites de compras coletivas	Dicas de produtividade
Abordagens policiais	Educação	Resposta a postagem internet	Sustentabilidade agrícola
Policial	Github education	Separação por kurt	Construção
Policiamento	Educacao	Análise de redes	Construção civil

Table 24. Sabiazinho-3 model, DepressBR (N), Best EWETC Metric. (Part 3)

케이팝	Literature	Mídia social	Sentimentos	São paulo	Romantico
러브 레터	Articles	Tendência mídia social	Sentimento existencial	Vôlei	Mensagem de fátima
스트레칭	Outback	Tendências mídia social	Sentimentos intensos	Fiéis fc	Menina desmaida
팬덤	Comeback	Estratégias mídia social	Sentimentos distantes	Ídolos fc	Indina menzel
아기	Original	Estatísticas mídia social	Sentimentos mistos	Vale	Mensagem romântica
Χάτρι	E-books	Plataformas mídia social	Sentimento tóxico	Santos católicos	Meninos desaparecidos
아이돌	Reading	Análise métricas	Sentimentos e emoções	Buenos aires	Marília mendonça
케이팝	Missing	Créditos mídia	Sentimentos fortes	Rio de janeiro	Mandar mensagem
감사 expressão	Lose	Desempenho mídia	Sentimentos	Blocos de rua	Comédia romântica
엑소	Look book	Performance mídia	Compartilhamento sentimentos	Jamaica	Convites românticos
아기제노	Books	Insights mídia	Arte e sentimento	Roberto carlos	Declaração romântica

Table 25. TND model, InstagramUFF (D), best NPMI metric.

Pos. Emo	Travel	2	Travel	4	Media	6	Soc. Proc.	Travel	Travel	Pos. Emo.	11	12	Travel	Media and Com.
voce	uff	dia	eu	foto	lover	eu	eu	uff	riodejaneiro	saudade	eu	eu	eu	eu
eu	europe	eu	summer	pra	rj	ele	amor	eu	brazil	tbt	querer	mulher	uff	photographyr
todo	lisbon	deus	praia	ta	smile	saber	amo	europe	eu	eu	ir	nós	eurotrip	photoofthedayr
amo	erasmusstudent	hoje	mar	eu	eu	poder	coracao	erasmusstudent	cabofrio	foto	pra	sobre	madrid	rio
vida	uffnoexterior	ano	naturar	ir	friends	estar	pra	autricher	rj	dia	ver	vida	erasmustorie	photography
bom	pics	bom	sol	tirar	tbt	ela	hora	erasmus	br	maravilhoso	nunca	direito	espanhar	sky
dia	erasmus	phn	verao	gente	nikiti	ir	sentir	erasmuslife	brazilianbeach	lugar	quanto	luta	templodedebod	canon
feliz	eurotrip	ele	beach	fazer	day	pra	familia	erasmusstories	arraialdocabo	semana	olhar	elenaor	spain	photooftheday
sempre	instadesign	estar	sun	saber	carnaval	tudo	ela	viena	errejotar	poder	fazer	trabalho	espano	omelhorclick
mundo	city	vir	goodvibe	aqui	don	fazer	tao	uffnoexterior	summer	incrivel	pro	algum	uffnoexterior	olhar

Table 26. NLDA model, InstagramUFF (D), best IRBO metric.

Travel	1	2	3	Media and Com.
uff	eu	pra	dia	tbt
europe	voce	amor	hoje	lover
uffnoexterior	estar	gente	ela	saudade
eurotrip	ele	ta	bom	riodejaneiro
instadesign	amo	novo	ainda	brazil
erasmus	saber	ficar	dizer	maravilhoso
lisbon	sempre	coracao	nós	smile
lifer	tudo	olhar	grande	tirar
pics	ano	tempo	mulher	errejotar
iphone	feliz	deixar	nunca	cabofrio

Table 27. BERTOPIC model, InstagramUFF (D), best EWETC metric.

0	Politics	Appearance	3
eu	luta	cabelo	chomp
não	fascismo	só	eu
dia	mulheres	não	não
pra	contra	cores	run
uff	dia	blusa	tudo
erasmusstudent	enquanto	mostrar	único
uffnoexterior	não	pra	just
amo	elenunca	eu	treino
você	pra	black	tá
eurotrip	mulher	hair	pra

Table 28. GPT Model, InstagramUFF (D), Best EWETC Metric. Anonymized (***). (Part 1)

Primeiras impressões de portugal	Cristianismo	Relação interpessoal	Cultura	Dia internacional da mulher
penapalace	Fé e religião	Dieta	Torcidas	Dia internacional da mulher
rafael	felizpáscoa	Reserva biológica estadual de guaratiba	Torcida	Pesquisa experimental
pena palace	Cristianismo na arte	Imaculada conceição	Melhor torcida	Fingindo
valente	Cristianismo	Aquecedores	dálmata	Conto de fadas
valeu a pena	cílios	Divulgação científica	Cultura de torcida	Luta pelos direitos dos trabalhadores
jorge***	feliznatal	cappuccinoespecial	Cultura japonesa	Patinhas
marcado na alma	Ciclismo	Citação de khalil gibran	Poesia romântica	Orgulho pela mulherada
praias de cabo frio	Otimismo	Aceitação das diferenças	Fenômenos naturais	Mulher misteriosa em sonhos
bronzeado	Aniversário de criança	Nome do população em situação de rua	Comida japonesa	Distribuição de renda
Rodrigo	citações de einstein	hungrydog	Mariposa	síndrome de down

Table 29. GPT Model, InstagramUFF (D), Best EWETC Metric. (Part 2)

Shows	Gratidão	Erasmus	Imagem pessoal	Presente
taylor swift	Gratidão e amor	Erasmusstories	Lights	Presente
adele	husbandandwife	Erasmus	Foto sem legenda	Presentes
rocknroll	Gratidão e amizade	Erasmus student	Foto sem filtro	Presentede2018
banda de rock	Gratidão familiar	Erasmusstory	Naturalidade das fotos	Presente incomum
rock	Gratidão à mãe	Vida de estudante erasmus	Filtros de imagem	2009
show de rock	Marriage	Erasmusstudent	Cosplayers	Ano 2019
glam rock	Gratidão a deus	Erasmus experience	Sessão de fotos	20102018
narrativa de suspense	Fé e gratidão	Austria viena erasmus	Blackmodel	Csa
show da pitty	Gratidão	experiência erasmus	IMAGEM PESSOAL	Que time
Pink Floyd	expressão de gratidão	programa erasmus	coreography	2019

Table 30. GPT Model, InstagramUFF (D), Best EWETC Metric. Anonymized (***). (Part 3)

Democracia	Mentalidade positiva	Bike	Política	Estudante
Democracia	Angústia e estresse mental	Rubywoo	Políticos e elites	Estudante
Informações de contato	Seremosresistência	Birdbox	Mulheres na política	Estreia de série
Exibição de confiança	Espiritualidade e bem-estar	Cobra	Políticas públicas	Estágio
Defesa de tese	Propaganda positiva	Voudelbike	Eleições e política	Estado de espírito
Exercício físico	Clima/emotividade	Harleydavidson	Debate sobre políticas públicas	Primeiro mês do ano
Lamento	Mentalidade positiva	@m***	Manifestações políticas	Vida de estudante
Sacrifício	Problemas emocionais	Cobrança de dívida	Preocupação política	Estação do ano
Reações e medidas contra discursos de ódio	Acompanhamento fitness	Daisyduck	Política	Estresse com estudos
Vento	Ideologia	Arquitetura niemeyer	Apoio político	Estresse
Simpósio	fingimento de atualidade	Bike	evento político	Estações do ano

Table 31. Sabiazinho-3 model, InstagramUFF (D), Best EWETC Metric. (Part 1)

Bem-estar	**Tecnologia**	**Happiness**	**Trabalho**	**Música**
Italianfood	Neymar	Soulmates	Reequilíbrio econômico	Dj
Sorte	Denúncia de maus-tratos	Smile	Paternidade	Letra musical
Comer próximo	Sinais	Happy	Transtorno mental	Power songs
Processamento de texto	Teorias	Soul connection	Experiências de vida	Eventos musicais
Influenciadores digitais	Tecnologia e jogos	Beautiful minds	Trabalho de campo	Black music
Confissão de fé	Máquinas agrícolas	Soulfull	Retorno ao trabalho	Turnê musical
Petitcomite	Ironia	Cute	Eternidade	Music
Rastreamento	Povos indígenas	Cutness	Bem-estar espiritual	Indie
Dor no pescoço	Tecnologia	Humor	Positividade corporal	Quarteto
Nadineefelipe	Mulher misteriosa	Happynewyear	Trabalho	Legado musical

Table 32. Sabiazinho-3 model, InstagramUFF (D), Best EWETC Metric. Anonymized (***). (Part 2)

Inclusão	**Estação**	**Paz**	**Amor**	**Entretenimento**
Acidente	Primãe	Chá	Amor pela faculdade	Dc
Instadesign	Juizdefora	Novo colega mesa	Amor por animais	Presentes
Afeto	Baile funk	Chamar atenção	Gratidão e amor	Presente
Acessórios	Primavera	Treino	Sol	Cd
Açai	Lyra	Eupriana	Pôr do sol	Cn
Afeto e camaradagem	Primavera dos artistas	Churrasco	Pôrdosol	
Expressões idiomáticas	Sua majestade	Chuva	Por do sol	Séries
Uniformizados	Beyourself	Montanhas	Amor pela uff	Makeaway
Expressões faciais	Verão	Coturno	Amor pelos animais	Showbiz
Saída esperadareminiscência	Malandragem	Bairro de ***	Relacionamento amoroso	Md

Table 33. Sabiazinho-3 model, InstagramUFF (D), Best EWETC Metric. (Part 3)

Instagram	**Relacionamento**	**Animal**	**Política brasileira**	**Aceitação**
Poses de fotos	Meio de relacionamento	Veterinária	Portugal	Meditação
Boliche vida instagram	Relacionamento	Comportamento animal	Clubenáutico	Aceitação própria
Endoftheyear	Relâmpago	Donald duck	Campeonato	Apresentação
Instagram	Sensacionais	Animalkingdom	Brasileiros na copa	Auto-melhoramento
Poses fotográficas	Relacionamento familiar	Petcare	Copa do mundo	Aceitação
Photooftheday	Fim de relacionamento	Animal care	Campeonato brasileiro	Recuperação médica
Picoftheday	Religião	Resgate animal	Lisbon	Votação
Visual	Nacionalismo	Hogwarts	Lisbonlife	Tonalização
Edição de fotos	Vemvitória	Vida de animal	Madrid	Vocação
Nude	Relacionamentofamiliar	Pets	Segunda-feira	Vocacao

Table 34. TND model, InstagramUFF (N), best NPMI metric.

0	Pos. Emo.	Trans.	Media and Com.	Culture	Travel	6
eu	dia	foto	tbt	inktober	sol	eu
voce	bom	pra	rj	day	dia	pra
ele	sempre	ano	photoofthedayr	dia	viver	todo
ir	gente	ver	vsco	art	mulhersolar	cada
saber	vida	saudade	riodejaneiro	drawing	destinorj	vida
fazer	tudo	vir	praia	artistoninstagr	lardocemar	vez
querer	amo	tbt	naturar	artsy	amor	voce
bem	feliz	primeiro	pictureoftheday	paintingr	todo	pessoa
sobre	bem	lugar	sunset	ink	mar	estar
ficar	todo	agora	natureza	illustration	orgulhodeserniteroi	dar

Table 35. NLDA model, InstagramUFF (N), best IRBO metric.

Media and Com.	1	2
inktober	pra	eu
day	bom	todo
art	tudo	fazer
saudade	hoje	ele
sol	bem	estar
foto	vez	saber
rj	gente	poder
artistoninstagr	mundo	querer
mar	amo	cada
praia	ficar	coisa

Table 36. NLDA model, InstagramUFF (N), best EWETC metric.

0	Culture	Social Processes	Media and Communication
dizer	drawing	algum	ano
palavra	artistoninstagr	olhar	coracao
conseguir	vsco	mulhersolar	levar
cara	artsy	corpo	uff
sorriso	ink	nunca	fim
parabem	illustration	nada	natureza
preciso	thi	mulher	niteroi
jeito	bonito	eles	pai
aprender	theme	lado	sair
qualquer	trilha	tirar	noite

Table 37. GPT Model, InstagramUFF (N), best EWETC metric. (Part 1)

Sentimentos	Protagonismo das mulheres na luta por melhores condições de trabalho	Fotos
Sentimentos positivos	Consultoria	Máscara
Sentimentosfamiliares	Sugestão criativa	Emojis
Expressão de sentimentos	Protagonismo das mulheres na luta por melhores condições de trabalho	Fotos de primos
Emoções e sentimentos	Study	Fotos de férias
Sentimentos pozitivis	Benefícios emocionais do exercício	Selfies
Sentimentos mistos	Ciência da computação	Fotos e vídeos
Sentimentos	Weworklabs	Foto impressa
Sentimento pessoal	Inteligência	Bordas em imagens
Sentimentos bons	Maioridade legal	Fotos
Sentimento de bem-estar	Realizações profissionais	Selfie

Table 38. GPT Model, InstagramUFF (N), best EWETC metric. Anonymized (***). (Part 2)

Moradia	Encantamento	Amor
Moradores de grajaú	Amor por lugares	Amor por lugares
Pamonha	Tias	Romance
Deus da salvação	Romance	Crush
Moradia	Crush	Amor pela matemática
Vale nevado	Amor pela matemática	Amor pela cidade
Barra da tijuca	Amor pela cidade	Amor duradouro
Chuva	Amor duradouro	Amor pelos filhos
Vinho	Amor pelos filhos	Amor pela equipe
Páscoa	Amor pela equipe	Amor pelos animais
Auto de páscoa ***	Amor pelos animais	Amor e luz

Table 39. Sabiazinho-3 model, InstagramUFF (N), Best EWETC Metric. (Part 1)

Futuro	**Presentes**	**Discriminação**	**Riograndedonortedunas**	**Art**
Likeincense	Gift	Racialidentity	Parceiros	Fã de artistas
Fimdetarde	Bares	Sensação de aventura	Samba	Artista nas redes sociais
Competições		Dissertação	Malu	Instalacao artistica
Desejos para o futuro	Drain	Senso de realização	Porto	Artsy
Futuro	Jantar	Resistência	Santanenses	Desenho artístico
Tematicasdedesenho	Wanting	Datas especiais	Cruzeiro da msc	Artistas latino-americanos
Companheirismo	Presente	Exploração laboral	Hoteleira	Releitura artística
Futuro promissor	Choices	Determinação	Rios	Exposição artistica
Parquenacional	Paper	Atividades físicas	Riodejaneiro	Palace of fine arts
Provérbios	Acceptance	Discriminação	Zueira	Creativechallenge

Table 40. Sabiazinho-3 model, InstagramUFF (N), Best EWETC Metric. (Part 2)

Luz do dia	**Marielle franco**	**Viagem**	**Artes**	**Esforço e superação**
Quarta-feira	Primavera o ano inteiro	Homenagens	Artes	Pelademocracia
Engenharia	Missões	Análise de postagem	Arte contemporânea	Neofogado
Caminhada	Milícia	Sfeelings	Arte abstrata	Empatia
Quintadaregaaleira	Marielle vive	Sorte	Artesvisuais	Amoessafoto
Serra dourada	Vida de mergulhador	Travel natureza	Arte e ilustração	Eladissequeia
Magreza não é elogio	Vida de animais	Lembranças viagem	Artes visuais	Apreciação e gratidão
Serra da canastra	Virada de ano	Planejamento viagem	Arte interativa	Finanças pessoais
Quehonra	Verão	Cores	Arte	Folia
Ii guerra mundial	Promessa	Letra	Arte conceitual	Pesquisa científica
Doação de sangue	Casal	Viajando	Arte digital	Famosos

Table 41. NLDA model, Reddit, best NPMI metric.

Work	1	2	Soc. Proc.	4	5	Neg. Emo.	7	Soc. Proc	Neg. Emo.
ano	amigo	grande	pai	saber	pra	depressao	pessoa	ele	dia
trabalho	nunca	sobre	casa	querer	ir	problema	voce	ela	sentir
estudar	tempo	dever	eles	sinto	achar	ajudar	vida	dizer	passar
faculdade	todo	social	familia	sintar	coisa	ansiedade	poder	falar	parecer
emprego	começar	apenas	voltar	ninguem	tar	tomar	outro	conversar	momento
aqui	gostar	reddit	deixar	motivo	ai	crise	porque	namorar	dor
dinheiro	pouco	parte	chegar	simplesmente	ver	remedio	mundo	amiga	tentar
curso	escola	pequeno	chorar	importar	pro	bem	algum	junto	hoje
pagar	primeiro	livro	cuidar	algo	merda	pois	alguir	terminar	sentimento
entrar	hoje	nós	ainda	tanto	tipo	psicologo	apenas	comecar	continuar

Table 42. NLDA model, Reddit, best IRBO metric.

Negative Emotion	Work	2
coisa	voce	falar
tudo	todo	la
sentir	grande	comecar
sinto	conseguir	sair
porque	trabalho	ta
medo	forma	passar
ninguem	mundo	pq
sintar	faculdade	cara
vontade	dinheiro	conversar
mal	social	voltar

Table 43. BERTOPIC model, Reddit, best EWETC metric.

0	1	2	Politics	4	5	6	7	Politics
eu	eu	eu	não	eu	não	eu	ano	partido
ela	não	não	brasil	não	você	não	eu	esquerda
não	pra	pra	país	ela	são	pra	não	não
ele	depressão	já	eu	pra	pode	música	pra	youtube
pra	ele	trabalho	governo	ele	pessoas	jogar	ela	pt
tudo	só	só	br	bem	está	dia	aprendi	brasil
sempre	fazer	fazer	já	só	suicídio	músicas	mim	watch
só	já	ela	argentina	coisas	sociedade	só	vó	eu
já	vida	vida	você	tudo	saúde	coisas	tudo	porque
mim	sei	tudo	anos	vida	vida	anos	já	presidente

Table 44. GPT Model, Reddit, Best EWETC Metric. (Part 1)

Efeitos colaterais e custo-benefício	Carência emocional	Sentimentos e emoções	Saúde mental e suicídio	Educação
Reações dos outros às confissões	Evitando clichês e positividade forçada	Desabafo e expressão de sentimentos	Problemas de saúde mental e pensamentos suicidas	Mobilidade social e educação
Benefícios dos exercícios físicos	Desconfiança em sistemas de apoio	Expressão de sentimentos reprimidos	Pensamentos suicidas e saúde mental	Desmotivação e desafios na educação
Recursos acessíveis e gratuitos	Consequências trágicas das ações individuais	Guardar sentimentos	Problemas de saúde mental e suicídio	Educação superior
Eficácia e efeitos colaterais dos tratamentos	Leitura e estudo sobre comportamento humano	Confusão de sentimentos	Luta contra a saúde mental	Experiência na educação superior
Efeitos colaterais e custo-benefício	Possibilidade de esquizofrenia	Introversão e sentimentos	Luto e saúde mental	Educação à distância
Atitudes e comportamentos dos pacientes	Sensacionalismo e insensibilidade	Sentimentos não correspondidos	Saúde mental e suicídio	Educação e transferência de bolsa
Efeitos colaterais da sertralina	Positividade	Sentimento de desconexão familiar	Luta com a saúde mental	Dificuldades na educação superior
Experiência com efeitos colaterais	Dor na língua	Sentimentos suicidas	Luta contra problemas de saúde mental	Crise na educação
Efeitos colaterais e melhora	Direito administrativo	Sentimento de desconexão	Suicídio e saúde mental	Planos de educação e medo do futuro
Efeitos colaterais e dependência	Esquizofrenia	Respeito aos sentimentos alheios	Impacto do suicídio na saúde mental	Acessibilidade e inclusão em educação

Table 45. GPT Model, Reddit, Best EWETC Metric. (Part 2)

Bullying	Uso excessivo da internet	Autoestima e terapia	Depressão em diversos contextos	Mudança de país e adaptação
Bullying e estereótipos	Decisão de uso excessivo do Twitter	Autoestima e terapia	Depressão e livros menos complexos	Busca por liberdade e identidade
Bullying e decepções pessoais	Uso excessivo de tecnologia e smartphones	Alcoolismo e autodestruição	Problemas emocionais e depressão	Recuperação e mudança para calistenia
Bullying	Comunidade de interessados	Autodestruição e desespero	Depressão e reprovação escolar	Dilemas de mudança e adaptação
Bullying e saúde mental	Comunidade	Dificuldades de autoimagem e autoaceitação	Depressão e borderline	Autenticidade e busca de identidade
Bullying no ensino médio	Jogo celeste	Cíclicos hábitos autodestrutivos	Depressão e isolamento	Adaptação e mudança de país
Bullying e suas consequências	Conflito familiar e jogos online	Insegurança e autojulgamento	Depressão e problemas mentais	Resiliência e busca por significado
Acusações falsas e bullying	Jogos e internet	Autoestima e medo de julgamento	Isolamento e depressão	Mudança para o exterior
Bullying e humilhação	Propaganda e likes	Comportamentos autodestrutivos	Depressão e dependência emocional	Oportunidades de mudança para o exterior
Bullying e isolamento social	Uso excessivo da internet	Autoestima e autoaceitação	Depressão em diversos contextos	Desejo de mudança e busca por liberdade
Reclusão e bullying	Jogos eletrônicos	Comportamento autodestrutivo	Maneiras de ajudar alguém com depressão	Mudança de estado e adaptação

Table 46. GPT Model, Reddit, Best EWETC Metric. (Part 3)

Crise existencial e questionamentos sobre a vida	Bolsonaro	Sexualidade
Existencialismo e questionamentos pessoais	Código penal	Abuso psicológico e sexual
Filosofia e moralidade	Notícias negativas e sociedade	LGBTQ+
Moralidade pessoal	Compra e venda de produtos usados	Autoaceitação e identidade LGBTQ+
Greve geral de 1886	Insatisfação com EAD	Atração física e desejo sexual
Pesquisa científica para decisões de vida	Ineptitude de Bolsonaro	Saúde sexual
Problemas pessoais e desafios na vida adulta	Apoio a Bolsonaro	Sextorsão
Autocuidado e soberania pessoal	Interação com ex-parceiro	Experiência sexual tardia
Vida profissional e pessoal	Documentário na América Latina	Descoberta da sexualidade
Conflito entre vida pessoal e cuidado familiar	Indignação com a mídia	Desempenho sexual
Estagnação profissional e insatisfação pessoal	Impeachment de Jair Bolsonaro	Conflito interno sobre sexualidade

Table 47. Sabiazinho-3 model, Reddit, Best EWETC Metric. (Part 1)

Inveja	Qualidade de vida no trabalho	Sentimentos	Vulnerabilidade humana	Transtorno mental
Pesquisa de livros	Ansiedade ambiental	Sentimento de inferioridade	Resultado busca por ajuda emocional	Transtorno de bipolaridade
Alívio de dor	Ambientes digitais positivos	Sentimento de fracasso	Altas habilidades e inteligência	Tratamento de autismo e ansiedade
Ler livros	Depressão no ambiente corporativo	Sentimento de isolamento	Habilidades profissionais	Bipolaridade e depressão
Terra plana	Colapso ambiental	Sentimento de inadequação	Impacto emocional	Autismo
Boa noite e paz	Depressão e ansiedade no trabalho	Sentimento de desamparo	Instabilidade emocional	Transtorno obsessivo compulsivo
Força de vontade	Ansiedade e depressão no ambiente de trabalho	Sentimento de inutilidade	Vulnerabilidade humana	Bipolaridade
Livros	Ansiedade no ambiente de trabalho	Sentimentos confusos	Vulnerabilidade	Obsessão
Viver de favor	Comportamento no ambiente de trabalho	Sentimentos negativos	Código penal	Transtorno obsessivo-compulsivo
Ensino privado	Ambiente de trabalho	Sentimento de desalinho com a realidade	Financiamento coletivo	Transtorno bipolar
Lar	Assédio moral no trabalho	Sentiment analysis	Evolução humana	Negatividade

Table 48. Sabiazinho-3 model, Reddit, Best EWETC Metric. (Part 2)

Justiça e direitos	Sexualidade	Saúde mental	Vida	Crise econômica
Diário	Movimentos feministas	Cannabis medicinal	Balanço de vida	Ditadura militar
Imaginação fértil	Homossexualidade e religião	Cannabis	Transição para a vida adulta	Crise econômica brasileira
Cachorro	Feminismo	Uso de medicamentos psicotrópicos	Estilo de vida	Percepção da polícia por região
Direitos individuais	Crossdressing	Efeitos colaterais de antidepressivos	Estilo de vida alternativo	Polícia civil
Leis e justiça	Homossexualidade no armário	Fisioterapia	Estilo de vida agitado	Policiais e suas ações
Direitos pessoais	Assexualidade	Fisioterapia alternativa	Estilo de vida saudável	Estado policiaresco
Escitalopram	Pansexualidade	Medicamentos psiquiátricos	Transição de vida	Crise econômica
Direito imobiliário	Homossexualidade	Efeitos colaterais de ansiolíticos	Estagnação na vida	Repercussões econômicas
Cachorros	Bissexualidade	Efeitos psicológicos da cannabis	Solidão como escolha de vida	Crescimento econômico
Fotografia	Transsexualidade	Medicação psiquiátrica	Relato de vida	Sistema econômico

Table 49. Sabiazinho-3 model, Reddit, Best EWETC Metric. (Part 3)

Internet	Educação	Autoconhecimento	Relacionamentos
Bts	Educação e aprendizado	Autocuidado emocional	Relacionamentos saudáveis
Correntes de internet	Educação e concurso	Autodepreciação	Consequências de atos
Startup	Sistema educacional	Autodestruição emocional	Relacionamento afetivo
Homens trans	Educação adulta	Autodisciplina	Conflito de relacionamento
Desabafos online	Educação inclusiva	Ideias de autodestruição	Relacionamento entre irmãos
Comunidades online saudáveis	Educação à distância	Autopunição	Relacionamentos difíceis
Censura na internet	Educação universitária	Autoaceitação	Relacionamentos afetivos
Estudos online	Educação	Educação financeira	Aplicativos de relacionamento
Amigas	Educação e desempenho escolar	Auto cuidado	Relacionamentos duradouros
Homens	Custos de educação	Auto cuidado	Relacionamento abusivo

Table 50. TND model, TwitterUFF (D), best NPMI metric.

Social Processes	Everyday Life	2	3
eu	pra	eu	eu
vc	eu	ir	ver
ai	todo	ano	fazer
querer	dia	gente	bom
falar	fazer	dizer	dar
amiga	querer	sobre	tudo
pq	hoje	ele	ir
ela	ir	estar	estar
ir	casa	voce	porque
gente	passar	ta	coisa

Table 51. NLDA model, TwitterUFF (D), best IRBO metric.

Everyday Life	1	Everyday Life	Social Processes
pra	ta	dia	voce
ir	estar	bom	gente
ele	achar	coisa	vc
ficar	dar	aqui	pessoa
hoje	pq	amo	poder
casa	tudo	vez	ai
porque	bem	vida	amiga
nunca	cara	mundo	ela
pro	nada	pensar	ano
vir	gostar	falar	passar

Table 52. BERTOPIC model, TwitterUFF (D), best EWETC metric.

0	Food	Politics
eu	pizza	odeio
não	bolo	eu
pra	comer	ódio
só	queria	não
tá	batata	legal
já	eu	bolsonaro
você	pra	really
gente	só	gostando
dia	fazer	mudou
vai	não	80

Table 53. CTM Model, TwitterUFF (D), Best EWETC Metric.

0	Everyday Life	Transition	Social Processes	4	Negative Emotions
the	bom	ir	voce	eu	raiva
in	ano	pra	gente	saber	vo
and	dia	fazer	poder	falar	chato
you	todo	ficar	ele	achar	aguentar
is	novo	casa	pessoa	querer	ranco
it	hoje	to	mulher	vez	kkkkkkkkk
of	primeiro	aqui	ela	pq	agr
on	semana	dar	vc	ver	kkkkkk
my	tudo	eu	dizer	ele	td
thi	ainda	querer	falar	pessoa	triste

Table 54. GPT Model, TwitterUFF (D), Best EWETC Metric. (Part 1)

Hábitos saudáveis	Cultura brasileira	Interação	Mãe
Termino de projeto	Artista de rua	Interação direta com seguidores	Posição de goleiro
Compartilhamento de conteúdo	Capa de álbum	Editora seguinte	Ações da igreja
Encerramento	Redes sociais de artistas	Pastora com peruca ruim	Texugo/cachorro
Enfermagem	Artistas de tatuagem	Interação com seguidor	Cataratas do Iguaçu
Reparos de dispositivo	Divulgação de trabalho artístico	Interação com seguidores	Cachorro rosa
Competição saudável	Artista convidada	Informação nova	Coelho quente
Apreciação de sorrisos	Classe artística	Documentação para usuários	Ansiedade para o carnaval
Encomendas de pinturas	Artistas brasileiros	Informação	Óculos com nariz anexado
Adolescência	Fantasia de noiva cadáver	Impostos de importação	Doja Cat
Erro técnico	Cena punk brasileira	Interação com fakes	Thaynão

Table 55. GPT Model, TwitterUFF (D), Best EWETC Metric. (Part 2)

Felicidade	Sentimentos	Biodiversidade	Memes
Pedidos de ajuda em tecnologia	Sentimentos de ciúme	Disciplina de ecologia	Figurinha de Telegram
Pessoas curadas com cloroquina	Sentimento de prostração	Propagação de conteúdo	Saga Rappi Uber Eats
Desigualdade salarial	Sentimento	Sensação de errado	Uber
Voluntariado	Expressão de sentimentos	Ocultação de ações	Figurinhas de WhatsApp
Achados de farmácia	Sentimentos e emoções	Preparação para exame OAB	Memes virais
Desejos de felicidade	Sentimentos	Procrastinação	Selfie
Heterossexualidade	Sentimento de desistência	Biodiversidade	Meme
Homenagem a vítimas	Sentimentos de rejeição	Recomendação de conteúdos	Fotos
Exemplo fechado	Compartilhamento de sentimentos	Reflexão sobre organização	Incômodo diário
Notas e lembretes	Sentimentos conflitantes	Limite de isenção	Gif

Table 56. Sabiazinho-3 model, TwitterUFF (D), Best EWETC Metric. (Part 1)

Cinema	**Juventude**	**Saúde**	**Produção de conteúdo**
Saga	Ignorância deliberada	Vestibulares	Diminuição da inteligência
Drama	Judiciário	Caligrafia	Avaliação de conteúdo
Vlog	Juventude	Hepatite c	Reutilização de conteúdo
Suspense	Ar condicionado	Dia da visibilidade lésbica	Transplante
Disney cinema	Dilemas da juventude	Bicicleta	Produtividade
Cinematografia	Vontade incontrolável	Gravidez	Normalização de corpos
Plot twist	Explanando	Olavistas	Delivery
Twist	Arquitetura de interiores	Gramática	Campanhas de conscientização
Cinema	Compartilhamento de conteúdo	Bichos	Produção de conteúdo
Filme de suspense	Monitoramento de preços	Gastronomia	Assessoria

Table 57. Sabiazinho-3 model, TwitterUFF (D), Best EWETC Metric. Anonymized (***). (Part 2)

Mulheres na segunda guerra mundial	**Política**	**Publicidade online**	**Vírus**
Exigiu decência	Crítica política	Publicidade online	Quiz viral
Coelho quente	Debate	Webinars	Vírus
Livros	Militância	Publicação retweet	Virus
Viola	Protesto	Serviços de internet	Infecção por vírus
Livro	Propaganda governamental	Problemas com google drive	Bugs
Demi lovato	Prioridades do governo	Abuso online	Viral
Raposinha	Antipolítica	Spotify	Coronavírus
@medicina	Anti-capitalismo	Transporte público	Viralcontent
@l***	Autocrítica	Conversas online	Contaminação viral
Salada caesar	Discurso politicamente incorreto	Hacking	Reação viral

Table 58. CTM model, TwitterUFF (N), best IRBO metric.

0	1	2	3	4	5
the	bom	ir	voce	eu	raiva
in	ano	pra	gente	saber	vo
and	dia	fazer	poder	falar	chato
you	todo	ficar	ele	achar	aguentar
is	novo	casa	pessoa	querer	ranco
it	hoje	to	mulher	vez	kkkkkkkkk
of	primeiro	aqui	ela	pq	agr
on	semana	dar	vc	ver	kkkkkk
my	tudo	eu	dizer	ele	td
thi	ainda	querer	falar	pessoa	triste

Table 59. LDA model, TwitterUFF (N), best EWETC metric.

Social Processes	1	2	3
ver	eu	eu	the
todo	pra	ir	to
mundo	ir	ele	bom
mulher	to	fazer	you
pra	voce	ta	of
falar	dia	pra	and
gente	ver	querer	dever
ai	vez	achar	is
sobre	querer	sim	in
eu	saber	ela	on

Table 60. GPT Model, TwitterUFF (N), best EWETC metric. (Part 1)

Entretenimento	Dança	Insatisfação Profissional	Sentimentos	Cruzeiro Esporte Clube
formulário	mc mirella	asfixia	sentimento de tristeza	campeonato principal
fórmula 1	expressão de raiva	indagação sobre entendimento	sentimentos dos brasileiros	libertadores
matheus	musa das tretas	pesquisa de monografia	sentimento de frustração	títulos libertadores e brasileiro
envolvimento da flay	danças sensuais	sacrifício emocional	sentimento pessoal	cruzeiro esporte clube
sugestão de entretenimento	caipirinha de maracujá	insatisfação profissional	comunicação de sentimentos	brasileiros na libertadores
assunto proibido	chegada em casa	esgotamento físico	sentimento de raiva	atlético x cruzeiro
foro privilegiado	compra de imóvel	análise de narrativas	sentimento de invisibilidade	campeonato brasileiro série a
procedimentos de voo	sandália	análise	sentimentos e emoções profundas	campeonato brasileiro
dicas de entretenimento	boca cheia d' água	afastamento	sentimento de inutilidade	copa
ignorância	raiva	denúncia	sentimentos	copacabana

Table 61. GPT Model, TwitterUFF (N), best EWETC metric. (Part 2)

Violência Policial	Diferentes Perspectivas Geracionais	Educação	Televisão
brutalidade policial	xingamentos e reclamações	dificuldades na educação	skyline sports news
repressão policial	romantização de sofrimento	crise na educação	série de televisão
urgências policiais	taxonomiacidadã	diferenças de gênero na educação	entrevistas de rádio
policiamento	reclamação dos correios	inovação na educação	dennis dj
interferência na polícia federal	conectividade ruim	homofobia na educação	gifs de gatinhos
morte por violência policial	diferentes perspectivas geracionais	condição da educação	gifs de gatos
polícia	porcentagem de rejeição	educação sobre saúde	gifs de animais
operação policial	ciência da computação	educação ambiental	programas de televisão
polícia federal	naturalização do uso de expressões	educação física	assistir tv
investigação polícia federal	preparação e adaptação	reeducação alimentar	gifs

Table 62. Sabiazinho-3 model, TwitterUFF (N), Best EWETC Metric. Anonymized (***). (Part 1)

Filosofia	Representatividade	Politics	Interações sociais
Worms	Exageradas	Activism	Friends appreciation
Bugs	Emoção triste	Revolta	Gratitude
Dinossauros	Argumentos pró e contras	Protestos	Kindness
Fimdomundo	Representatividade	Protesto	Friends
Filosofia da ciência	Inquérito	Revolta social	Responsabilidade social
Reflexões filosóficas	Ações da seudolar	Protesto ambiental	Influência social
Fiqueemcasa	Inutilidade	Revolta política	Social inequality
Filosofia	Compreendendo diferenças	Protesto acadêmico	Falta de habilidade social
Doenças infecciosas	Output@a***	Protestos nos eua	Relations in society
Fimdepoder	Ventríloquo	Política de saúde	Desapontamento parental

Table 63. Sabiazinho-3 model, TwitterUFF (N), Best EWETC Metric. (Part 2)

Recomendação	Futebol	Jadon sancho	Marvel	Autoaceitação
Comparação entre eras	Clube de leitura	Bandana	Supernatural	Aceitação
Intervenção criativa	Projeto clube-empresa	Patriarcado	Lucifer	Auto-aceitação
Blocos de anotação	Lyon	Cães farejadores	Satanás	Autoavaliação
Paródia	Libertadores	Jairbolsonaro	War ficção	Autoaceitação
Pagamentos por aproximação	Hamburguer	Museu	Marvels runaways	Autocaracterização
Perspectiva xenófoba	Copa libertadores	Piada	Capitã marvel	Cadeirinhas automotivas
Recomendação de aplicativos	Campeonatos	Padaria	Marvel	Auto-deprecacao
Organização mundial da saúde	Borussia dortmund	Rocinha	End of the world	Auto aceitação
Cpi	Clubes	O vinho	Hahahaha	Autoidentificação
Algoritmos de recomendação	Campeonato	Verão	Star wars	Auto-realização

Table 64. Sabiazinho-3 model, TwitterUFF (N), Best EWETC Metric. (Part 3)

Séries televisivas	Educação	Falta de estrutura em saúde	Conteúdo online
Podcast	Educação física	Sistema único de saúde sus	Navegadores web
Bbc	Educação militar	Nivel de estresse	Digital signage
Disney channel	Educação	Expressão de cuidado	Open source
Cbc	Educação a distância	O gabarito da questão é que é bom	Assédio online
Emmy awards	Educação online	Estilo de moda	Editoras
Dramas televisivos	Educação esportiva	Mau comportamento em sala de aula	Benefícios do networking
K-drama	Notáveis educadores	Falta de estrutura em saúde	Apple
Showbiz	Acesso a educação	Alphonso davies	Privacidade online
Vlogs	Comunicação e educação em saúde	Existência finita	Badge
Animated series	Educação familiar	Último dia de aula	Download

B Prompts

Prompt 1: (Theme generation) Você será responsável por gerar os tópicos relacionados a uma publicação proveniente de uma rede social. A publicação estará contida entre três aspas simples (`'''`). Para realizar essa tarefa, siga as seguintes etapas:

1. Examine cuidadosamente o conteúdo da publicação, que está localizada entre as três aspas simples.
2. Determine quais são os tópicos predominantes e mais relevantes presentes na publicação.
3. Certifique-se de obter exatamente `{n_topics}` tópico(s) separados por `|`.
4. Você deve fornecer apenas o nome do tópico, evitando quaisquer outras informações adicionais.

The n_topics value is defined by the length of the input text. If the text is less than 30 characters, it will have only one topic. If the text is less than 100 characters, it will have two topics, and three topics otherwise.

Prompt 2: (Cluster naming) Você será responsável por gerar o tópico central dentre uma lista de tópicos. A lista de tópicos é: `{classes}`

Para realizar essa tarefa, siga as seguintes etapas:

1. Examine cuidadosamente a lista de tópicos fornecida acima.
2. Determine qual é o tópico central da lista de tópicos.
3. Forneça o tópico que abstrai a ideia central da lista, forneça apenas o nome do tópico, evitando quaisquer outras informações adicionais.

The list $classes$ contains all themes (keywords) within a cluster.