#Pragmatic or #Clinical: Analyzing TikTok Mental Health Videos

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ABSTRACT

As mental health content on platforms like TikTok increases steeply, it is important for us to characterize and understand how it is shared. Unfortunately, there are no precise mechanisms for identifying different types of mental health content or for users to indicate content preferences. Expanding on prior work and a qualitative typology we discovered, we present a preliminary exploration of features from 169 hand-labeled videos from a dataset of 19,000+ videos related to clinical and pragmatic mental health content. Our findings provide opportunities for future advancements in moderating mental health content and personalizing users' interactions.

CCS CONCEPTS

• **Human-centered computing** → *Social media*; • **Mathematics of computing** → *Exploratory data analysis.*

KEYWORDS

TikTok, Mental Health, Data Analysis

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1 INTRODUCTION

Online mental health communities (OMHCs) are an important form of participation and support. Prior work shows that participation in OMHCs provides stress relief, social support, and therapeutic benefits for eating disorders, depression, and minority stress communities [1, 6, 13, 24]. TikTok in particular has active OMCHs [17] and much mental illness content [3, 9, 16, 19]. Communities on TikTok are formed via its algorithmically-curated continuous feed (known as the For You Page or FYP), which was the focus of CSCW and HCI research [4, 12, 20, 21].

While TikTok and its OMHCs empower individuals experiencing mental illnesses [17], it is challenging to balance safe information without harming community social support when moderating mental health content. Moderation can encourage participation by removing harmful behaviors [23] and keeps misinformation [19] and dangerous content [7, 8] off the platform. However, moderation also disrupts social support when content is removed because it does not conform to a single idea of what mental health is and looks like [14, 18], which is often what is sanctioned by community guidelines. These problems are exacerbated when social platforms like TikTok use AI-based content moderation that lacks the nuance of the intentions and outcomes of sharing mental health content [5]. TikTok is especially prone to this lack of nuance in its moderation strategy, as it aggressively moderates legitimate conversations about suicide prevention on the platform [22].

We argue that **a crucial part of more effectively moderating mental health content is through more fine-grained moderation strategies that account for contextual nuances.** Our recent work has found that three types of content exist in TikTok mental health communities: *clinical content* that is directly related to medical mental health experience and knowledge, *pragmatic content* that is about how mental illness impacts people's daily lives but is not explicitly about clinical care, and *comfort content* that affects individual mental health despite not being deliberately or directly related to it [17]. Participants in this work said they thought about moderation differently for these content types [17]. We are interested in studying these content types to facilitate better and more fine-grained detection and moderation strategies that may ultimately improve individual and community experiences on TikTok.

This poster shows our first steps toward demonstrating the computational feasibility of more nuanced moderation tools on TikTok content. Using our prior work and the qualitative types of mental health content as a basis for our study [17], we collected 19,453 videos from popular mental health hashtags on TikTok. From this set, we randomly sampled 200 English-language videos for which we hand-labeled as clinical, pragmatic, or other content. We present a quantitative analysis of 169 videos to understand the differences between the content types and features related to engagement metrics and textual components.

Our findings show that engagement features such as digg (likes), play, share, comment count, the time of day a video is posted, and its duration may help distinguish between different mental health content types. Unlike in prior work [5, 8], hashtags do not seem to be good indicators of content types, but several TikTok-based affordances (keywords of descriptions and stickers) hold some insights. Notably, features related to video creators and sentiment do not differentiate content types. We discuss what this means for analyzing social media data and our future research plans.

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2 METHODS

2.1 Data Collection

At the time of this work, TikTok had not released its official API for public research. However, an unofficial TikTok API[1] was available which we used to collect data in November and December 2022. First, we searched for content on 17 mental health hashtags, based on prior work [7] and our experiences with mental health content on TikTok. These included general mental health hashtags(#mentalhealth, #mentalillness) as well as ones about specific disorders (#adhd, #anxiety)[2]. We sampled approximately 1000 videos per tag, totaling 16,000 during a week-long data collection.

Building on [8]'s strategy for Instagram, we extracted associated hashtags on each post and calculated the co-occurrence of a hashtag with our base data set to get a more diverse sample. We took the top 1% of co-occurring hashtags ignoring platform-specific hashtags (e.g. #fyp), which resulted in adding 10 additional hashtags: #therapy, #sad, #dissociativeidentitydisorder, #depresion, #bpdtiktok, #bpd, #borderlinepersonalitydisorder, #mental health, and #mentalhealthawareness. We then scraped videos from the additional 10 tags for another week. After removing missing videos or deleted content, our final data set had 19,453 TikTok videos.

2.2 Human Labeling for Types of Mental Health Content

Translating qualitative scales and findings to quantitative data is a tricky endeavor [15]. As mentioned, our prior work identifies three types of content on TikTok: *clinical content*, *pragmatic content*, and *comfort content*[17]. Two authors began with the definitions in Milton et al. [17] and labeled content with each of the three types. We then viewed a sample of 20 videos to further illuminate aspects of the three types that differentiated videos of one type from another. We identified themes that appeared in clinical and pragmatic content but were presented differently. The third author consulted with the team as they worked on their mappings.

Table 1 shows the final three types of content, definitions, and additional sub-themes. We did not include the detection of comfort content because it is highly subjective and personalized. We added a third category, where we labeled anything not clinical or pragmatic as other, regardless of its possible connection to comfort. We observed that videos labeled as pragmatic contained both clinical and personal information. For instance, one creator would talk about how effective their therapist's advice was for them in a pragmatic video. Differentiating pragmatic and general content was also contextually dependent on one's exposure to the content. While we acknowledge that a video can fall into more than one label given our definitions, we only consider one label per video for this study. As such, the authors reached a consensus on any videos that disagreed with the label.

After several rounds of labeling and refining our categories, we coalesced on definitions for each content type, then calculated inter-rater reliability to measure our agreement on the labeling task. The first and second authors then labeled 200 random videos. Cohen's Kappa was 0.64, which indicated substantial agreement. Our final data set contained 169 labeled videos because we excluded videos if a label could not be agreed upon or if the video was not in English.

[1]https://github.com/davidteather/TikTok-Api

[2]The 17 hashtags we searched included #mentalhealth, #mentalhealthmatters, #mentalillness, #mentallyill, #depressed, #depressionanxiety, #anxiety, #ptsd, #trauma, #didsystem, #personalitydisorder, #bipolar, #borderline, #neurodivergent, #adhd, #adhdtiktok, and #MentalHealthAwareness.

3 ANALYSIS AND RESULTS

Next, we analyze the 169 labeled videos to gain insights into clinical, pragmatic, and general mental health content on TikTok. We do so along several dimensions, such as text content, descriptive and author features, and engagement. We highlight statistically significant differences using Kruskal-Wallis and Pairwise T-Tests where appropriate, with $p < 0.05$ unless otherwise noted. We caveat that our statistical analyses are sometimes limited given dataset size, and recognize this as a limitation of our approach. We provide qualitative insights to contextualize findings.

3.1 Descriptive Features

3.1.1 *Video Descriptive Features.*

First, we examine the descriptive features of the videos. Specifically, we examined information about whether a video is an advertisement, the time of day when videos were created, and the duration of the videos. Additionally, we considered the hashtags, descriptions, and stickers from videos. We selected the above features based on prior work [5] and our experiences on TikTok, thus using all features scraped from TikTok videos except video location (which we took out since we excluded non-English videos) and video comments.

Some videos on TikTok are advertisements indicated in a video's metadata. In our set, only 1% of pragmatic videos were ads, while 11% of general mental health videos were ads. No clinical videos were ads. Additionally, videos can be uploaded at any time of day, and the timing may be salient in mental health expression [10]. Figure 1 shows that the distribution for general videos is relatively normal with most videos being posted around 10 am to 1 pm Eastern Standard Time (EST). However, clinical content is more skewed toward earlier in the day, with most videos posted from 6 am to 10 am EST. Pragmatic content interestingly has two visible peaks where videos are posted around 6 am to 8 am EST and then again from 1 pm to 4 pm EST. No clinical videos are posted late at night, between 12 am and 5 am EST, whereas there is a small volume of pragmatic and general videos. We hypothesize that the creators of clinical videos are more likely to be professionals working in the mental health space, such as therapists.

When considering the length of videos by label, the average duration of clinical videos (54.36 seconds) is significantly greater ($p < 0.01$) than both pragmatic (26.17 seconds) and general (29.62 seconds) content. Both pragmatic and general content are very close in length.

3.1.2 *Text Features.*

Each TikTok video can be accompanied by a text description, hashtags within the description, and "stickers" that appear over the video itself. We extracted the description text and the hashtags from the post, which we then cleaned using text pre-processing.

We find that hashtags are not as distinctive of content type as they have been on other social media platforms, such as Instagram [7]. There were 1,450 total hashtags and 843 unique hashtags,

Content Type	Definition	Sub-Themes
Clinical	"Content directly related to clinical mental health experiences and knowledge. This includes symptoms, diagnosis, therapy, treatment, and other content specifically about the clinical and informational aspects of illnesses" [17]	- Specific diagnostic steps and treatments - Medical information - Direct connection to mental illness - Symptoms as they relate to diagnostics - Methods that will treat/cure mental illness - Purpose of providing medical information
Pragmatic	"Content that, while not explicitly about clinical mental illness treatment or care, is integral to how mental illness and well-being impact people's daily lives." [17]	- Experiences with diagnosis and treatment - Tools and tips for dealing with mental illness - May not be explicitly related to mental illness - Lived experience with symptoms - Methods that will help relieve symptoms - Purpose of providing awareness and support
General	Content that does not fall into either clinical or pragmatic types. Also includes videos that are not related to mental illness but contained mental health hashtags.	- Using mental health diagnoses or treatments as jokes - Well-being information not related to mental health - Content about general sadness - Mental health creators making other content

Table 1: Definitions and Themes used to Label the Content Types

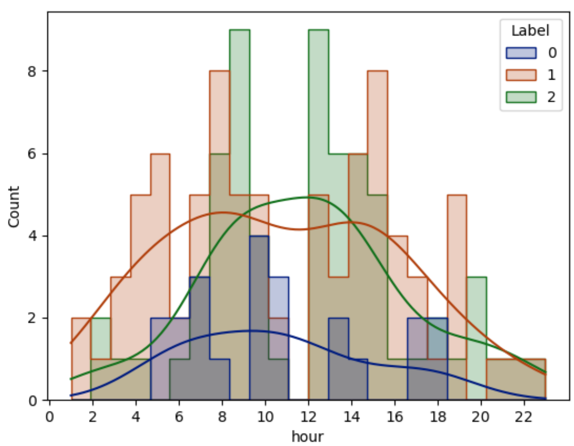

Figure 1: Frequencies at which videos of all three types were posted during the day.

meaning an average TikTok post in our data set had 8.58 total hashtags (median = 6, mode = 5, with six posts having one hashtag). Next, we consider the most frequently occurring hashtags with each label, ignoring platform-specific hashtags (e.g., #fyp). 29 of the unique hashtags appear in all three labels out of our sample, with the most frequent being #mentalhealth, #mentalhealthmatters, #bpd, #adhd, and #mentalhealthawareness. This is unsurprising, given the hashtags we sampled from in the methods. More interesting is the lack of *distinctive* hashtags. There was a high overlap with hashtags of all three categories, showing that hashtags are not a reliable differentiator of mental health content. This could occur due to creators' suspecting that using certain popular tags such as #mentalhealth could get their videos higher numbers of videos or that specific trends lead creators to co-opt mental health-related hashtags [11].

Next, we move to descriptions, which show specific language used between our three content types. As mentioned, we conducted standard NLP preprocessing, such as removing stop words, expanding contractions, and removing special characters, such as emojis. We calculated the overall frequency of a word appearing in a category to examine the most popular words in each category, similar to TF-IDF on a category basis. The top words in clinical videos were "trauma", "release", "experience", "shake", and "stressful." On the other hand, the top words in pragmatic video descriptions were "communication", "know", "social", "people", and "like." Qualitatively, the top words for clinical videos have a common theme of receiving professional help and describing symptoms, whereas the most popular words on pragmatic focus on people and social aspects. Finally, the top words for general video descriptions were "day", "calorie", "tdee", "range", and "eat". Qualitatively, the top words for the general content have content related to fitness and dieting, a popular kind of content on TikTok that could be loosely associated with mental health.

There is little overlap of common words among the three categories in post descriptions, indicating the text description may be a promising feature. We measure this with the co-occurrence of words across labels. There is only about 1.75% overlap of description words across all three labels. What is more telling than the overlap is that 67% of clinical, 82% of pragmatic, and 78% of general description words are unique.

Finally, stickers showed high distinctiveness between the categories. The top stickers for clinical content were centered on specific experiences with mental illness (trauma, time, love, mom, people), while the top sticker words in pragmatic videos had a theme of ADHD and borderline personality disorder (BPD) experiences (like, adhd, feel, bpd, know). Sticker words from general content did not have a coherent theme related to mental health (like, wife, need, gi, know). Similar to description words, there is only about 3% overlap in sticker words across all three labels. Instead, 63% of clinical, 73% of pragmatic, and 64% of general sticker words are unique to videos from each respective label.

Sentiment can be an informative perspective when looking at text for mental health [10], and thus we conducted sentiment analysis on description and sticker words using SentiWordNet [2]. There was no significant difference in sentiment across the three post types.

3.1.3 *Creator/Author Features.*

Next, we examine the features of the creators who post these videos. We hypothesize that creators may focus on some kinds of content and their popularity on the platform could influence information diffusion. For authors, we examined the number of followers they have (follower count), the number of other authors they are following (following count), the number of likes they have given (digg count), the number of likes an author (or video author) has received across all the TikTok videos they posted (heart count), whether they are verified (true/false), and the number of TikTok videos they posted (video count).

	Author Counts				
Type	Follower	Following	Heart	Digg	Video
Clinical	633986.5	683.73	17291113.64	18569.41	638.45
Pragmatic	507717.56	1079.05	23852243.90	35474.54	**668.93***
General	643908.83	967.52	21651210.77	33243.15	**431.98***

Table 2: Average Count of Author Features by Label. Symbols (^ and *) indicate p < 0.05 for pairwise t-test.

Table 2 shows our analysis of creator features. We did not find any significant difference among the average follower counts, following count, heart count, and digg count of the three categories. However, we did find that, while not significant, there is a difference between the average video count of authors for videos. Upon further investigation, when doing a pairwise T-Test there is a significant difference between pragmatic and general mental health content, with pragmatic authors posting significantly more videos than general content authors. When considering author verification, we found a total of 11 authors verified in our labeled sample. When contextualizing within each of the types, 9% of clinical videos, 2% of pragmatic videos, and 11% of general content were verified.

3.2 Engagement Features

We examined engagement features, including the number of likes a video receives (digg count), the number of times a video is played (play count), the number of times a video is shared (video share count), and the number of comments a video has (comment count).

	Video Counts			
Type	Digg	Play	Comment	Share
Clinical	184882.45^	1117154.55^	2010.59	7918.55
Pragmatic	242678.98*	1385310.74*	1995.56*	4931.20
General	471719.46^*	3836829.86^*	5486.85*	7876.46

Table 3: Average Engagement Features. Gray cells are p<0.05 for Kruskal-Wallis. Symbols (^ and *) are p<0.05 for pairwise t-test.

Different types of videos have different engagement patterns, indicating that they may be a promising source of information for downstream classification tasks. Table 3 shows a significant difference in the average video digg count between general, clinical, and pragmatic content. In considering the average play and comment counts, general videos have significantly higher counts than clinical and pragmatic videos. There is no significant difference between the average share count for all three groups. We hypothesize that general videos likely have a higher digg, play, and comment count because the content is more applicable to a larger audience.

4 DISCUSSION AND FUTURE WORK

Discussion. Our findings show that engagement and descriptive features of posts differentiate videos in our hand-labeled dataset, implying that these features may assist in differentiating clinical and general mental health content. We also note that video duration was highly distinctive for clinical videos – they were much longer than pragmatic or general mental health videos. However, we note a paradox in using engagement features to classify content types – these are *post-hoc* measures of a content's reception and reach and would not be available while pre-screening content with an online moderation system. Likewise, the length of the video may be one signal for clinical content, but more important is the content of the video itself (which we do not study in this analysis).

Our findings also point to new patterns of behavior emerging on TikTok. While our findings showed substantial overlap in hashtags, hashtags were not as distinctive of a signal as other descriptive means to differentiate content type. This implies that they may not be a good indicator of different types of content, running counter to prior work on mental health in Twitter [10] and Instagram [8]. However, TikTok-specific features, like stickers, could be promising. While our findings illustrate the distribution of videos posted throughout the day may be limited in effect size, these results still show interesting trends that should be examined with a larger labeled data set to see if this feature is helpful for detection.

The above features can ultimately be used to help develop more specified moderation strategies for moderating short-form videos about mental health content. Existing AI-based content moderation approaches may factor in these features to make better, context-dependent decisions and to improve on decisions of what content to forward to human moderators. In this way, we can mitigate the disruption moderation often causes systems of social support in mental health communities such as the ones on TikTok.

Future Work. Our plans include expanding our labeled data set and using a selection of these features to cluster TikTok videos into three different categories. Future work may examine how AI moderation approaches for mental health can then be improved using user feedback for their specific mental health content preferences.

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