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ABSTRACT

Bipolar disorder (BD) is closely associated with an increased risk of suicide. However, while the prior work has revealed valuable insight into understanding the behavior of BD patients on social media, little attention has been paid to developing a model that can predict the future suicidality of a BD patient. Therefore, this study proposes a multi-task learning model for predicting the future suicidality of BD patients by jointly learning current symptoms. We build a novel BD dataset clinically validated by psychiatrists, including 14 years of posts on bipolar-related subreddits written by 818 BD patients, along with the annotations of future suicidality and BD symptoms. We also suggest a temporal symptom-aware attention mechanism to determine which symptoms are the most influential for predicting future suicidality over time through a sequence of BD posts. Our experiments demonstrate that the proposed model outperforms the state-of-the-art models in both BD symptom identification and future suicidality prediction tasks. In addition, the proposed temporal symptom-aware attention provides interpretable attention weights, helping clinicians to apprehend BD patients more comprehensively and to provide timely intervention by tracking mental state progression.

CCS CONCEPTS

• Computing methodologies → Multi-task learning; Natural language processing; • Applied computing \rightarrow Health informatics.

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KEYWORDS

Temporal sequence learning, Suicide, Bipolar disorder, Multi-task learning, Mental health

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1 INTRODUCTION

Suicide is a severe health concern worldwide. According to the OECD, 14.1 per 100,000 people die yearly from suicide in the United States¹. Unfortunately, most suicides have been committed by individuals with mental illness [72]. Particularly, people living with bipolar disorder (BD) are more vulnerable to suicide than people with other psychiatric disorders [29, 62]. It has been reported that the suicide rate for BD patients is up to 30 times higher than that of the general population [59], and suicide fatalities occur in 10-20% of adults who suffer from BD [23].

With increasing importance in understanding and analyzing BD patients [62], recently, there has been an effort to analyze distinct behavioral characteristics of BD patients and assess their mental states [12, 14, 70] using social media data where they share their daily lives and emotions [34, 40]. However, while the prior work has revealed valuable insights into understanding the behavior of BD patients revealed on social media, little attention had been paid to developing a model that can predict the future suicidality of a BD patient. Although a few studies have proposed methods to identify the current risk of suicide in a given social media post [30, 43, 44], suicidal ideation can often quickly lead to an actual attempt, thereby making them ineffective in preventing suicide [9, 10, 41, 52]; hence, exploring the BD's risk factors that can lead to suicide ideation for predicting future suicidality is crucial. Therefore, this paper aims to predict the future suicidality of BD patients based on their mood

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¹https://data.oecd.org/healthstat/suicide-rates.htm

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Bipolar Disorder Symptom Current Suicidality Future Suicidality

Figure 1: An example of a Reddit user who wrote posts about his/her mental illness on a bipolar disorder-related subreddit and then revealed suicidality 6 months later.

symptoms history revealed in their past social media data, which has not been thoroughly investigated.

To this end, we first create a novel BD dataset clinically validated by psychiatrists, including future suicidality and bipolar symptoms. Here, we focus on which bipolar symptoms users have, rather than what diagnosed bipolar types they have, because a transdiagnostic approach helps improve understanding of comorbidity, enabling proper interventions than a diagnostic approach [26]. BD is a mood disorder characterized by manic and depressive episodes where two phases show a recurrent pattern that appears and increases over a while, but the following important attribute is not easily considered; many psychological processes are shared in various diagnoses [15, 26], e.g., anxiety can appear in both depression and manic episodes of BD [8]. Figure 1 illustrates example posts written by an individual with BD gradually leading to suicide. Therefore, timely tracking of mood symptoms that affect future suicidality is inevitable for early intervention, leading to shorter treatment periods and better prognosis in BD patients. However, with the rapid mood swings in BD and limited self-reports from patients, there is a significant gap in understanding the actual path of mood changes between the real world and the conventional clinical setting where clinicians can only see patients under limited conditions and rely on the subjective words of the patients [27]. Hence, using real-world data derived from patient reports at the nonclinical scene, such as social media, is helpful to understand better BD symptoms [31, 48, 63, 78].

Particularly, we collect social media posts from BD communities on Reddit. We then labeled our dataset, which contains 7,592 posts published by 818 users, following the guidelines outlined in the Columbia Suicide Severity Rating Scale (C-SSRS) [60] and Bipolar Inventory of Symptoms Scale (BISS) [8] for annotating suicidality and bipolar-related symptoms, respectively. Given the significance of clinical understanding, two psychiatrists validate the annotated dataset with a pairwise annotator agreement of 0.77 and a groupwise agreement of 0.88. Unlike the existing datasets [22, 31, 68, 70], the proposed dataset both includes (i) future suicidality of BD patients and (ii) a user's mood history that can be important features for diagnosing mood episodes [55] and future suicidality [32].

Based on the developed BD dataset, we propose a novel multitask learning framework to jointly learn (i) the future suicidality of a given BD user and (ii) their BD symptoms over time. Since a BD symptom can contribute to future suicidality differently depending on when it occurs, we suggest a temporal symptom-aware

attention method to determine which symptoms are the most influential for predicting future suicidality over time. In particular, the proposed multi-task learning model has three components: (i) the contextualized post-encoder, (ii) a temporal symptom-aware attention layer, and (iii) a task-dependent multi-task decoder. After the model generates post representations using the pre-trained Sentence-BERT (SBERT) [61] in the contextualized post encoder, the bi-LSTM layer encodes a sequential context of post representations considering variable time intervals between posts. The temporal symptom-aware attention layer then calculates the attention weights of posts to give more weight to critical symptoms affecting the risk classification decision. Finally, the multi-task decoder estimates the probability of future suicidality levels and BD symptoms. For effective multi-task learning, we sum up the losses for each task using the uncertainty weight loss method [38], evaluating the task-dependent uncertainty of each task. The proposed model can capture the progressive patterns of BD symptoms and outperform the state-of-the-art methods for predicting future suicidality by leveraging the benefits of multi-task learning. Furthermore, investigating the attention weights based on BD symptoms helps to interpret how they affect the user's future suicidality over time. The provided interpretability from our model can support clinicians in improving their understanding of connections between psychiatric conditions and allowing proper interventions for at-risk people.

We summarize the contributions of this work as follows.

- We release our codes and a novel BD dataset², which contains both the future suicidality and BD symptoms labels, validated by two psychiatrists. The dataset can benefit researchers aiming to develop methods for suicide prevention.
- To the best of our knowledge, this is the first study that proposes a multi-task learning model for predicting the future suicidality of BD patients on social media by leveraging the knowledge of bipolar symptoms (i.e., manic mood, somatic complaints). The model can accurately capture bipolar symptom transition patterns and outperform the state-of-the-art methods for detecting future suicidality.
- The proposed temporal symptom-aware attention method provides interpretability, which can help clinicians understand BD patients more comprehensively, thereby providing timely interventions by tracking mental state progression.

2 RELATED WORK

Social Media to Understand Bipolar Disorder. With the proliferation of social media, many studies have attempted to address the severe social problems of BD using user activity data on social media [40, 66, 68]. For example, Šnajder [70] showed differences in language use between users with and without BD on Reddit, and this characteristic has been utilized to discover the risk of BD [12, 14, 70]. Several studies have analyzed (i) the living experience of BD patients [31, 48, 63] and (ii) an understanding of how people perceive their mental states and share their experiences [78] using social media data through qualitative studies. However, while the prior work on BD analysis has revealed valuable insight into the characteristics of individuals with BD, little attention has been paid to predicting the future suicidality of BD patients. Because suicidal

²https://sites.google.com/view/daeun-lee/dataset/kdd-2023

ideation can often be developed into an actual attempt [9, 10, 41, 52], such a model that predicts future suicidality of BD patients can be used for BD patients who usually have suicidal ideation [27].

Future Suicidality Assessment Using Social Media Data. While most of the work has focused on identifying the current suicidality revealed in a given post from social media [3, 43, 44, 64, 65], a few studies have investigated monitoring a transition of users who have not yet shown suicidality but would potentially reveal it in the future. Lekkas et al. [45] strived to predict whether adolescents will show suicidal intentions within a month of using Instagram with an ensemble model. Similarly, De Choudhury et al. [17] attempted to discover the current suicidality of individuals who posted on mental-health-related communities on Reddit by identifying whether a user would write on SuicideWatch, a suiciderelated subreddit. They found that users who show suicidality tend to reveal changes in linguistic structures, interpersonal awareness, and social interactions. Unlike the previous work, we predict future suicidality of BD patients by considering the past temporal transition behavior since BD patients suffer from such mood change symptoms. To the best of our knowledge, this is the first work that proposes a future suicidality prediction model by jointly learning two tasks, predicting (i) future suicidality and (ii) BD symptoms.

3 BIPOLAR DISORDER DATA

3.1 Data Collection and Preprocessing

Collecting Data. We collected posts published between January 1st, 2008, and September 30th, 2021, from the three representative bipolar-related subreddits, including *r/bipolar* (BPL), *r/BipolarReddit* (BPR), and *r/BipolarSOs* by using the open-source *Reddit* API³. To identify individuals who exhibit suicide ideation, we also collected all the posts during the same data collection period from *r/SuicideWatch*, where people share their suicidal thoughts with others. Among the collected posts, we used the posts written by users who have been professionally diagnosed with BD [31] in this study. For example, users who reported BD diagnosis, e.g., a user who wrote, "I was diagnosed with Bipolar type-I last year.", were included in our study. Thus, posts regarding BD symptoms of other individuals, including family members or friends but not themselves, were excluded. Finally, our dataset contains 7,592 posts published by 818 users, i.e., BD patients.

Preprocessing Data. We first anonymized the collected posts by removing information that could be used as personal identifiers. We then converted the texts to lowercase, removed special characters, striping whitespaces, and stopwords, and lemmatized them.

3.2 Annotation Process

To label the collected Reddit dataset, we recruited four researchers, knowledgeable in psychology and fluent in English, as annotators. With the supervision of a psychiatrist, the four trained annotators labeled 818 users and their 7,592 anonymized Reddit posts using the open-source text annotation tool *Doccano* [51]. During annotations, we mainly consider two different label categories: (i) BD symptoms (e.g., manic, anxiety) and (ii) suicidality levels (e.g., ideation, attempt). We further annotate the diagnosed BD type (e.g., BD-I,

Table 1: Summary of annotated labels in our BD data.

	Total Num	Category	Num (%)
A Diaman I		BD-I	224 (27.3%)
A. Diagnosed	818 users	BD-II	501 (61.2%)
Bipolar Disorder Type		NOS	93 (11.3%)
		Depressed	3,628 (47.7%)
B. Bipolar Disorder		Manic	981 (12.9%)
	7,592 posts	Anxiety	859 (11.3%)
		Irritability	508 (6.6%)
		Remission	523 (6.8%)
Symptom		Other	1,093 (14.3%)
		Somatic	1,293 (74.0%)
	1,747 posts	Psychosis	429 (24.5%)
		Both	25 (1.4%)
		Indicator	6,302 (83.0%)
C. Suisidality	7 502 monto	Ideation	918 (12.0%)
C. Suicidality	7,592 posts	Behavior	266 (3.5%)
		Attempt	106 (1.3%)

BD-II) for data analysis. If there is any conflict in the annotated labels across the annotators, all the annotators discuss and reach an agreement under the supervision of the psychiatrists. The information about the final annotated labels in our data is summarized in Table 1. We now briefly describe the definition of each category; more details about each category and the corresponding examples are described in Appendix A.2.

A. Diagnosed Bipolar Disorder Types: We label users into one of the three BD diagnosis types based on the self-report in their posts. The BD diagnosis types include *Bipolar Disorder-I* (BD-I), *Bipolar Disorder-II* (BD-II), and *Not Otherwise Specified Bipolar Disorder* (NOS) based on the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [2] and the International Statistical Classification of Diseases and Related Health Problems (ICD-10) [54].

B. Bipolar Disorder Symptoms: We employed the Bipolar Inventory of Symptoms scale (BISS) [8] to cover mood polarity (i.e., manic, depressed) and the spectrum of BD symptomatology (i.e., psychosis, somatic complaints). Accordingly, we first annotate mood symptoms consisting of *Depressed, Manic, Anxiety, Remission, Irritability*, and *Other*. Note that *Other* covers moods that do not fall into the other five mood symptoms. If we find any BD somatic symptoms, we annotate an additional somatic symptom label that includes *Somatic complaint, Psychosis*, and *Both*.

C. Levels of Suicidality: We also annotate the posts to categorize them into different suicidality levels. We utilize the existing criteria from [22, 68] that provide common five levels of suicidality, including *No risk* (NR), *Suicide Indicator* (IN), *Suicidal Ideation* (ID), *Suicidal Behavior* (BR), and *Actual Attempt* (AT), based on the Columbia Suicide Severity Rating Scale (C-SSRS) [60]. We merge *No Risk* with *Suicide Indicator* since people with bipolar disorder are already considered more at risk than the general population in suicide [29, 62].

3.3 Evaluation of Annotation

3.3.1 Expert Validation. Since the accuracy of the labels (e.g., suicidality, BD symptoms) in the dataset is crucial, we validate the annotated BD dataset with two psychiatrists, as domain experts, by providing 212 randomly selected posts published by 25 users.

³https://www.reddit.com/dev/api/

 Table 2: Expert validation results in our BD data. (E1, E2:

 Expert Psychiatrists / I: Internal Annotators)

	Suicidality		Mood Symptom			Somatic Symptom			
Krippendorff's α	0.88			0.76			0.72		
Cohen's <i>k</i>	E1	E2	Ι	E1	E2	Ι	E1	E2	Ι
E1	1 -		-	1	-	-	1	-	-
E2	0.89	1	-	0.81	1	-	0.80	1	-
I	0.77	0.77 0.77 1		0.72	0.66	1	0.77	0.66	1

Table 3: Comparisons with existing datasets.

	Ours		dality asets	Bipolar Disorder datasets			
		Gaur et al [22]	Shing et al [68]	Jagfeld et al [31]	Sekulić et al [67]		
Current Suicidality	1	1	1	×	×		
Future Suicidality	1	X	×	×	×		
BD Diagnosis	1	×	×	✓	1		
BD Symptom	1	X	×	X	X		
Publicly Available	1	1	1	×	×		
Expert Validation			1	×	×		
Duration	2008-2021	2005-2016	2008-2015	2006-2019	2005-2018		
# of users	818	500	934	19,685	3,488		
# of posts	7,592	15,755	-	21,407,595	-		

Table 2 summarizes the Krippendorff's alpha-reliability [42] and Cohen's Inter-Annotator Agreement [13] among the experts and annotators. The results suggest that our annotations in the dataset are reliable as the overall Krippendorff scores show high agreement, for example, 0.88 for suicidality and 0.76 for mood symptoms, which is similar or even higher than previous studies (e.g., α =0.69 [22]). The maximum and minimum pairwise Cohen's scores present a fair agreement of 0.89 and 0.66, respectively.

3.3.2 Comparison with Existing Datasets. We compare our BD dataset with four widely-used datasets [22, 31, 67, 68] from prior studies on suicide and mental health in Table 3. First, we find that only two datasets have been released publicly, while the other datasets have not been disclosed. More importantly, no existing dataset has both suicidality and BD symptom labels. The existing suicide datasets [22, 68] do not include BD-specific and future suicide information. The prior BD datasets [31, 67] have no suicidality labels, and their BD diagnosis labels were generated computationally without expert validation. The proposed BD dataset, on the other hand, includes future suicidality and BD symptom labels, which are validated by clinical experts.

3.4 Timeline (Post Sequence) Construction

BD patients tend to have more severe symptom changes over time than other mental disorders; thus, suicidality constantly changes. Since users' posts on different timelines show disparate BD symptoms and suicidality levels, it is crucial to predict future suicidality in each timeline and understand how long past posts should be learned to predict future suicidality. Therefore, we construct multiple timelines (i.e., post sequences) for each user, as shown in Figure 2. We set a timeline by selecting the past *l* months for BD Daeun Lee, Sejung Son, Hyolim Jeon, Seungbae Kim, & Jinyoung Han

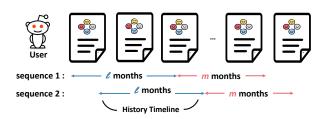


Figure 2: Post sequences (timelines) construction by considering temporal sliding windows.

symptom observation and the future *m* months for suicidality identification. We then slide this timeline window within a given user's posts to obtain multiple post sequences from each user. We assign the future suicidality label as the highest level of the suicidality that appeared in posts over the next *m* months and exclude sequences with less than three posts in the training period (i.e., past posts). By experimenting with different sets of *l* and *m*, we set (l, m) = (6, 1), i.e., using the past 6 months for training and the future 1 month for suicidality label extraction, as it shows the best performance. We present the performances of our model with different postsequence durations in Section 6.3. Therefore, we obtain 5,961 post sequences *S*. The distribution of suicidality labels for the sequences is 5,056 (IN), 591 (ID), 215 (BR), and 99 (AT).

3.5 Data Analysis

In this section, we analyze our BD dataset to understand distinct BD symptom patterns for BD patients who potentially have high suicidality in the future. We then assess the survival probability using the Kaplan-Meier estimation [35] for each BD type (i.e., BD-I, BD-II, and NOS).

3.5.1 BD Symptoms Affecting Future Suicidality. To verify the factors associated with the risk of suicide in the future, we classify the dataset into two groups: i) low-risk group (i.e., IN) and ii) severe-risk group (i.e., ID, BR, AT). We then compare the two groups in terms of the LIWC (Linguistic Inquiry and Word Count) [57] results of the users' posts and the annotation results using the t-test.

As shown in Table 4, the target group shows a significantly higher level of past suicidality than the control group. This reveals that a history of suicidality is a significant suicide risk factor in BD patients [1, 4, 33, 47]. Furthermore, we observe that the severe-risk group shows more elevated depressed mood, irritability, and psychosis than the low-risk group but is less manic. This observation aligns with the clinical studies that identified dominant depression mood [1, 4, 69, 77], irritability [4, 25], and psychotic features [25, 50] as major suicide risk factors in BD patients, but the mania status is not significantly related [50]. We also find similar results in the LIWC categories, which reveal higher values in negemo, sad, and anger for the severe-risk group. Unlike previous studies [1, 4, 25], the ratios of anxiety for the two groups are not statistically different. This implies that social media posts make it difficult to detect clinical anxiety accompanied by physical symptoms like agitation, raised blood pressure, or sweating [36].

Furthermore, we compare the social characteristics of the two groups. We discover that the target group uses more family-related

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Table 4: Differences between the target (severe-risk) and control (low-risk) groups. * indicates the p-value of the feature is less than 0.05 (**: p<0.005), which is considered highly statistically significant.

Suicidality	t	BD Symptom	t	LIWC	t
Indicator	-11.91**	Depressed	5.43**	negemo	3.51**
Ideation	9.50**	Manic	-3.88**	anger	2.85**
Behavior	6.59**	Irritability	-6.07**	sad	5.16**
Attempt	3.39**	Anxiety	-0.35	death	8.03**
		Remission	-0.28	family	2.23*
		Somatic	1.11	work	-2.38*
		Psychosis	2.44^{*}	achieve	-2.59*

words. It could link to negative experiences with family, which often affect their lives, such as a lack of family support, divorce, or unmarried [20, 25]. We also find that most people who mentioned work-related words belong to the control group, indicating they might be paid employees or students. According to the previous study [20, 25], unemployment is also associated with higher suicide rates. Overall, the analysis results demonstrate that the diverse symptom-related factors affecting users' future suicidalities revealed in social media data show a similar pattern with a clinical trial, which helps understand the living experience of BD patients when clinicians make decisions. More details are included in Table 9 in Appendix.

3.5.2 Survival Analysis. We next assess the survival probability for each BD subtype (i.e., BD-I, BD-II, and NOS) using the Kaplan-Meier estimation [35]. Following the estimation method [35], we observe 180 days after a certain time to verify whether a user is still alive in our dataset. Note that we assume a user has not survived if the user has never posted within the observation period. Figure 3 shows that BD-II patients have the lowest survival rate, followed by BD-I. This interpretation aligns with the prior clinical studies that present BD-II as having higher suicidality than BD-I, and the rapid cycling of BD-II is hazardous [58].

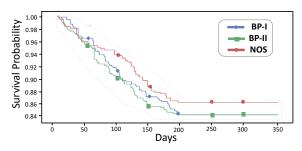


Figure 3: Analysis of survival probability for BD types.

3.6 Ethical Concerns

We carefully consider potential ethical issues in this work: (i) protecting users' privacies on Reddit and (ii) avoiding potentially harmful uses of the proposed dataset. The Reddit privacy policy explicitly authorizes third parties to copy user content through the Reddit API. We follow the widely-accepted social media research ethics policies that allow researchers to utilize user data without explicit consent

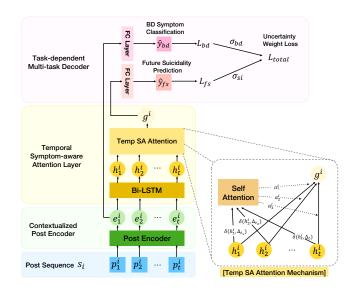


Figure 4: The overall architecture of the proposed multi-task learning model.

if anonymity is protected [7, 76]. Any metadata that could be used to specify the author was not collected. In addition, all content is manually scanned to remove personally identifiable information and mask all the named entities. More importantly, the BD dataset will be shared only with other researchers who have agreed to the ethical use of the dataset. This study was reviewed and approved by the Institutional Review Board ((SKKU2022-11-038)).

4 FUTURE SUICIDALITY PREDICTION MODEL FOR BIPOLAR DISORDER PATIENTS

4.1 Problem Statement

The proposed multi-task learning model aims to (i) predict the future suicidality $y_{fs} \in \{IN, ID, BR, AT\}$ of s_i through a sequence of BD posts P_i in the timeline and (ii) classify BD symptoms $y_{bd} \in \{$ No mood, Depressed, Manic, Irritability, Anxiety, and Remission or Somatic complaint and Psychosis $\}$ that appeared in a post $p_{t_n}^i$. We suppose each post shows one BD mood symptom and, at most, two BD somatic-related symptoms. To be more specific, assume that there is a post sequence $s_i \in S = \{s_1, s_2, ..., s_i\}$, it can be defined as $s_i = \left\{ P^i, \left\{ y_{bd_n} \right\}_{n=1}^{|P^i|}, y_{fs} \right\}$. Here, $P_i = \left\{ p^i_{t_1}, p^i_{t_2}, ..., p^i_{t_n} \right\}$ represents a set of posts ordered by the posting time where *n* denotes the number of posts of s_i and t_n indicates the posting time of the n_{th} post. Also, y_{bd} n is a set of BD symptom labels of p_{tn}^i , and y_{fs} is a future suicidality label of s_i . Note that the time interval between t_n and t_1 is within l months since we take the past l months dataset for feature extraction (See §3.4). Figure 4 illustrates the overall architecture of the proposed model. The model includes three main components: a Contextualized Encoder, a Temporal Symptom-aware Attention

4.2 Contextualized Post Encoder

Layer, and a Task-dependent Multi-task Decoder.

Each post includes BD-related information about a user. A sequence of posts can show the progressive mood states, which is important

information for assessing future suicidality [32]. To generate the semantic representation of each post, we employ the pre-trained Sentence-BERT (SBERT) [61], which showed promising results in detecting moments of change in the mood [3] and representing historical tweets [65]. SBERT is a modification of the pre-trained BERT network that uses siamese and triplet network structures to derive semantically meaningful sentence embeddings by computing the mean of output vectors for all tokens to derive a fixed-size sentence embedding. We encode each post p_t^i as follows:

$$e_t^i = SBERT(p_t^i) \in \mathbb{R}^{1024} \tag{1}$$

4.3 Temporal Symptom-aware Attention Layer

4.3.1 Sequential context modeling. To encode a sequential context of each timeline, we leverage the bidirectional LSTM, a popular method for capturing long-term dependency on social media [11, 64, 66]. Specifically, post-encoding e_t^i is fed into a Bidirectional LSTM to derive text representation h_t^i . This process is repeated twice, each of which processes the post sequence from left to right (i.e., forward) and right to left (i.e., backward). Finally, the hidden state vectors from each procedure are concatenated as follows:

$$\overrightarrow{h_t^i} = LSTM\left(e_t^i, \overrightarrow{h_t^i}_{t-1}\right)$$
(2)

$$\overleftarrow{h_t^i} = LSTM\left(e_t^i, \overleftarrow{h_{t+1}^i}\right) \tag{3}$$

$$h_t^i = \left[\overrightarrow{h_t^i}, \overleftarrow{h_t^i}\right] \tag{4}$$

In this way, the BiLSTM converts the sequence representation of posts $E = \begin{bmatrix} e_{t_1}^i, e_{t_2}^i, ..., e_{t_n}^i \end{bmatrix}$ into contextual representations $H = \begin{bmatrix} h_{t_1}^i, h_{t_2}^i, ..., h_{t_n}^i \end{bmatrix} \in \mathbb{R}^{d \times n}$ where *d* is the dimension of the hidden state vector.

4.3.2 Temporal symptom-aware attention mechanism. We then apply the attention mechanism to pay more attention to a critical mental state affecting the risk classification decision. However, conventional attention mechanisms, such as self-attention [75], do not consider the BD characteristics that each symptom can contribute differently depending on when it occurs. Since the time intervals between posts may vary considerably, identifying these patterns can be essential in interpreting the mood status over time [74]. Therefore, we propose temporal symptom-aware attention (Temp SA attention) as follows:

$$g^i = \sum_{t=1}^{I_n} a_t^i h_t^i \tag{5}$$

$$a_t^i = \frac{exp(tanh(\mathcal{F}(\delta(h_t^i, \Delta_t))))}{\sum_{t=1}^{t_n} exp(tanh(\mathcal{F}(\delta(h_t^i, \Delta_t))))}$$
(6)

$$\delta(h_t^i, \Delta_t) = sigmoid(\theta_h - \mu_h \Delta_t)h_t^i$$
(7)

where \mathcal{F} is a fully-connected layer and tanh() is the activation function. θ_h is the symptom-specific learnable parameter influenced by h_t^i , and μ_h is also a learnable parameter representing how the influence of h_t^i changes over time. Δ_t is the time interval between the most recent post $h_{t_n}^i$ and target post h_t^i . The sigmoid function transforms $\theta_h - \mu_h \Delta_t$ into a probability between 0 and 1. Finally, we derive a sequence representation $g_i \in G = \{g_1, g_2, ..., g_i\}$ where a_t^i indicates how symptom-specific information $\delta(h_t^i, \Delta_t)$ at Δ_t ago affects the future condition.

4.4 Task-dependent Multi-task Decoder

4.4.1 Future suicidality prediction. To predict the suicidality of each sequence in the future, the proposed decoder generates the final prediction vector as follows:

$$\hat{y}_{fs} = \mathcal{F}_a(ReLU(\mathcal{F}_b(g_i))) \tag{8}$$

where $\mathcal{F}_a, \mathcal{F}_b$ are fully-connected layers and ReLU is an activation function.

Inspired by Sawhney et al. [66], we apply the ordinal regression loss [19] as an objective function. Rather than employing a one-hot vector representation of the actual labels, a soft encoded vector representation is used to consider the ordering nature between suicidality. Assume that $Y_{fs} = \{IN = 0, ID = 1, BR = 2, AT = 3\} =$ $\{r_{i=0}^3\}$ denotes ground truth labels, then soft labels are computed as probability distributions $y_{fs} = [y_0, y_1, y_2, y_3]$ of Y_{fs} as follows:

$$y_{fs_i} = \frac{e^{-\phi(r_t, r_i)}}{\sum_{k=1}^{\lambda} e^{-\phi(r_t, r_i)}} \forall r_i \in Y_{fs}$$

$$\tag{9}$$

where $e^{-\phi(r_t,r_i)}$ is a cost function that penalizes the distance between the actual level r_t and a risk-level $r_i \in Y$, which is formulated as $e^{-\phi(r_t,r_i)} = \alpha |r_t - r_i|$, where α is a penalty parameter for inaccurate prediction. Finally, the cross-entropy loss is calculated as follows:

$$\mathcal{L}_{fs} = -\frac{1}{b} \sum_{j=1}^{b} \sum_{i=1}^{\lambda} y_{fs_ij} \log \hat{y}_{fs_ij}$$
(10)

where *b* is the batch size, and λ is the number of risk levels.

4.4.2 BD symptom classification. In addition to future suicidality prediction as the main task, we propose to enhance the model by regarding an auxiliary task, bipolar disorder symptom classification. If the post features are good predictors for BD symptoms, the derived information from post features in the auxiliary task can also be leveraged into the main task. By taking the representation, e_t^i derived from the post encoder layer for each post p_t^i , the model calculates the logits of symptom classification as follows:

$$\hat{y}_{bd} = \mathcal{F}_c(ReLU(\mathcal{F}_d(e_t^l))) \tag{11}$$

where \mathcal{F}_c , \mathcal{F}_d are fully-connected layers and *ReLU* is an activation function. BD symptom classification can also be treated as a multilabel classification. Hence, the objective function can be written as follows:

$$\mathcal{L}_{bd} = -\frac{1}{b} \sum_{j=1}^{b} \sum_{i=1}^{\gamma} y_{bd_{ij}} \log \hat{y}_{bd_{ij}} + (1 - y_{bd_{ij}}) \log(1 - \hat{y}_{bd_{ij}})$$
(12)

where b is the batch size, and γ is the number of symptom categories.

4.4.3 Multi-task learning. Since our multi-task learning model aims to solve tasks with different scales, i.e., post-level BD symptom prediction and sequence-level suicidality prediction, tuning weights between each task's loss is complicated and costly. Therefore, for effective multi-task learning, we employ the uncertainty weight loss [38] that weighs multiple loss functions to simultaneously learn various scales of different units by evaluating the task-dependent uncertainty of each task. Finally, the ultimate objective for multitask learning is summing up the losses.

$$\mathcal{L}_{total} = \frac{1}{2\sigma_{fs}^2} \mathcal{L}_{fs}(W) + \frac{1}{2\sigma_{bd}^2} \mathcal{L}_{bd}(W) + \log\sigma_{fs}\sigma_{bd}$$
(13)

where σ_{bd} , σ_{fs} are the learnable parameters representing uncertainty for each task, and W is the weight parameter.

5 EXPERIMENTS

5.1 Baselines

Since predicting future suicidality from BD patients has not been explored in the literature, we compare against baseline approaches from the related tasks, i.e., identifying current risks of suicidality. All the baseline models were developed by considering a sequential context of post representations in detecting suicidality.

- Suicide Detection Model (SDM) [11]: The SDM adopts the LSTM layer with an attention mechanism. Fine-tuned FastText embeddings are utilized for encoding posts.
- C-CNN [68]: The C-CNN is trained with posts that are encoded by ConceptNet word embeddings [71].
- **SISMO** [66]: The SISMO uses Longformer [6] and the Bidirectional LSTM to obtain dynamic post embeddings.
- **STATENet** [65]: The STATENet is a time-aware transformerbased model that uses emotional and temporal contextual cues for suicidality assessment.
- **UoS** [3]: UoS is the best performing model at the CLPsych 2022 shared task with Zirikly et al. [79] to capture moments of change in a suicidal individual's mood. The obtained embeddings from the pretrained Sentence BERT are fed into a biLSTM layer and a multi-head attention layer.

5.2 Experimental Settings

To solve the imbalanced data issue, the random oversampling technique [49] is used to generate new train samples by randomly sampling each class independently with the replacement of the currently available samples. All experiments are performed with the stratified 5-fold cross-validation, ensuring that the users in the test set are entirely disjoint and do not overlap with those in the training set. We use 10% of the training set as validation during training to tune our models' hyper-parameters. For reproducibility, detailed experimental settings are summarized in Appendix B.

6 **RESULTS**

6.1 Model Performance

Table 5 summarizes the weighted average precision, recall, and F1-score of the proposed model and the baselines for the future suicidality and the bipolar symptom prediction tasks.

Future suicidality task: Since our dataset is disproportionate across the suicide risk levels as shown in Table 1, we conduct experiments over the three classification tasks: (i) 2-level, (ii) 3-level, and (iii) 4-level classifications, as shown in Table 5. For example, we combine AT and BR categories to the highest risk level for the 3-level classification; we merge AT, BR, and ID for the 2-level

classification. As shown in Table 5, we find that the proposed model outperforms all the baseline methods regardless of how the suicide risk level is structured. We observe that STATENet [65] shows the lowest performance among the baseline methods. That is because STATENet fails to utilize sequential data, while other baselines consider users' posts over time as input sequences. Although other baselines perform better than STATENet by exploiting sequential data, our model surpasses them by learning the temporal dynamics of BD symptoms.

BD symptom task: The results show that our proposed model improves BD symptom prediction performance compared to UoS [3]. While our model directly utilizes contextualized post embeddings to predict BD symptoms in each post, UoS considers post sequences. This implies that considering the post sequence may interfere with BD symptom prediction of each post since bipolar patients have a characteristic of rapidly changing mood.

Multi-task learning: To evaluate the performance of multi-task learning, we train the proposed model separately for each task (i.e., Single-task learning (STL)). We find that the proposed multi-task learning (MTL) improves prediction performances from single-task learning (STL) in both BD symptom identification and future suicidality prediction tasks by achieving 61.24% and 82.30%, respectively. This suggests that jointly learning BD symptom information helps forecast future risks of suicidality by sharing informative presentations and parameters.

6.2 Ablation Study

Model Component. We perform an ablation study to examine the effectiveness of each component. Applying the uncertainty weight loss function is a common technique in multi-task learning that can address the challenge of tuning loss coefficients for different tasks with different prediction levels. In our case, the two tasks, suicidality prediction, and BD symptom classification, show different granularities, hence we use the uncertainty parameters to balance their weights during training. This can prevent one task from dominating the objective function and improve the model's overall performance. As shown in Table 6, there is a significant drop in performance when the uncertainty weight loss is not used. Overall, Table 6 shows that the performance is inferior when the selfattention mechanism is applied instead of the proposed temporal symptom-aware attention mechanism. By adding symptom-specific information, we suppose the model can learn that each symptom contributes differently to future suicidality over time. This indicates that not only understanding time intervals but also mood swings over time is essential to predict the future suicidal risk of BD users. Bipolar Symptom. We conjecture that the effects of mood and somatic symptom information of BD for predicting future suicidality would differ. To validate this, we train the multi-task model with either mood or somatic symptoms. Note that 'w/o somatic' refers to a case where only information on the six mood symptoms is included, but any information on the somatic symptoms is excluded. On the other hand, 'w/o mood' refers to a case where only information on the somatic symptoms is included, but any information on the mood symptoms is excluded. As shown in Table 6, the multi-task model trained with only mood symptoms ('w/o somatic') achieves a higher performance (81.77% of F1-score) than the model trained with only

Table 5: Performance comparisons of the proposed model and baselines. We report the average of results over 5-fold cross-validation. * indicates that the result is significantly better than C-CNN (p < 0.05) under Wilcoxon's Signed Rank test. Bold denotes the best performance and *Italics* denotes the second best.

			4 levels			3 levels			2 levels	
Task	Model	(IN / ID / BR / AT)			(IN / ID / BR+AT)			(IN / ID+BR+AT)		
		Prec. \uparrow	Rec. ↑	F1 ↑	Prec. \uparrow	Rec. ↑	F1 ↑	Prec.↑	Rec. ↑	F1 ↑
	STATENet [65]	76.56	36.84	47.76	76.49	42.73	51.77	76.87	59.40	64.99
	SISMO [66]	73.94	64.66	68.71	73.30	59.85	65.18	77.12	52.15	58.21
	UoS (STL) [3]	73.14	73.11	72.99	75.15	78.05	76.51	78.71	78.11	78.40
Euturo Suicidality	UoS (MTL All) [3]	73.72	75.39	74.47	75.33	76.39	75.82	79.01	79.30	79.15
Future Suicidality	SDM [11]	72.97	73.87	73.20	77.86	80.45	78.95	77.52	80.18	77.34
	C-CNN [68]	80.42	83.67	78.44	72.40	80.37	76.17	76.21	83.12	77.19
	Ours (STL)	79.02	84.50	81.62	76.61	84.07	79.40	80.26	83.54	81.59
	Ours (MTL All)	81.84*	86.58*	82.30*	76.68*	84.47*	79.50*	82.37*	86.52*	82.21*
		8 B	8 BD symptoms							
	UoS (STL) [3]	59.71	64.86	59.98	-	-	-	-	-	-
Bipolar Symptom	UoS (MTL All) [3]	57.75	70.73	60.66	-	-	-	-	-	-
	Ours (STL)	57.62	70.65	60.65	-	-	-	-	-	-
	Ours (MTL All)	58.63	7 0. 77	61.24	-	-	-	-	-	-

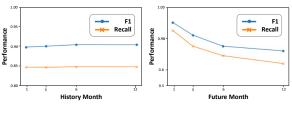
Table 6: Ablation study results over the proposed model components.

	Model					
	Ours (MTL ALL)	86.58	82.30			
Model	- w/o Uncertainty Loss	83.78	80.95			
Component	84.05	81.35				
	- w/o Bi-LSTM	87.19	81.69			
Bipolar	- w/o Somatic	86.40	81.77			
Symptom	- w/o Moods	80.27	79.35			

somatic symptoms ('w/o mood'). Although somatic symptoms are prominent suicidality for BD patients [25, 50], they appear less frequent than mood symptoms. Thus, the improved performance in the final model (MTL All) signifies that both symptoms play a complementary role in solving the main task.

6.3 Observational and Predictable Periods

As illustrated in Section 3.4, we conduct experiments to find how many months $l \in \{1, 3, 6, 12\}$ we should observe in predicting the future suicidality on the next period $m \in \{1, 3, 6, 12\}$. Figure 5a shows the weighted average F1 score and recall for predicting suicidality in 1 month by training $l \in \{1, 3, 6, 12\}$ months. We find that the performance increases as more past days are trained, but no improvement beyond 6 months. This implies that the 12 months observation period is too long to capture informative recent patterns to predict future suicidality. However, the longer the future period to be predicted, the worse the performance is trained for 6 months, as shown in Figure 5b. We interpret that this is because the mood swings of individuals with BD tend to be radical and impulsive [53, 73], limiting the model's ability to predict the far distant future from historical records. Therefore, the performance of the proposed model is the best when (l, m) = (6, 1). According to previous studies, BD patients hospitalized by suicide attempts are likely to commit suicide again between 3 and 6 months after



(a) Varying Observation Period (b) Varying Forecast Period

Figure 5: Performance of the model by varying observational period $l \in \{1, 3, 6, 12\}$ and predictable period $m \in \{1, 3, 6, 12\}$.

discharge [18]. The proposed model can help offer proper treatment by diagnosing BD symptoms and suicidality early.

6.4 Interpretability of the Model

To demonstrate the interpretability of the proposed model by analyzing attention weights related to BD symptoms, we examine two example sequences, s1 and s3, extracted from the same user A, where their levels of future suicidality are different. In particular, we compare the proposed model with and without the temporal symptom-aware attention mechanism (i.e., 'MTL All' vs. 'MTL w/o Temp att') in Figure 6. As shown in Figure 6(a), both models correctly predict BD symptoms for each post, but only 'MTL all' correctly identifies future suicidality of s_1 and s_3 . This implies that temporal tracking is useful since bipolar patients have a characteristic of rapid mood swings. We further analyze how the model assigns the temporal symptom-aware attention a_t^i (in Equation 6) to each post over time in predicting future suicidality. In the s_1 sequence, 'MTL All' assigns a lower attention score to p_1^1 , whereas giving more attention to $p_2^1 - p_4^1$. It indicates that *irritability/somatic* and depressed/psychosis are crucial for predicting future suicidality [4, 50, 77]. Also, we find a similar tendency for the BD symptoms' attention weights in Figure 6(b); as the risk of suicide increases, the importance of attention weights to anxiety decreases, while the importance of depressed and irritability increases significantly.

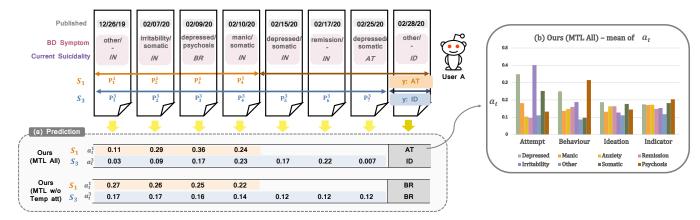


Figure 6: (a) Two example sequences from a single user on how the proposed model assigns attention weights. Such an analysis can provide interpretability in using the proposed model. (b) Average BD Symptoms' temporal attention weights a_t depending on the *Future Suicidality* level.

Notably, s_3 has identical posts with s_1 (i.e., $p_1^3 - p_4^3$), but the model differently gives attention weights to them. By focusing on a *manic* symptom in p_4^3 , the model forecasts lower suicidality than s_1 , which implies user A's mental status is shown to be improved. Moreover, we find that our model tends to focus on recent posts, giving more attention to the manic symptoms of p_4^1 , which is a new observation compared to a previous work that claimed that manic episodes less contribute to future suicidality [50]; a future validation is required. We believe the proposed future suicidality prediction model with an interpretable function, as exemplified in Figure 6 can be used for screening and identifying individuals with mental illness on social media to prioritize early intervention for clinical support.

7 CONCLUDING REMARKS

In this study, we proposed a novel end-to-end multi-task learning model to jointly learn (i) the future suicidality and (ii) BD symptoms of individuals with BD over time. The proposed model for predicting the future suicidality using temporal symptom-aware attention can (i) accurately capture BD transition patterns and (ii) outperform the state-of-the-art methods for detecting future suicidality for BD patients. We plan to open our codes and dataset, which contains the future suicidality and BD symptom labels, validated by two psychiatrists. The proposed model and dataset have great utility in identifying the potential suicidality of users in the future, hence preventing individuals from potential suicidality at an early stage. Clinical Applicability. As an interdisciplinary study, our work contributes to both machine learning and Psychiatry communities. Most BD applications do not provide a suicide warning function and rely solely on self-assessment. On the other hand, we proposed an interpretable and automatic model for predicting the future suicidality of BD patients by introducing a temporal symptomaware attention mechanism based on sequential context learning. With the advantage of the proposed model that can help identify complex mood changes and future suicidality in a real context, it can be used for monitoring risks of suicidality for those who are underrepresented in a clinical setting, such as minorities, uninsured people, or patients with a lack of insight. In addition, more concise and timely tracking of mood symptoms can reduce the diagnosis

duration, leading to shorter treatment periods and better prognosis in BD patients. Our dataset can help to establish a prevention system for early detection and immediate intervention of BD patients with high-risk suicidality for clinical support. This will enable us to reduce mental health-related social costs and promote public health. Limitation. Assessing future suicidality on social media can be subjective [37], and the analysis of this paper can be interpreted in various ways by the researchers. The experiment data may be sensitive to demographic, annotators, and media-specific biases [28]. Although we carefully selected the users who have been clinically diagnosed as BD based on their Reddit posts [31], possibly noisy data can be included if the users misunderstood their diagnoses or did not tell the truth. Moreover, there might be linguistic discrepancies between Reddit and other social media users (e.g., Twitter users) who self-reported BD diagnosis. Lastly, using digital-trace data from social media for predicting mental health can cause low performance depending on the condition of a clinical setting [16, 21]. Future Work. Unfortunately, BD is often misdiagnosed as a depressive disorder since the depressive phase occupies most of the mood episodes [56]. It has been reported that 9 years were taken on average to clinically diagnose BD [24], which can potentially delay treatment opportunities and increase the risk of suicide [39]. Further research could focus more on comparing similar symptoms in different diagnoses to make precise detection (e.g., depressed mood in major depression). We also aim to apply the proposed model to data collected in the clinical field, such as EMR data, to validate the proposed model's effectiveness to determine the potential for practical applications.

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REFERENCES

- Lena Nabuco de Abreu, Beny Lafer, Enrique Baca-Garcia, and Maria A Oquendo. 2009. Suicidal ideation and suicide attempts in bipolar disorder type I: an update for the clinician. *Brazilian Journal of Psychiatry* 31 (2009), 271–280.
- [2] American Psychiatric Association. 2013. Diagnostic and statistical manual of mental disorders: DSM-5 (5th ed. ed.). Autor, Washington, DC.
- [3] Tayyaba Azim, Loitongbam Singh, and Stuart Middleton. 2022. Detecting moments of change and suicidal risks in longitudinal user texts using multi-task learning. In Proceedings of the Eighth Workshop on Computational Linguistics and Clinical Psychology. 213–218.
- [4] Elizabeth D Ballard, Cristan A Farmer, Bridget Shovestul, Jennifer Vande Voort, Rodrigo Machado-Vieira, Lawrence Park, Kathleen R Merikangas, and Carlos A Zarate Jr. 2020. Symptom trajectories in the months before and after a suicide attempt in individuals with bipolar disorder: A STEP-BD study. *Bipolar disorders* 22, 3 (2020), 245–254.
- [5] Jakob E Bardram, Mads Frost, Károly Szántó, and Gabriela Marcu. 2012. The MONARCA self-assessment system: a persuasive personal monitoring system for bipolar patients. In Proceedings of the 2nd ACM SIGHIT International Health Informatics Symposium. 21–30.
- [6] Iz Beltagy, Matthew E Peters, and Arman Cohan. 2020. Longformer: The longdocument transformer. arXiv preprint arXiv:2004.05150 (2020).
- [7] Adrian Benton, Glen Coppersmith, and Mark Dredze. 2017. Ethical research protocols for social media health research. In Proceedings of the first ACL workshop on ethics in natural language processing. 94–102.
- [8] Charles L Bowden, Vivek Singh, P Thompson, JM Gonzalez, MM Katz, M Dahl, Thomas J Prihoda, and X Chang. 2007. Development of the bipolar inventory of symptoms scale. Acta Psychiatrica Scandinavica 116, 3 (2007), 189–194.
- [9] Craig J Bryan, Jonathan E Butner, Sungchoon Sinclair, Anna Belle O Bryan, Christina M Hesse, and Andree E Rose. 2018. Predictors of emerging suicide death among military personnel on social media networks. *Suicide and Life-Threatening Behavior* 48, 4 (2018), 413–430.
- [10] Craig J Bryan and M David Rudd. 2016. The importance of temporal dynamics in the transition from suicidal thought to behavior. *Clinical Psychology: Science* and Practice 23, 1 (2016), 21–25.
- [11] Lei Cao, Huijun Zhang, Ling Feng, Zihan Wei, Xin Wang, Ningyun Li, and Xiaohao He. 2019. Latent Suicide Risk Detection on Microblog via Suicide-Oriented Word Embeddings and Layered Attention. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 1718–1728.
- [12] Arman Cohan, Bart Desmet, Andrew Yates, Luca Soldaini, Sean MacAvaney, and Nazli Goharian. 2018. SMHD: a Large-Scale Resource for Exploring Online Language Usage for Multiple Mental Health Conditions. In Proceedings of the 27th International Conference on Computational Linguistics. 1485–1497.
- [13] Jacob Cohen. 1960. A coefficient of agreement for nominal scales. Educational and psychological measurement 20, 1 (1960), 37–46.
- [14] Glen Coppersmith, Mark Dredze, and Craig Harman. 2014. Quantifying mental health signals in Twitter. In Proceedings of the workshop on computational linguistics and clinical psychology: From linguistic signal to clinical reality. 51–60.
- [15] Tim Dalgleish, Melissa Black, David Johnston, and Anna Bevan. 2020. Transdiagnostic approaches to mental health problems: Current status and future directions. *Journal of consulting and clinical psychology* 88, 3 (2020), 179.
- [16] Munmun De Choudhury and Emre Kiciman. 2017. The language of social support in social media and its effect on suicidal ideation risk. In *Eleventh International* AAAI Conference on Web and Social Media.
- [17] Munmun De Choudhury, Emre Kiciman, Mark Dredze, Glen Coppersmith, and Mrinal Kumar. 2016. Discovering shifts to suicidal ideation from mental health content in social media. In Proceedings of the 2016 CHI conference on human factors in computing systems. 2098–2110.
- [18] Rani A Desai, David J Dausey, and Robert A Rosenheck. 2005. Mental health service delivery and suicide risk: the role of individual patient and facility factors. *American Journal of Psychiatry* 162, 2 (2005), 311–318.
- [19] Raul Diaz and Amit Marathe. 2019. Soft labels for ordinal regression. In Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition. 4738–4747.
- [20] Peter Dome, Zoltan Rihmer, and Xenia Gonda. 2019. Suicide risk in bipolar disorder: a brief review. *Medicina* 55, 8 (2019), 403.
- [21] Sindhu Kiranmai Ernala, Michael L Birnbaum, Kristin A Candan, Asra F Rizvi, William A Sterling, John M Kane, and Munmun De Choudhury. 2019. Methodological gaps in predicting mental health states from social media: triangulating diagnostic signals. In Proceedings of the 2019 chi conference on human factors in computing systems. 1–16.
- [22] Manas Gaur, Amanuel Alambo, Joy Prakash Sain, Ugur Kursuncu, Krishnaprasad Thirunarayan, Ramakanth Kavuluru, Amit Sheth, Randy Welton, and Jyotishman Pathak. 2019. Knowledge-aware assessment of severity of suicide risk for early intervention. In proceedings of the 2019 World Wide Web Conference (San Francisco, CA, USA). 514–525.
- [23] John R Geddes and David J Miklowitz. 2013. Treatment of bipolar disorder. The lancet 381, 9878 (2013), 1672–1682.

- [24] S Nassir Ghaemi. 2007. Bipolar Disorder: How long does it usually take for someone to be diagnosed for bipolar disorder? *Retrieved on* (2007), 02–20.
- [25] Xenia Gonda, Maurizio Pompili, Gianluca Serafini, Franco Montebovi, Sandra Campi, Peter Dome, Timea Duleba, Paolo Girardi, and Zoltan Rihmer. 2012. Suicidal behavior in bipolar disorder: epidemiology, characteristics and major risk factors. *Journal of affective disorders* 143, 1-3 (2012), 16–26.
- [26] June Gruber, Polina Eidelman, and Allison G Harvey. 2008. Transdiagnostic emotion regulation processes in bipolar disorder and insomnia. *Behaviour research* and therapy 46, 9 (2008), 1096–1100.
- [27] Daisy Harvey, Fiona Lobban, Paul Rayson, Aaron Warner, Steven Jones, et al. 2022. Natural Language Processing Methods and Bipolar Disorder: Scoping Review. JMIR mental health 9, 4 (2022), e35928.
- [28] Dirk Hovy and Shannon L Spruit. 2016. The social impact of natural language processing. In Proceedings of the 54th Annual Meeting of the Association for Computational Linguistics (Volume 2: Short Papers). 591–598.
- [29] Mark A Ilgen, Amy SB Bohnert, Rosalinda V Ignacio, John F McCarthy, Marcia M Valenstein, H Myra Kim, and Frederic C Blow. 2010. Psychiatric diagnoses and risk of suicide in veterans. Archives of general psychiatry 67, 11 (2010), 1152–1158.
- [30] Daniel Izmaylov, Avi Segal, Kobi Gal, Meytal Grimland, and Yossi Levi-Belz. 2023. Combining Psychological Theory with Language Models for Suicide Risk Detection. In Findings of the Association for Computational Linguistics: EACL 2023. 2385-2393.
- [31] Glorianna Jagfeld, Fiona Lobban, Paul Rayson, and Steven JM Jones. 2021. Understanding who uses Reddit: Profiling individuals with a self-reported bipolar disorder diagnosis. In Proceedings of the Seventh Workshop on Computational Linguistics and Clinical Psychology: Improving Access. 1–14.
- [32] Sheri L Johnson, Charles S Carver, and Jordan A Tharp. 2017. Suicidality in bipolar disorder: The role of emotion-triggered impulsivity. *Suicide and Life-Threatening Behavior* 47, 2 (2017), 177–192.
- [33] Masoud Kamali, Erika FH Saunders, Alan R Prossin, Christine B Brucksch, Gloria J Harrington, Scott A Langenecker, and Melvin G McInnis. 2012. Associations between suicide attempts and elevated bedtime salivary cortisol levels in bipolar disorder. Journal of affective disorders 136, 3 (2012), 350–358.
- [34] Jiwon Kang, Jieun Kim, Taenyun Kim, Hayeon Song, and Jinyoung Han. 2022. Experiencing Stress During COVID-19: A Computational Analysis of Stressors and Emotional Responses to Stress. *Cyberpsychology, Behavior, and Social Networking* 25, 9 (2022), 561–570.
- [35] Edward L Kaplan and Paul Meier. 1958. Nonparametric estimation from incomplete observations. *Journal of the American statistical association* 53, 282 (1958), 457–481.
- [36] Alan E Kazdin, American Psychological Association, et al. 2000. Encyclopedia of psychology. Vol. 8. American Psychological Association Washington, DC.
- [37] John G Keilp, Michael F Grunebaum, Marianne Gorlyn, Simone LeBlanc, Ainsley K Burke, Hanga Galfalvy, Maria A Oquendo, and J John Mann. 2012. Suicidal ideation and the subjective aspects of depression. *Journal of affective disorders* 140, 1 (2012), 75–81.
- [38] Alex Kendall, Yarin Gal, and Roberto Cipolla. 2018. Multi-task learning using uncertainty to weigh losses for scene geometry and semantics. In Proceedings of the IEEE conference on computer vision and pattern recognition. 7482–7491.
- [39] Kamyar Keramatian, Jairo V Pinto, Ayal Schaffer, Verinder Sharma, Serge Beaulieu, Sagar V Parikh, and Lakshmi N Yatham. 2022. Clinical and demographic factors associated with delayed diagnosis of bipolar disorder: data from Health Outcomes and Patient Evaluations in Bipolar Disorder (HOPE-BD) study. *Journal of Affective Disorders* 296 (2022), 506–513.
- [40] Jina Kim, Jieon Lee, Eunil Park, and Jinyoung Han. 2020. A deep learning model for detecting mental illness from user content on social media. *Scientific Reports* 10, 1 (2020), 1–6.
- [41] E David Klonsky, Alexis M May, Boaz Y Saffer, et al. 2016. Suicide, suicide attempts, and suicidal ideation. Annu Rev Clin Psychol 12, 1 (2016), 307–30.
- [42] Klaus Krippendorff. 2018. Content analysis: An introduction to its methodology. Sage publications.
- [43] Daeun Lee, Migyeong Kang, Minji Kim, and Jinyoung Han. 2022. Detecting Suicidality with a Contextual Graph Neural Network. In Proceedings of the Eighth Workshop on Computational Linguistics and Clinical Psychology. 116–125.
- [44] Daeun Lee, Soyoung Park, Jiwon Kang, Daejin Choi, and Jinyoung Han. 2020. Cross-Lingual Suicidal-Oriented Word Embedding toward Suicide Prevention. In Proceedings of the 2020 Conference on Empirical Methods in Natural Language Processing: Findings. 2208–2217.
- [45] Damien Lekkas, Robert J Klein, and Nicholas C Jacobson. 2021. Predicting acute suicidal ideation on Instagram using ensemble machine learning models. *Internet interventions* 25 (2021), 100424.
- [46] Ilya Loshchilov and Frank Hutter. 2017. Decoupled weight decay regularization. arXiv preprint arXiv:1711.05101 (2017).
- [47] Gin S Malhi, Tim Outhred, Pritha Das, Grace Morris, Amber Hamilton, and Zola Mannie. 2018. Modeling suicide in bipolar disorders. *Bipolar disorders* 20, 4 (2018), 334–348.
- [48] Anika Mandla, Jo Billings, and Joanna Moncrieff. 2017. "Being Bipolar": A Qualitative Analysis of the Experience of Bipolar Disorder as Described in Internet

Blogs. Issues in mental health nursing 38, 10 (2017), 858-864.

- [49] Giovanna Menardi and Nicola Torelli. 2014. Training and assessing classification rules with imbalanced data. *Data mining and knowledge discovery* 28, 1 (2014), 92–122.
- [50] Jacob N Miller and Donald W Black. 2020. Bipolar disorder and suicide: a review. Current psychiatry reports 22, 2 (2020), 1–10.
- [51] Hiroki Nakayama, Takahiro Kubo, Junya Kamura, Yasufumi Taniguchi, and Xu Liang. 2018. doccano: Text Annotation Tool for Human. https://github. com/doccano/doccano
- [52] Matthew K Nock, Guilherme Borges, Evelyn J Bromet, Jordi Alonso, Matthias Angermeyer, Annette Beautrais, Ronny Bruffaerts, Wai Tat Chiu, Giovanni De Girolamo, Semyon Gluzman, et al. 2008. Cross-national prevalence and risk factors for suicidal ideation, plans and attempts. *The British journal of psychiatry* 192, 2 (2008), 98–105.
- [53] Lisa A O'Donnell, Alissa J Ellis, Margaret M Van de Loo, Jonathan P Stange, David A Axelson, Robert A Kowatch, Christopher D Schneck, and David J Miklowitz. 2018. Mood instability as a predictor of clinical and functional outcomes in adolescents with bipolar I and bipolar II disorder. *Journal of affective disorders* 236 (2018), 199–206.
- [54] World Health Organization. 2016. International Statistical Classification of Diseases and related health problems. Vol. 10. World Health Organization.
- [55] Abigail Ortiz, Kamil Bradler, and Arend Hintze. 2018. Episode forecasting in bipolar disorder: Is energy better than mood? *Bipolar disorders* 20, 5 (2018), 470–476.
- [56] Ives C Passos, Pedro L Ballester, Rodrigo C Barros, Diego Librenza-Garcia, Benson Mwangi, Boris Birmaher, Elisa Brietzke, Tomas Hajek, Carlos Lopez Jaramillo, Rodrigo B Mansur, et al. 2019. Machine learning and big data analytics in bipolar disorder: a position paper from the International Society for Bipolar Disorders Big Data Task Force. *Bipolar Disorders* 21, 7 (2019), 582–594.
- [57] James W Pennebaker, Martha E Francis, and Roger J Booth. 2001. Linguistic inquiry and word count: LIWC 2001. *Mahway: Lawrence Erlbaum Associates* 71, 2001 (2001), 2001.
- [58] Laura Plans, Evaristo Nieto, Antoni Benabarre, and Eduard Vieta. 2019. Completed suicide in bipolar disorder patients: a cohort study after first hospitalization. *Journal of affective disorders* 257 (2019), 340–344.
- [59] Maurizio Pompili, Xenia Gonda, Gianluca Serafini, Marco Innamorati, Leo Sher, Mario Amore, Zoltan Rihmer, and Paolo Girardi. 2013. Epidemiology of suicide in bipolar disorders: a systematic review of the literature. *Bipolar disorders* 15, 5 (2013), 457–490.
- [60] Kelly Posner, Gregory K Brown, Barbara Stanley, David A Brent, Kseniya V Yershova, Maria A Oquendo, Glenn W Currier, Glenn A Melvin, Laurence Greenhill, Sa Shen, et al. 2011. The Columbia–Suicide Severity Rating Scale: initial validity and internal consistency findings from three multisite studies with adolescents and adults. *American journal of psychiatry* 168, 12 (2011), 1266–1277.
- [61] Nils Reimers and Iryna Gurevych. 2019. Sentence-BERT: Sentence Embeddings using Siamese BERT-Networks. In Proceedings of the 2019 Conference on Empirical Methods in Natural Language Processing and the 9th International Joint Conference on Natural Language Processing (EMNLP-IJCNLP). 3982–3992.
- [62] Zoltán Rihmer and Kitty Kiss. 2002. Bipolar disorders and suicidal behaviour. Bipolar Disorders 4 (2002), 21–25.
- [63] Puneet KC Sahota and Pamela L Sankar. 2020. Bipolar disorder, genetic risk, and reproductive decision-making: A qualitative study of social media discussion boards. *Qualitative health research* 30, 2 (2020), 293–302.

- [64] Ramit Sawhney, Harshit Joshi, Lucie Flek, and Rajiv Shah. 2021. Phase: Learning emotional phase-aware representations for suicide ideation detection on social media. In Proceedings of the 16th conference of the european chapter of the association for computational linguistics: main volume. 2415–2428.
- [65] Ramit Sawhney, Harshit Joshi, Saumya Gandhi, and Rajiv Shah. 2020. A timeaware transformer based model for suicide ideation detection on social media. In Proceedings of the 2020 conference on empirical methods in natural language processing (EMNLP). 7685–7697.
- [66] Ramit Sawhney, Harshit Joshi, Saumya Gandhi, and Rajiv Ratn Shah. 2021. Towards Ordinal Suicide Ideation Detection on Social Media. In Proceedings of the 14th ACM International Conference on Web Search and Data Mining. 22–30.
- [67] Ivan Sekulić, Matej Gjurković, and Jan Šnajder. 2018. Not just depressed: Bipolar disorder prediction on reddit. arXiv preprint arXiv:1811.04655 (2018).
- [68] Han-Chin Shing, Suraj Nair, Ayah Zirikly, Meir Friedenberg, Hal Daumé III, and Philip Resnik. 2018. Expert, crowdsourced, and machine assessment of suicide risk via online postings. In Proceedings of the Fifth Workshop on Computational Linguistics and Clinical Psychology: From Keyboard to Clinic. 25–36.
- [69] Sylvia G Simpson and Kay R Jamison. 1999. The risk of suicide in patients with bipolar disorders. Journal of clinical psychiatry 60, 2 (1999), 53–56.
- [70] Ivan Seuklic Matej Gjurkovic Jan Šnajder. 2018. Not Just Depressed: Bipolar Disorder Prediction on Reddit. WASSA 2018 (2018), 72.
- [71] Robyn Speer and Joanna Lowry-Duda. 2017. ConceptNet at SemEval-2017 Task 2: Extending Word Embeddings with Multilingual Relational Knowledge. In Proceedings of the 11th International Workshop on Semantic Evaluation (SemEval-2017). 85-89.
- [72] Steven John Stack. 2014. Mental illness and suicide. The Wiley Blackwell Encyclopedia of Health, Illness, Behavior, and Society (2014), 1618–1623.
- [73] SA Strejilevich, Diego Javier Martino, A Murru, J Teitelbaum, G Fassi, Eliana Marengo, A Igoa, and F Colom. 2013. Mood instability and functional recovery in bipolar disorders. Acta Psychiatrica Scandinavica 128, 3 (2013), 194–202.
- [74] Hajime Sueki. 2015. The association of suicide-related Twitter use with suicidal behaviour: a cross-sectional study of young internet users in Japan. *Journal of* affective disorders 170 (2015), 155–160.
- [75] Ashish Vaswani, Noam Shazeer, Niki Parmar, Jakob Uszkoreit, Llion Jones, Aidan N Gomez, Łukasz Kaiser, and Illia Polosukhin. 2017. Attention is all you need. Advances in neural information processing systems 30 (2017).
- [76] Matthew L Williams, Pete Burnap, and Luke Sloan. 2017. Towards an ethical framework for publishing Twitter data in social research: Taking into account users' views, online context and algorithmic estimation. *Sociology* 51, 6 (2017), 1149–1168.
- [77] Siqi Xue, John Hodsoll, Ameer Bukhsh Khoso, Muhammad Omair Husain, Imran B Chaudhry, Allan H Young, Juveria Zaheer, Nusrat Husain, Benoit H Mulsant, and Muhammad Ishrat Husain. 2021. Suicidality in patients with bipolar depression: Findings from a lower middle-income country. *Journal of affective disorders* 289 (2021), 1–6.
- [78] Minjoo Yoo, Sangwon Lee, and Taehyun Ha. 2019. Semantic network analysis for understanding user experiences of bipolar and depressive disorders on Reddit. *Information Processing & Management* 56, 4 (2019), 1565–1575.
- [79] Ayah Zirikly, Philip Resnik, Ozlem Uzuner, and Kristy Hollingshead. 2019. CLPsych 2019 shared task: Predicting the degree of suicide risk in Reddit posts. In Proceedings of the sixth workshop on computational linguistics and clinical psychology. 24–33.

A ANNOTATION CRITERIA



Figure 7: The screenshot of the annotation tool for creating data.

A.1 Annotation Process

In this study, we aim to develop a model to predict the risks of future suicidality of bipolar disorder (BD) patients using past social media data. To this end, we create a BD dataset that includes the labels of future suicidality and bipolar symptoms clinically verified by psychiatrists. This section briefly states how we create a BD dataset based on our annotation guideline. As our first step, we collect social media posts published between January 1, 2008, and September 31, 2021, from three bipolar-related subreddits using the open-source Reddit API⁴. Among the collected posts, we used posts written by users who have been diagnosed with BD by professionals [31] and users who reported BD diagnosis (e.g., "I was diagnosed with Bipolar type-I last year."). Based on the criteria, our dataset contains 7,592 posts published by 818 users, i.e., BD patients. For the preprocessing, we anonymize the collected posts and convert the texts. Then we conduct annotation with four trained annotators using the opensource text annotation tool Doccano in Figure 7.

A.2 Annotation Guideline

For our annotation, we consider three different label categories that include the diagnosed BD type (e.g., BD-I, BD-II), the BD symptom (e.g., manic, anxiety), and the level of suicidality (e.g., ideation, attempt). Discussion with the psychiatrist selected the criteria of three different label categories. We briefly describe the details of the annotation guideline in the following subsections.

A.2.1 Diagnosed Bipolar Disorder Types. To use only posts of users diagnosed with bipolar by medical institutions, we classify users whose self-reports are bipolar related to diagnoses (e.g., "Hey, I'm diagnosed bipolar II posts being diagnosed with schizophrenia."). We label users into three BD diagnosis types, including *Bipolar Disorder-I* (BD-I), *Bipolar Disorder-II* (BD-II), and *Not Otherwise Specified Bipolar Disorder* (NOS). Table 7 describes the definition of three BD diagnosis types inspired by the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [2] and the Statistical Classification of Diseases and Related Health Problems (ICD-10) [54], which classify bipolar disorder into several sub-types based on the

frequency and intensity of episodes. For example, BD-I requires at

least one manic episode, while *BD-II* shows at least one hypomanic and one major depressive episode during their lifetime. Moreover, we annotate *NOS* when a patient shows some symptoms of BD but does not necessarily satisfy all the criteria.

A.2.2 Bipolar Disorder Symptoms. We can filter out posts without BD diagnosis type from Appendix A.2.1. We annotate BD symptoms for each post that fits the requirement to track users diagnosed as bipolar with time series. Based on the BISS(Bipolar Inventory of Symptoms Scale) Bowden et al. [8] and discussions with the psychiatrist, our annotation criteria came out. We annotate users in case bipolar-related symptoms are exposed. Table 8 describes the definition and the corresponding examples of BD symptoms used in this study. For more systematic annotation, we consider mood and somatic symptoms. We first annotate the most prominent mood symptoms among Depressed, Manic, Anxiety, Remission, Irritability and Other. Additionally, we add Other to cover moods that do not fall into the other five mood symptoms. Moreover, simultaneously with some posts, we annotate an additional somatic symptom label in option with Somatic complaint, Psychosis, and Both, which are considered vital factors of suicidality [5, 69]. While annotating, we delete advertising posts that do not fit the purpose.

A.2.3 Risks of Suicidality. To determine the user's different levels of suicidality while tracking BD symptoms, we also simultaneously annotate the risks of suicidality. Based on the post contents, we label the risk of suicidality, which fits the current situation. We utilize the existing criteria from [22] that provide five levels of suicidality, including No Risk (NR), Suicide Indicator (IN), Suicidal Ideation (ID), Suicidal Behavior (BR), and Actual Attempt (AT), based on the Columbia Suicide Severity Rating Scale (C-SSRS) [60]. For our annotation, we merge No Risk with Suicide Indicator since people with bipolar disorder are already considered more at risk than the general population in suicide [29, 62]. In the suicide indicator level, posts reveal risk indicators such as a history of divorce, chronic illness, or suicide of a loved one. Suicidal ideation posts mention the willingness to take own life (e.g., "I still want to die. I still should die."), and suicidal behavior posts contain actions with higher risks, such as planning a suicide attempt. Posts show deliberate action at the actual attempt level that can lead to death (e.g., "I failed to commit suicide last night, what do I do now?"). Table 8 details each category's descriptions and examples of Risks of Suicidality.

B EXPERIMENT SETTINGS

We tune hyperparameters based on the highest F1 score obtained from the cross-validation set for the models. We use the grid search to explore the dimension of hidden state $H \in \{32, 64, 128, 256, 512\}$, number of LSTM layers $n \in \{1, 2, 5\}$, dropout $\sigma \in \{0.1, 0.2, 0.3, 0.4, 0.5\}$, initial learning rate $lr \in \{1e - 5, 2e - 5, 3e - 5, 5e - 5\}$, and control the parameter for ordinal regression $\alpha \in \{0, 0.2, ..., 3.8\}$. The optimal hyperparameters were found to be: $H = 512, n = 2, \sigma = 0.1$, lr = 1e - 5, and $\alpha = 1.8$. We implement all the methods using PyTorch 1.6 and optimize with the mini-batch AdamW [46] with a batch size of 64. We use the Exponential Learning rate Scheduler with gamma 0.001. We train the model on a GeForce RTX 2080 Ti GPU for 200 epochs and apply early stopping with patience of 20 epochs.

⁴https://www.reddit.com/dev/api/

Table 7: Definition of diagnosed BD types.

BD Type	Definition
BD-I	At least one-lifetime manic sepisode and one major depressive episode.
BD-II	At least one hypomanic and one major depressive episode.
NOS	Shows some symptoms of BD but does not necessarily satisfy all the criteria.

Table 8: The descriptions and examples in Bipolar Disorder symptoms and risks of suicidality

Category	Symptom	Description & Example
BD Symptom	Depressed	sadness, feeling of inadequacy, psychomotor slowing, social withdrawal, reduced sex drive, etc
		"I've always had unstable moods and antidepressants have only ever made things worse for me."
	Manic	elated mood, hyperactive, increased sexuality, risky behavior, impulsive, distractible, etc
		"I have so much adrenaline that I'll start laughing to myself at my own jokes, singing or shouting."
	Anxiety	anxious mood, somatic anxiety, agitation, sense of nervousness, obsession, etc
		"But what if i'm just having a good week, i get nervous now i don't know what to think or feel."
	Remission	symptom relief, excellent, feeling of comfort, happiness, etc
		"As for how I feel, I feel a massive sense of relief."
	Irritability	irritable mood, annoyance, impatient, anger, sensitiveness, scream, etc
		"I'm just so annoyed with everyone and everything all I wanna do is scream."
	Somatic	insomnia/hypersomnia, decreased/increased appetite, impaired concentration, amnesia, etc
		"At first my appetite was normal but now it's been going away. I feel no hunger during the day."
	Psychosis	persecutory idea, delusion, hallucinations, impaired insight, etc
		"I feel paranoid, have been having delusions and I saw people."
Suicidality	Indicator	Risk indicators such as a history of divorce, chronic illness, or suicide of a loved one.
		"I've been waking up and crying first thing every day for the past several days."
	Ideation	Any mention of wanting to take one's own life.
		"I still want to die. i still should die. i feel sorry for anyone who knows me."
	Behavior	Actions with higher risk such as cutting or planning for a suicide attempt.
		"Imma go cut myself into pieces like I deserve. World is a much better place without me."
	Attempt	Letter asking for help after the suicide attempt, will, deliberate action that can lead to death.
		"I failed suicide last night, what do I do now? I thought I took enough pills to kill myself last night."

Table 9: Differences between target and control groups based on LIWC results and annotated results.

Annotated	LIWC							
	t	р		t	р		t	р
Current Suicidality			Mood			Body		
- Indicator	-11.91	0.000 *	- posemo	0.96	0.339	- percept	-1.41	0.159
- Ideation	9.50	0.000 *	- negemo	3.51	0.000 *	- see	-1.71	0.087
- Behavior	6.59	0.000 *	- anx	-1.47	0.143	- hear	-1.12	0.263
- Attempt	3.39	0.001 *	- anger	2.85	0.004 *	- feel	1.24	0.216
BD Symptom			- sad	5.16	0.000 *	- bio	1.70	0.089
- Manic	-3.88	0.000 *	- death	8.03	0.000 *	- body	1.58	0.115
- Anxiety	-0.36	0.722	Social			- health	1.58	0.264
- Irritability	-6.07	0.000 *	- social	-1.84	0.066	- achieve	-2.59	0.010 *
- Remission	-0.28	0.778	- family	2.23	0.026 *	Liguistic		
- Somatic	1.11	0.267	- friend	0.98	0.325	- i	5.73	0.000 *
- Psychosis	2.44	0.01	- affiliation	-0.90	0.370	- we	-1.37	0.171
			- work	-2.38	0.017 *	- you	-1.88	0.060
			- money	-2.22	0.027 *	- shehe	-1.87	0.061
			- relig	1.41	0.159	- they	-0.05	0.957
			- risk	2.03	0.042 *			