Noname manuscript No.
(will be inserted by the editor)

Micro-Journal Mining to Understand Mood Triggers

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Received: date / Accepted: date

Abstract In computational linguistics, binary sentiment analysis methods have been proposed to predict whether a document expresses a positive or a negative opinion. In this paper, we study a unique research problem - identifying environmental stimuli that contribute to different moods (mood triggers). Our analysis is enabled by an anonymous micro-journalling dataset, containing over 700,000 short journals from over 67,000 writers and their self-reported moods at the time of writing. We first build a multinomial logistic regression model to predict the mood (e.g., happy, sad, tired, productive) associated with a micro-journal. We then examine the model to identify predictive words and word trigrams associated with various moods. Our study offers new data-driven insights into public well-being.

1 Introduction

Emotion triggers are defined as environmental stimuli that bring about emotions [8]. Research finds that a detailed understanding of emotion triggers helps people regulate their negative emotions and prevent negative thoughts and feelings from driving their behaviour [6]. Many social science studies have explored relationships between particular sets of mood triggers and moods, either through qualitative methods or by analyzing survey data. One study concludes that victimization history can predict anxiety or depression syndromes among teenagers, based on their responses to surveys [2]. Sentiment analysis has also been studied in computational linguistics, where most of the work has focused on optimizing predictive algorithms to detect sentiment in text.

Unlike social science studies that rely on survey data or sentiment analysis work in computational lingusitics that focuses on improving sentiment detection accuracy, our goal is to understand mood triggers through text mining.

To do so, we use a unique micro-journalling dataset provided by a journalling platform. The dataset consists of over 700,000 short journals written by over 67,000

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anonymous users. Users of the platform write down text that describes how they feel, and they choose from a pre-defined list of 17 moods to label their journals: *Angry, Sad, Stressed, Frustrated, Down, Lonely, Anxious, Overwhelmed, Tired, Okay, Calm, Good, Productive, Accomplished, Happy, Excited, and Ecstatic*. To extract potential mood triggers from journals, we leverage ground-truth mood labels by first building a multinomial logistic regression model to predict the mood using textual features in journals. Next, we use coefficients of textual features to select predictive terms that may indicate mood triggers. Then, we recover the context of predictive terms by extracting word trigrams where the predictive terms appear. In the last step, we manually summarize those trigrams into mood triggers, which offers data-driven insights into public well-being.

We remark that by using the term "mood trigger", we are not claiming any cause-and-effect relationships. Instead, our mood triggers correspond to contexts in which predictive words for the given mood are frequently used. For example, we do not claim that "crying" causes a *Sad* mood; in fact, the reverse may be true. However, we identify that when a journal mentions crying about something, it is often labelled with the mood *Sad*.

Contributions and organization: We apply a well-known text classification method, logistic regression, to identify predictive terms for various moods. Our novelty lies in the use of a unique and large training dataset, with ground-truth mood labels, and the subsequent interpretation of the logistic regression model to identify potential mood triggers. Unlike common interpretation approaches that only examine predictive words or manually inspect a small sample of the original text [1], we recover the context of predictive words by extracting related trigrams. We obtain insights that can help improve public well-being. For example, we find that job interviews can trigger both anxiety and excitement, meaning that pre-interview anxiety could be mitigated by focusing on the exciting aspects of the experience. We review prior work in Section 2, discuss our dataset and method in Section 3, present our results in Section 4, and offer concluding remarks and directions for future work in Section 5.

2 Prior work

In this paper, we aim to understand potential mood triggers through text mining. A variety of prior research is related to our work: psychology studies, sentiment analysis, and emotion analysis using computational linguistics methods.

Many psychology studies investigate emotion triggers through qualitative methods, surveys, and experiments [9]. Being aware of potential emotion triggers was found to contribute to better emotional health [6]. Conclusions such as "things affecting welfare" and "memories of past emotional experiences" offer a high-level summary of possible types of emotion triggers [3]. Some research concludes particular triggers among college students [12]. Victimization history is found to predict anxiety or depression syndromes among teenagers [2]. Our work discovers potential triggers for different types of emotions, and our uniqueness is that our results are based on a large dataset. Also, we draw conclusions about specific emotion triggers, rather than high-level summaries, based on word features and their context.

In computational linguistics, there is a great deal of work on *sentiment analysis*. Much of this work focuses on predicting the sentiment of a product or service review [17,25]. For sentiment datasets that do not have ground-truth sentiment labels, general methods include human annotation [20] or emoticons [5]. Later sentiment classification work increases the number of sentiment classes by adding a strength component and finds a decrease in prediction accuracy [16,23]. Our work is different in that we aim to predict a fine-grained mood label from text rather than a coarse-grained sentiment.

Going one step further, there is recent work on emotion classification and emotion cause extraction from text [7,14]. While ground-truth mood labels are difficult to collect, some studies infer mood labels using lists of basic emotion words and their synonyms [24]. Besides common textual features, social media online activities are found to be predictive of individuals' mood changes [10]. Also, ones' previous mood status and social forces among online community groups are found to improve emotion prediction's accuracy [21]. Extracted high-level emotion triggers are used as additional word features to classify emotions [11,4]. However, similar with most sentiment analysis work, emotion classification studies focus on optimizing model accuracy [13] rather than exploring mood triggers, which is the objective of our work. Although some studies explore contributing factors to emotions and study emotion triggers, their main focus is to use those factors as predictive features to improve mood prediction. Therefore, most emotion analysis works do not provide insights into emotion triggers for different types of emotions.

3 Data and Method

Our mircro-journal dataset is extracted from a social media platform whose users write journals to express their moods and monitor their mood trends over time. It contains over 700,000 short journals that are written by 67,000 anonymous users during an 18-month period (from July 1, 2015 to Dec 31, 2016). Each journal is labelled with the time and date of creation, and a self-reported mood, chosen from the 17 moods mentioned earlier.

Table 1 lists the steps of our method to extract potential mood triggers. First, we perform the following data pre-processing steps: we remove duplicate journals (i.e., those with the same text and the same mood label), we remove all journals with mood label *Okay* (following the common practice of removing neutral documents in sentiment analysis; in our dataset, journals labelled as *Okay* are mostly used to log daily activities and do not contain obvious mood triggers), and we remove journals containing only one sentence (by manual inspection of a small sample of journals, we found that short journals are unlikely to include a cause for the mood). We also convert all journals to lower-case. We do not perform *word stemming* since stemmed words may be difficult to interpret. After performing these steps, we have 739,762 journals. The average number of words per journal is 28, and there are no statistically significant differences in journal lengths for different moods.

We then train multinomial logistic regression models using standard word n-gram TF-IDF features[1] to predict the mood label given the text of a journal. We experimented with various types of features: word unigrams, word bigrams,

[1] TF-IDF is the frequency of a given word in a given journal divided by the logarithm of the fraction of journals this word appears in.

Table 1 Steps to extract mood triggers from text

1: Pre-process the data.
2: Train a multinomial logistic regression model to predict mood from text.
3: Run Peason's chi-squared test on word unigram features.
4: Select top 100 predictive word unigrams for each mood.
5: For each predictive word unigram and mood pair, concatenate all micro-journals with that mood to a single long document, among which we extract 5 most frequent word trigrams containing the predictive unigram.

and word trigrams, to compare their prediction power, removing frequent word n-grams that appear in more than 70, 80 or 90% of the journals to remove stop words [15], and removing rare words that appear in less than 0.001, 0.006, 0.01 or 0.02% of the journals. Measured by mean 10-fold cross-validation accuracy, we obtained the best model accuracy (32.8%) by using only word unigram features that appear at least 0.006% and at most 90% of the journals. For comparison, we also experimented with linear support vector machine models and random forest models with the different word n-gram features described above. However, their best accuracies (32.4% and 29.4% respectively) were lower than that of the multinomial logistic regression model.

After training the logistic regression model, we run Pearson's chi-squared test between word features and mood classes to remove words that are statistically independent of the mood label. Setting the p-value threshold at 0.005, we retain a total of 2,131 words that are significantly dependent on mood labels. Within the retained words, for each mood, we select the top 100 most predictive words based on their logistic regression coefficients. Our final step is to recover the context of those top predictive words to extract potential mood triggers. For every pair of predictive word and mood, we concatenate all journals labelled with that mood into a long document, and then we extract top 5 most frequent word trigrams that contain that predictive word. Finally, for each mood, we manually inspect the frequent word trigrams and we group them into potential mood triggers.

We use Python's scikit-learn package for the above experiments. We use RandomizedSearchCV to find optimal parameter settings for feature extraction and model training. For multinomial logistic regression, the best model uses the following parameters: one-vs-rest scheme, "saga" solver, a maximum number of 2000 iterations, and a L2 regularization with an inverse regularization parameter of 0.9. The best LinearSVC model uses intercept and inverse regularization parameters of 0.4. The best random forest model uses 280 trees and the minimum number of samples at leaf nodes is 0.001% of the total training data.

We also implemented several *unsupervised learning* methods that could potentially identify mood triggers, including: vectorizing each journal using an average of pre-trained word embeddings and then applying k-means clustering; and applying TF-IDF vectorization to all journals followed by non-negative matrix factorization for topic modelling. Then, for each cluster or factor, we inspected the frequently occurring trigrams. However, we were unable to obtain any obvious mood triggers from those trigrams as they are not selected based on discriminative models, and contain stop-words and emotional words that are not relevant to mood triggers.

Table 2 Overall mood label distribution

Good	Calm	Tired	Happy	Sad	Down	Anxious	Frustrated
16.1%	13.5%	10.3%	9.2%	6.2%	6.0%	6.0%	5.4%
Overwhelmed	Productive	Accomplished	Lonely	Angry	Stressed	Excited	Ecstatic
5.0%	4.8%	3.6%	3.1%	3.0%	2.9%	2.8%	2.0%

Table 3 Mood label distribution for each day of the week

Emotions	Monday	Tuesday	Wednesday	Thursday	Friday	Saturday	Sunday
Tired	10.4%	10.8%	10.9%	10.6%	10.2%	9.5%	9.2%
Happy	8.8%	8.1%	8.4%	8.7%	9.7%	10.9%	10.6%
Anxious	6.4%	6.4%	6.4%	6.1%	5.7%	5.2%	5.5%
Overwhelmed	5.3%	5.5%	5.5%	5.3%	4.8%	4.2%	4.5%
Average of the other 12 moods	5.8%	5.8%	5.7%	5.8%	5.8%	5.9%	5.8%

4 Results

4.1 Mood Distribution and Mood Correlation

Table 2 shows the distribution of mood labels, indicating that *Good*, *Calm*, *Tired* and *Happy* are the most common moods. Next, Table 3 shows the distribution of selected mood labels for each day of the week (other mood labels did not show any obvious patterns). The frequency of *Tired*, *Anxious* and *Overwhelmed* mood labels drops on weekends, whereas the frequency of *Happy* journals increases.

To explore correlations among mood labels, we compute the Pearson correlation score for each pair of moods using the logistic regression coefficients. We show the results as a heat map in Figure 1. The blue and red regions suggest that there are two groups of correlated moods: the positive ones and the negative ones. Setting a correlation cut-off at 0.5, we group moods with a pairwise correlation greater than or equal to the cut-off. In the end, we have six groups of correlated of moods, listed in Figure 1. Notably, the *Tired* mood is not highly correlated with any other mood. Additionally, *Angry* is more correlated with *Frustrated* than with the other negative moods.

4.2 Mood Trigger Extraction

Our first result is that the same word can be predictive of different moods, and the context in which it is used may be different for different moods. This underscores the need for the final step of our method, which is to explore the context (in our case, word tri-grams) in which predictive words are used. Table 4 shows several examples. The second and fourth columns list several top predictive words and their associated mood labels, respectively. The "Context" column summarizes the context in which the predictive words were used, according to our manual inspection of frequent word trigrams containing the given predictive word (as described in Section 3). The first column further lists high-level mood trigger categories that we manually assigned according to predictive words and their context. For example, when mention in the context of friends being busy, "busy" is predictive of *Lonely*; when expressed as "had a busy day", "busy" is predictive of *Tired* or *Productive*.

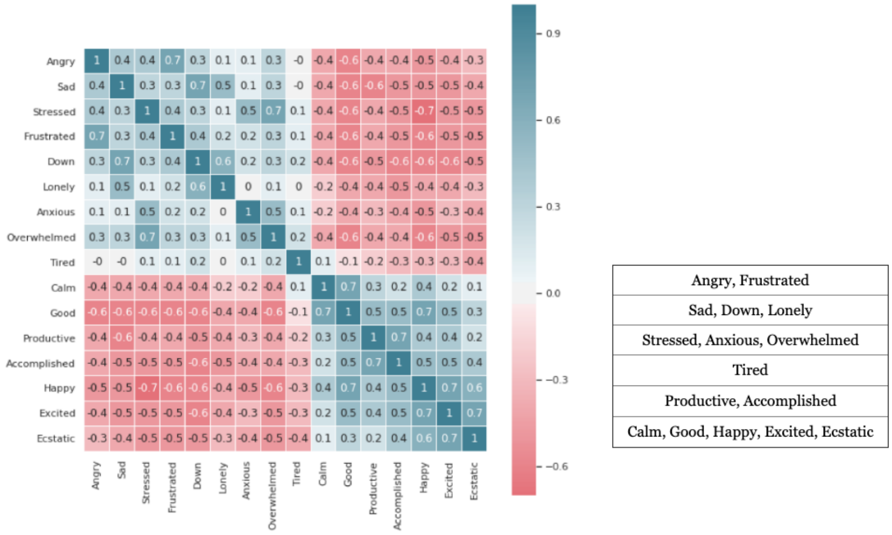

Fig. 1 Heat map of mood correlations and groups of highly correlated moods

Table 4 Predictive words that predict different moods

Categories	Predictive words	Context	Moods
Work-related	busy	feeling left out	Lonely
		had a busy day	Tired, Productive
	finish	facing deadlines	Stressed, Overwhelmed
		going to finish	Productive
	interview	job interviews	Anxious, Excited
	presentation	will give a presentation	Anxious
		gave a presentation	Accomplished
Sleep-related	slept	not slept well	Tired
		well rested	Calm, Good
	nap	need to take naps	Tired
		well rested	Calm, Good
School-related	essay	facing deadlines	Stressed
		school life, essay done	Productive
	homework	facing deadlines	Stressed, Overwhelmed
		school life, homework done	Productive
	paper	facing paper deadlines	Stressed, Overwhelmed
		school life, paper done	Productive
Others	passed	death of loved ones	Sad
		school life, passed tests	Accomplished
	packing	packing up	Overwhelmed, Productive

Our second result is as follows: during manual inspection of predictive words and their context through related tri-grams, we found that many predictive words are essentially synonyms of the corresponding mood labels and do not reveal any mood triggers. In terms of emotion prediction, emotional terms make sense in that their occurrence is a strong signal for a specific emotion. As a result, sentiment lexicon libraries contain mostly emotional words to make predictions [22]. For example, the word “mad” predicts *Angry*, but it is used mainly to express the mood (e.g., “I am really mad!”), not suggest why one feels angry. Table 5 shows the percentages of top 100 predictive terms for each mood that only reiterate the mood

Table 5 Percentage of top 100 predictive terms that only reiterate the mood, or that are swear words

Emotions	Down	Good	Anxious	Calm	Ecstatic	Excited	Tired	Happy
Mood-reiterating words	61%	59%	56%	56%	53%	52%	50%	47%
Swear words	1%			2%				
Emotions	Lonely	Stressed	Overwhelmed	Sad	Frustrated	Accomplished	Angry	Productive
Mood-reiterating words	47%	44%	43%	40%	39%	36%	32%	24%
Swear words	1%	6%		1%	17%		20%	

Table 6 Potential triggers for Angry, Frustrated, Sad, Down, Lonely, Stressed, Anxious, Overwhelmed and Tired

Mood trigger categories	Angry	Frustrated	Sad	Down	Lonely	Stressed	Anxious	Overwhelmed	Tired
Illness	✓	✓	✓	✓	✓	✓	✓	✓	✓
Relationships	✓	✓	✓	✓	✓		✓	✓	
Self-disappointment		✓	✓	✓	✓		✓		
Work		✓				✓	✓	✓	✓
Politics	✓						✓		
Medication & Treatment							✓		
School						✓	✓	✓	
Sleep				✓			✓		✓
Arguing	✓	✓	✓	✓		✓		✓	
Being mistreated	✓	✓			✓				
Body image	✓	✓	✓	✓					
Failure	✓	✓	✓	✓		✓		✓	
Self-hatred	✓	✓	✓	✓	✓	✓		✓	
Infidelity	✓								
Self-harm	✓		✓	✓		✓		✓	
Crying			✓	✓	✓			✓	
Financial situation						✓		✓	

and the percentages that are swear words. For many moods, half the predictive words simply repeat the mood. The moods that include the fewest mood-reflecting predictive words are *Productive* and *Accomplished*, suggesting that these journals are more likely to include a reason for the mood. On the other hand, nearly one fifth of the predictive words for *Angry* and *Frustrated* are swear words, with no other mood having more than 6% of such words in their predictive word sets (recall that we also found *Angry* and *Frustrated* to be correlated in Figure 1).

In the remainder of this section, we present our analysis of triggers for each mood. We begin with two high-level summary tables: Table 6 includes negative moods and Table 7 includes positive moods. In both tabes, the “Mood trigger categories” are labels we manually assigned to potential mood triggers after inspecting the word tri-grams identified in the last step of our method. Note that “Physical exercise”, “Food and meals”, “Getting things done”, “Leisure activities”, “Making progress”, “Self-recognition”, and “Weather” only trigger positive emotions.

For each of the six groups of correlated moods identified in Figure 1, we now examine their potential triggers in more detail.

4.2.1 Triggers for Angry and Frustrated

The high correlation between *Angry* and *Frustrated* is also evident in the details of the triggers for these two moods, shown in Table 8. Many of these common triggers are associated with personal conflicts with others, including loved ones. However, there are also some differences between these two moods. For example, infidelity and self-harm are not mentioned in the context of frustration. On the other hand, issues at work and self-disappointment appear more likely to make someone frustrated than angry.

Table 7 Potential triggers for Productive, Accomplished, Calm, Good, Happy, Excited and Ecstatic

Mood trigger categories	Productive	Accomplished	Calm	Good	Happy	Excited	Ecstatic
Relationships			✓	✓	✓	✓	✓
Work	✓						
Medication & Treatment							
School	✓	✓					✓
Sleep			✓	✓	✓		
Body image	✓	✓				✓	✓
Financial situation		✓					
Physical exercise	✓	✓				✓	✓
Food and meals		✓	✓		✓		
Getting things done	✓	✓					✓
Leisure activities			✓	✓	✓	✓	✓
Making progress	✓	✓	✓				
Self-recognition	✓	✓		✓		✓	✓
Weather			✓	✓	✓		
Therapy			✓				

Table 8 Details of potential mood triggers for Angry and Frustrated

Mood triggers	Angry	Frustrated
Arguing	Arguing with someone, being yelled at	Arguing with someone
Being mistreated	Being lied to, being ignored, being treated disrespectfully/unfairly/badly/like a child/rudely	Being treated inconsiderately/rudely/unfairly
Illness	Respiratory problem, pain	Headaches, migraines, pain
Body image	Concerns about body weight	Concerns about body weight, calories intake
Failure	Failing, being unable to handle things	Failing
Self-hatred	Hating oneself	Hating oneself
Relationships	Parents, siblings	Parents
Self-disappointment		Being expected to do something, disappointing oneself, lack of patience
Work		Feeling difficulty, being stuck, having an issue
Infidelity	Being betrayed, being cheated on, cheating on someone	
Politics	Concerns about the presidential election	
Self-harm	Hurting oneself, suicidal thoughts	

4.2.2 Triggers for Sad, Down, and Lonely

In Figure 1, we found that *Sad* is more correlated with *Down* than *Lonely*. This is consistent with the details of the triggers shown in Table 9. *Sad* and *Down* share similar triggers, but *Down* may additionally be triggered by lack of sleep. Furthermore, while *Lonely* shares many triggers with the other two moods (such as self-hatred and self-disappointment), it does not appear to be triggered by body image concerns, failure or self-harm. On the other hand, being ignored or excluded may trigger loneliness, but not sadness or feeling down.

4.2.3 Triggers for Stressed, Anxious, and Overwhelmed

Figure 1 shows that *Stressed* is closer to *Overwhelmed* than *Anxious*. Table 10 also demonstrates this: there are many common triggers of *Stressed* and *Overwhelmed*. Notably, while failure may also trigger *Angry* and *Frustrated*, the context for those two moods is that of past failure. On the other hand, concerns about failing in the future appear to trigger being *Stressed* and *Overwhelmed*. Furthermore, unlike *Anxious* and *Overwhelmed*, relationship issues do not appear likely to trigger

Table 9 Details of potential mood triggers for Sad, Down and Lonely

Mood triggers	Sad	Down	Lonely
Illness	Pain, depression, mental breakdown	Pain, depression	Pain
Self-hatred	Hating oneself	Hating oneself	Hating oneself
Relationships	Parents, being hated by loved ones, death of loved ones, funerals, breakups, goodbyes, lack of friends and love, being rejected	Death of loved ones, funerals, lack of friends and love, missing someone	Breakups, marriage, divorce, homesick, lack of friends and love, missing someone, being rejected, lack of belonging, lack of companionship
Crying	Cries	Cries	Cries
Self-disappointment	Disappoint in oneself, feel useless	Disappoint in oneself, feel useless	Disappoint in oneself, being unsure
Arguing	Arguing with someone, being yelled at	Arguing with someone, being yelled at	
Being mistreated			Being ignored, did not get invited
Body image	Concerns about body weight	Concerns about body weight	
Failure	Failed, being unable to handle things	Failed	
Self-harm	Hurt oneself, thinking about suicide	Hurt oneself, thinking about suicide	
Sleep		Lack of sleep	

Table 10 Details of potential mood triggers for Stressed, Anxious and Overwhelmed

Mood triggers	Stressed	Anxious	Overwhelmed
Illness	Anxiety attacks, headaches, migraines, pain, vomiting	Anxiety attacks, chest pain, dizziness, obsessive compulsive disorder, shaking, stomach pain	Anxiety attacks
School	Upcoming exams, grades, homework due	Upcoming exams	Upcoming exams and school projects due, falling behind in school
Work	Being late for work	Going to give a presentation, job interviews	Too much work, lack of preparation, moving, procrastination
Arguing	Arguing with someone, being yelled at		Arguing with someone
Failure	Going to fail, being unable to handle things		Going to fail, being unable to handle things
Self-hatred	Hating oneself		Hating oneself
Self-harm	Suicidal thoughts		Suicidal thoughts
Relationships		Love and romance	Breakup
Financial situation	Bills		Bills
Politics		Concerns about the presidential election	
Crying			Crying about something
Medication and Treatment		Taking medication, doctor appointments	
Self-disappointment		Over-thinking and self-doubt	
Sleep		Nightmares, too much caffeine, too much noise	

Stressed. Finally, *Anxious* differs from *Stressed* and *Overwhelmed* in that it may be triggered by medical issues or sleep difficulties.

4.2.4 Triggers for Tired

According to Table 11, feeling tired has three potential triggers: being overworked, not sleeping well, or illness. Specifically, about 25% of the predictive terms reflect sleep issues whereas 20% are related to specific illness such as allergies, flu or migraines.

Table 11 Details of potential mood triggers for Tired

Mood triggers	Tired
Work	Too much work
Sleep	Issues with falling asleep, nightmares, not slept well, feeling sleepy, stayed up late, wake up early
Illness	Allergies, cold, coughing, fever, flu, headaches, infections, migraines, pain, soreness

Table 12 Details of potential mood triggers for Productive and Accomplished

Mood triggers	Productive	Accomplished
Body image	Painting nails	Lost weight
Physical exercise	Running, workout	Climbing, cycling, hiking, hit 10k steps, running, walking, workout, yoga
Getting things done	Going to finish something, went shopping, productive meetings, cooking	Achieved goal, figured things out, handled things well, survived challenges
Making progress	Making progress	Making progress
School	Finished something, got a good grade	Gave a good presentation, finished something, got a good grade
Self-recognition	Proud of oneself	Proud of oneself, reward oneself, self-confidence
Financial situation		Bonus from work
Food and meals		Cooked meals, eat healthy food
Work	Had a busy day	

4.2.5 Triggers for Productive and Accomplished

In Table 12, we show that *Productive* and *Accomplished* are both triggered by getting things done either in school or at work. The differences are that having a busy day at work is more likely to make one feel productive, whereas eating a healthy meal and obtaining a raise or a bonus at work is more of a trigger for feeling accomplished. In particular, it appears that losing weight, healthy eating, and reaching workout goals such as 10,000 steps bring feelings of accomplishment.

4.2.6 Triggers for Calm, Good, Happy, Excited, and Ecstatic

Based on Tables 13, we find that being proud of oneself can elicit *Good*, *Excited*, and *Ecstatic* feelings. Furthermore, rainy and warm weather may be a trigger for *Calm*, while sunshine can trigger *Good* and *Happy*. Additionally, meditation may trigger calmness while taking care of one's appearance may trigger *Excited* and *Ecstatic*. Finally, we note that while we found that sleep issues may trigger *Down*, *Anxious*, and *Tired*, sleeping well can contribute to *Calm*, *Good*, and *Happy*.

5 Discussion and Conclusions

Motivated by the importance of emotional well-being, we presented a data-driven study to identify mood triggers from online micro-journals. We explored a unique journalling dataset that contains ground-truth mood labels associated with the text, which allowed us to build classification models and select predictive terms. Our main insights into public health are as follows.

1. Fatigue is a more common mood in our dataset than happiness, and people report being tired more on weekdays than weekends. We identify three main

Table 13 Details of potential mood triggers for Calm, Good, Happy, Excited and Ecstatic

Mood triggers	Calm	Good	Happy	Excited	Ecstatic
Relationships	Family relationships, hanging out with friends	Hanging out with friends, talking or laughing with friends, having a meal with friends	Hanging out with friends, having fun and laughing with friends	Love and romance, hanging out with friends	Love and romance, hanging out with friends
Leisure activities	Listening to music, reading and writing, watching TV and movies, relaxing	Playing games, going shopping, watching TV and movies, relaxing	Playing games, outdoor activities, watching TV and movies, relaxing	Playing games, going out, travelling, watching TV and movies	Playing games, going out, travelling, watching TV and movies, relaxing
Self-recognition		Proud of oneself, self-acceptance, self-confidence		Proud of oneself, self-confidence	Proud of oneself, self-confidence
Sleep	Rested well	Rested well	Rested well		
Weather	Raining, storm, warm	Sunny	Sunny		
Food and meals	Drinking tea		Eating delicious food, eating comfort food		
Therapy	Massage, meditation				
Making progress	Making progress				
Body image				Haircut	Haircut
Exercises				Dancing	Dancing, swimming
Getting things done					Getting accepted to university
School life					Starting school

triggers for *Tired*: work overload, sleep issues, and illness. Prior work also found that sleep issues are commonly related to mental health problems [18], highlighting the importance of healthy sleep habits and work-life balance.
2. Negative moods may potentially be triggered by external (relationships with others, work and school issues, finances) and internal factors (illness, sleep issues, self-hatred, body image issues).
3. Unlike most studies that focus only on negative emotions, we identify several potential triggers for positive moods: resting well, eating healthy and comfort food, exercising, massage, and meditation.

Based on a recent survey of demographics of social media users [19], young and middle-aged people are more likely to use social media. Therefore, one limitation of this study is that the insights may be limited to populations similar to ours, namely young technology-savvy adults likely to use social media and online platforms such as the journalling platform that enabled this analysis. An important direction for future work is to explore the public health of other populations in a data-intensive way, including children, seniors and minorities.

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