Emotion Granularity from Text:
An Aggregate-Level Indicator of Mental Health

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February 21, 2026

Abstract

We are united in how emotions are central to shaping our experiences; yet, individuals differ greatly in how we each identify, categorize, and express emotions. In psychology, variation in the ability of individuals to differentiate between emotion concepts is called emotion granularity (determined through self-reports of one's emotions). High emotion granularity has been linked with better mental and physical health; whereas low emotion granularity has been linked with maladaptive emotion regulation strategies and poor health outcomes. In this work, we propose computational measures of emotion granularity derived from temporally-ordered speaker utterances in social media (in lieu of self-reports that suffer from various biases). We then investigate the effectiveness of such text-derived measures of emotion granularity in functioning as markers of various mental health conditions (MHCs). We establish baseline measures of emotion granularity derived from textual utterances, and show that, at an aggregate level, emotion granularities are significantly lower for people self-reporting as having an MHC than for the control population. This paves the way towards a better understanding of the MHCs, and specifically the role emotions play in our well-being.

1 Introduction

Emotions play a central role in how we construct meaning and communicate with those around us. Yet, individuals vary in their understanding and experience of emotions, or "emotional expertise" [Hoemann et al.2021b]. Some people are able to recognize, identify, and describe what they feel using precise, context-specific terms like guilt, anger, frustration, or helplessness; others tend to use more broad terms to convey a general sense of feeling bad or feeling low. Emotion granularity (EG), aka emotion differentiation, is defined by psychologists as the ability of an individual to experience and categorize emotions in very specific terms [Barrett et al.2001]. Highly granular individuals have a broad range of highly situated and differentiated emotion concepts, and can reliably describe these concepts using language—for example, distinguishing between when they are feeling angry vs. when they are feeling sad, or when they are feeling elated from when they are feeling content.

Evidence collected in the last two decades provides consistent support for a link between emotional granularity and mental health [Erbas et al.2014, Erbas et al.2018, Starr et al.2017, Seah et al.2020], physical health [Hoemann et al.2021b, Bonar et al.2023], and adaptive health behavior [Dixon-Gordon et al.2014, Kashdan et al.2015]. Note that this is different from other findings that study how the prevalence of specific emotions varies with mental health (for example, people with depression tend to use more sadness-associated words). The link between EG and mental health suggests that there is a fundamental difference in how one perceives an emotion (broadly or specifically), and that in turn can impact their mental health.

Typically, granularity is measured across emotions with the same valence; one can therefore have a measure of negative emotion granularity, measured as the granularity of negative emotions (such as anger, sadness, and fear) and positive emotion granularity, measured as the granularity of positive emotions (such as joy, excitement, and satisfaction). Some works also look at the co-endorsement of emotions that express opposite valence, such as joy and sadness [Lindquist and Barrett2008].

In psychology and the affective sciences, emotion granularity is often measured using repeated measurements, where individuals are asked to rate the intensity of experiencing certain emotions multiple times over a period of days (e.g., 2–3 times each day for 5 days), i.e., with self-reports of emotions felt. An individual's emotional granularity is then operationalized as the extent to which multiple emotions are co-endorsed over time, i.e., how similarly the emotions are rated across all measurements, using the intraclass correlation coefficient (ICC) [Shrout and Fleiss1979], which measures the extent to which the emotions co-vary in reports at the aggregate level. Individuals who tend to frequently rate multiple emotions at the same intensity levels are defined as low in granularity—the frequent co-endorsement across time indicates that they are failing to differentiate between these emotions in their reports. In contrast, individuals high in emotion granularity co-endorse multiple emotions less frequently over time [Tugade et al.2004, Hoemann et al.2021a, Lee et al.2017, Reitsema et al.2022].

While prior work in NLP has studied the link between emotions and mental health, these have largely been limited to measuring the prevalence or intensity of positive and negative emotions. In this work, we, for the first time, propose a way to compute emotion granularity from the textual utterances of an individual. Our method uses the temporal sequence of the utterances to first construct emotion arcs along multiple emotions, and computes granularity as the correlation of these emotion arcs. We hypothesize that this measure is indicative of the individual consistently expressing the same set of emotions together over a period of time, and can therefore act as a proxy measure of emotional granularity.

We then study the relationship between aggregate, population-level measures of emotion granularity in text for eight Mental Health Conditions (MHCs), namely attention-deficit hyperactivity disorder (ADHD), anxiety, bipolar disorder, depression, major depressive disorder (MDD), obsessive-compulsive disorder (OCD), postpartum depression (PPD), and post-traumatic stress disorder (PTSD), and compare them to a control group. We use two social media datasets where users have chosen to self-disclose their mental health diagnosis [Suhavi et al.2022, Losada et al.2017, Losada et al.2018]. We compute emotion granularity metrics for each of these groups to answer the following questions:

1. Do measures of emotional granularity differ between the MHCs and the control group?

2. Which measures of emotion granularity are the most effective at differentiating between the MHCs and the control group?

3. Which emotion pairs lead to the greatest difference in granularity between an MHC and the control group?

Exploring this line of questions helps us better understand how emotion granularity presents itself in text, whether emotion granularity from text can be a useful tool to study MHCs, and how an MHC impacts our perception of emotions (and perhaps even, how the perception of emotions impacts our mental health).

Our results establish baseline measures of emotion granularity from text, and show that these measures function as reliable indicators, at the aggregate-level, for the presence of many of the mental health conditions we study. Our work makes an important contribution to the growing wealth of research on textual measures of emotional expression as biosocial markers of MHCs, and has a broader utility in functioning as an additional indicator of the mental well-being of populations.[1] All our code will be made available through the project webpage.[2]

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[1]The term biosocial marker [Lena2021] was coined to indicate the crucial role social factors (e.g., socioeconomic status, years of education, bilingualism, etc.) have on quantitative features associated with medical conditions (biomarkers).

[2]https://github.com/priya22/emotion-granularity-from-text

2 Related Work

2.1 Emotions and Mental Health

Measures of emotional experience and their patterns of change over time have been extensively studied as markers of mental and physical well-being [Lewis et al.2010]. The Emotion Dynamics framework in psychology quantifies the patterns with which emotions change over time, allowing researchers to better understand emotional experiences and individual variation [Kuppens and Verduyn2017]. The framework includes several measures such as the duration, intensity, variability, and granularity of one's emotional experiences. Numerous studies in psychology have shown emotion dynamics correlate with overall well-being, mental health, and psychopathology (the scientific study of mental illness or disorders) [Kuppens and Verduyn2017, Houben et al.2015, Silk et al.2011, Sperry et al.2020].

Emotion granularity in particular is positively associated with adaptive behaviour in adverse conditions—accurately labeling our emotions can inform us of the right coping strategies to use in different contexts. Individuals with higher emotion granularity tend to use a broader range of strategies to deal with negative emotions, and are more successful at doing so [Barrett et al.2001]. Several studies have shown that emotion granularity is lower in individuals with mental health conditions like bipolar disorder [Suvak et al.2011, Dixon-Gordon et al.2014], manic depressive disorder [Demiralp et al.2012], schizophrenia [Kring et al.2003], autism spectrum disorder [Erbas et al.2013], and affective disorders like anxiety [Seah et al.2020] and depression [Starr et al.2017, Willroth et al.2020]. Lower granularity is also associated with increased tendencies to engage in maladaptive behaviour, such as alcohol consumption [Kashdan et al.2015, Emery et al.2014] and aggression [Pond Jr et al.2012].

Researchers in affective science typically measure emotional granularity through experience sampling methodologies (ESMs), or ecological momentary assessments (EMAs), where individuals (participants) are repeatedly asked to report on their emotional states on several occasions throughout the day, for several days. For example, participants may be asked to endorse a series of ten emotion words (e.g., anger, fear, happy, etc.) on a Likert scale across several sampling instances. Emotional granularity would then be computed as the intraclass correlation (ICC) of ratings across sampling instances. A high ICC would suggest that a participant experiences all of the emotions in a similar way across trials (treating them as synonyms for more general affectual states such as "unpleasantness" or "pleasantness"), whereas a low ICC would suggest that a participant experienced emotions in a granular and context-specific way.

While emotion granularity is generally measured between emotion categories that are close to each other in the affective space (i.e., express similar valence), the concept of dialecticism refers to the coincidental experience of both negative and positive emotions [Lindquist and Barrett2008]. Dialecticism can therefore be operationalized as the co-endorsement of emotion pairs that express positive and negative valence.

2.2 Language and Mental Health

Given the limitations of self-report surveys (e.g., limited data coverage and time spans, biases, etc. [Kragel et al.2022]), another approach to measure well-being indicators is through one's language usage. Some well-known linguistic indicators of mental health include the proportion of pronouns used for those with depression [Koops et al.2023], syntax reduction for anorexia nervosa [Cuteri et al.2022], certain lexical and syntactic features for mild cognitive impairment and dementia [Calzolari et al.2021, Gagliardi and Tamburini2021], and semantic connectedness for schizophrenia [Corcoran et al.2020].

Recently, another linguistic feature that researchers leveraged for insights into overall well-being, are the emotions expressed in language. Largely, only sentiment has been explored and mainly from social media data (a rich source of language data). For example, more negative sentiment was expressed in text by individuals with depression [De Choudhury et al.2013, Seabrook et al.2018, De Choudhury et al.2021]. Other work has found that suicide watch, anxiety, and self-harm subreddits had markedly lower negative sentiment compared to other mental health subreddits such as Autism and Asperger's [Gkotsis et al.2016].

[Hipson and Mohammad2021] and [Vishnubhotla and Mohammad2022] introduced Utterance Emotion Dynamics (UED), a framework to quantify patterns of change of emotional states associated with utterances along a longitudinal (temporal) axis (using data from screenplays and tweets). [Teodorescu et al.2023] found that measures of emotion dynamics from text correlate with various mental health diagnoses.

These works overall show that the average emotion expressed in text and also the characteristics of individual emotion change over time (e.g., variability) are meaningful indicators of well-being. In this work, we explore whether the degree of co-expression of pairs of emotions in text (emotion granularity) is a meaningful indicator of mental health.

3 Datasets

We use the Twitter-STMHD dataset [Suhavi et al.2022] for our experiments and also verify our results with a smaller Reddit eRisk [Losada et al.2017, Losada et al.2018] dataset. We describe both of them below.

Twitter-STMHD dataset: [Suhavi et al.2022] identified tweeters who self-disclosed as having an MHC diagnosis using carefully constructed regular expression patterns and manual verification. We summarize key details on the dataset creation process in Appendix A. The control group consists of users identified from a random sample of tweets (who posted during approximately the same time period as the MHC tweets). These tweeters did not post any tweets meeting the MHC regex described above. Additionally, users who had any posts about mental health discourse were removed from the control group. Note that this process does not guarantee that users in the control group did not have an MHC diagnosis, but rather the group as a whole may have very few tweeters from these MHC groups. The number of users in the control group was selected to match the size of the depression dataset, which had the largest number of users.

For the final set of users, four years of tweets were collected for each user: two years before self-reporting a mental health diagnosis and two years after. For the control group, tweets were randomly sampled from between January 2011 and May 2021 (same date range as the other MHC classes).

Reddit eRisk dataset: To further add to our findings, we also included the eRisk 2018 dataset [Losada et al.2017, Losada et al.2018] in our experiments. It consists of users who self-disclosed as having depression on Reddit (expressions were manually checked), and a control group (individuals were randomly sampled). The dataset includes several hundred posts per user, over approximately a 500-day period. We combined users and their instances from both the training set (which is from the eRisk 2017 task [Losada et al.2017]) and the test set (from the eRisk 2018 task [Losada et al.2018]).

3.1 Preprocessing

We further preprocessed both the Twitter-STMHD dataset and the eRisk dataset for our experiments (Section 4), as we are specifically interested in the relationship between emotion granularity and each disorder. Several users self-reported as being diagnosed with more than one disorder, referred to as comorbidity. We found a high comorbidity rate between users who self-reported as having anxiety and depression, as is also supported in the literature [Pollack2005, Gorman1996, Hirschfeld2001, Cummings et al.2014]. Since we wanted to focus on each MHC separately (and not on co-morbidity) we only considered users who self-reported as having one MHC. We also performed the following preprocessing steps:

- We only considered posts in English.

- We filtered out posts that contained URLs (the text in such posts is often not self-contained).

- We removed retweets (identified through tweets containing 'RT', 'rt'). This is to focus exclusively on texts written by the user.

- To ensure that we did not include users that post very infrequently or very frequently, we excluded users based on the number of posts per individual. We discarded data from those who either had

less than 100 posts (as was similarly done in [Vishnubhotla and Mohammad2022]) and those who had posted more than 1.5 times the interquartile range above quartile three (75th percentile) of the control group.[3]

Table 1 shows key details of the filtered Twitter-STMHD and Reddit eRisk datasets.

Table 1: The number of users in each MHC, the average number of posts per user, and the average number of tokens per post in the preprocessed version of the Twitter-STMHD and Reddit eRisk datasets.

Dataset, Group	#people	Av. #posts	Av. #tokens
Twitter-STMHD			
MHC ADHD	907	2,590.48	17.59
Anxiety	1,932	2,497.43	17.46
Bipolar	6,356	2,921.05	17.46
Depression	3,036	2,820.17	17.32
MDD	1,061	2,526.62	16.75
OCD	4,855	2,640.69	16.40
PPD	219	2,388.73	18.38
PTSD	1,009	2,581.19	19.18
Control	119	2,533.85	19.41
Reddit eRisk			
Depression	2,609	2,420.50	16.16
Control	6,001	47.22	41.09

4 Emotion Granularity from Text

The core metric that we want to capture from the text utterances of an individual is emotion granularity—what psychologists term the "co-endorsement" of pairs of emotions. Analogous to their operationalization of granularity in terms of the Intra-Class Correlation (ICC) of repeated emotion intensity measurements along emotion adjectives, we use textual utterances to derive a temporal sequence of emotion states, referred to as an emotion arc for the speaker (Section 4.1), and operationalize granularity as the correlations of these arcs. We construct emotion arcs for multiple emotions, for each user in the MHC groups and the control group.

Emotion Dimensions: A key requirement of our computational method is that we must be able to quantify the emotional score of a text along a selected emotion dimension. We are therefore limited by the resources and models available to compute such a score for an emotion dimension.

Here, keeping in mind the necessity of including multiple emotion dimensions that are similarly-valenced, we work with the eight emotions represented in the NRC Emotion Intensity Lexicon: anger, anticipation, disgust, fear, joy, sadness, surprise, and trust [Mohammad2018].

We partition these emotions into three groups based on the valence association: joy and trust are in the positive valence group; anger, sadness, fear, and disgust are in the negative valence group; and anticipation and surprise are in the variable valence group. The distinction for surprise and anticipation is necessary because specific instances of these emotions can have a positive or a negative connotation (e.g., a good or a bad surprise).

4.1 Constructing Emotion Arcs

We order the utterances for each user based on timestamp information in the metadata. We construct emotion arcs for the temporal sequence of utterances of each user, along each of the eight emotions, in

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[3]The interquartile range is from the 25th to 75th percentile.

two ways pertaining to different window sizes. This is to make sure that the results are largely robust even when varying the window size to some extent.

Utterance-level Window: Emotion scores (for each emotion category) are computed for each utterance (i.e., tweet or Reddit post). Here, an utterance is assumed to represent the speaker's emotion state at a particular point in time (analogous to sampling instances). The sequence of utterance emotion scores for a user forms their temporal emotion arc.[4]

Word-Count based Window: Here, the emotion score at a point in time is computed for a window of words (say, 100 words) that are uttered around that point, and the window is moved forward by a fixed step size (say, 1 word at a time) to obtain the emotion score for the next time step. In prior work on constructing emotion arcs from temporally-ordered text, such sliding windows are usually employed to ensure smoother arcs that more accurately capture the flow of emotions over time.

[Teodorescu and Mohammad2023] conducted extensive quantitative evaluations of several hyperparameters involved in emotion arc construction, on datasets from diverse domains (including tweets) annotated with emotion scores. We follow many of their recommendations to construct emotion arcs for the utterances of each of our users.

The texts are tokenized using the twokenize package[5] to obtain a similarly-ordered sequence of words. Emotion scores are computed with window sizes of 100 words and 500 words each, and the window is moved forward by one word at each timepoint to obtain a series of overlapping emotion scores.

Emotion scoring method: Keeping in mind the necessity of an interpretable method of emotion scoring, we use word-emotion lexicons to compute the emotion scores of text spans. For each window, the emotion scores of its constituent words are averaged to obtain the window-level score for that emotion. [Teodorescu and Mohammad2023] showed that emotion arcs constructed with lexicon-based scoring methods, when used with sliding window sizes of 100 instances or more, can mimic the ground-truth emotion arcs with an accuracy of 0.9 or more.

Word-emotion scores are obtained from the NRC Emotion Intensity Lexicon, which associates close to 10,000 English words with a real-valued score between 0 and 1 for each dimension. A score of 0 indicates that the word has little to no association with that particular emotion, and a score of 1 indicates a high association.

Qualitative Checks on Emotion Lexicons: Lexicon-based methods for constructing emotion arcs are reliable and interpretable; however, it is good practice to modify the lexicon to the specific domain of use, in order to account for terms that are expected to be used in the target domain in a sense different from the predominant word sense [Mohammad2023].

We identify and remove words and bigrams whose usage on Twitter (and sometimes more colloquially) is markedly different from the predominant word sense annotated in the lexicons, such as *like* and *chaotic evil*. We also remove words and bigrams that are explicitly associated with mental health, such as *anxious*, *disorder* and *panic attack*. Though our EG metric does not explicitly rely on the presence of such terms to find associations with MHCs, we remove them in order to capture more fundamental differences in emotional expression between users in the MHC groups and the control group. The full list of stopwords is in Appendix B.

Hyperparameters: We additionally make the following choices of hyperparameters for constructing and comparing a pair of emotion arcs:

- For a given pair of emotions, we drop all emotion terms that are common to the two lexicons before constructing their emotion arcs. This ensures that we are not using words associated with both emotions, giving us a clearer indication of co-endorsement.

- An utterance (or window) with no emotion terms from a particular emotion lexicon is assigned a score of 0. An alternative is to assign them a score of nan, in which case they are not considered

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[4]The frequency and time of posting often differs between users, but we ignore that for now.

[5]https://github.com/myleott/ark-twokenize-py

a part of the emotion arc.[6]

A visualization of the emotion arcs obtained using the utterance-level window for a sampled user from the Twitter-STMHD dataset is presented in Appendix E.

4.2 Quantifying Emotion Granularity

We compute the emotion granularity metric as the negative of the Spearman correlation between each pair of emotion arcs, for each user.[7] A high correlation between two arcs indicates that the speaker is consistently and repeatedly expressing the two emotions concurrently; we hypothesize that this is an indicator of a lower ability to differentiate between the two emotions, and therefore a lower emotion granularity.[8] For each person, we average the correlation scores between emotion pairs in the different valence groups to obtain the following measures of emotion granularity (EG):

- **EG(pos):** The negative of (i.e., -1 times) the average of the correlation scores between each of the pairs of emotions in the positive valence group (joy-trust).

- **EG(neg):** The negative of the average of the correlation scores between each of the pairs of emotions in the negative valence group (anger-fear, fear-disgust, etc.).

- **EG(var):** The negative of the average of the correlation scores between each of the pairs of emotions in the variable valence group (surprise-anticipation).

- **EG(overall):** Overall emotion granularity, measured as the negative of the average of the correlation scores between emotion pairs whose constituents are in the same group. Here, the average is taken across all of the emotion pairs drawn from the positive valence group, the negative valence group, and the variable valence group.

- **EG(cross):** Emotion granularity of cross-group emotion pairs. That is, the negative of the average of the correlation scores between emotion pairs whose constituents come from different groups. This measure to some extent quantifies the amount of dialecticism (expressing both positive and negative emotions in a narrow window of time); however, note that EG(cross) also includes emotions that express variable valence (surprise and anticipation), rather than only considering positive-negative valence emotion pairs.

We consider EG(overall) to be the bottom line measure of emotion granularity for a user (analogous to that used in psychology studies). Note that cross-group pairs are not included in this measure.

5   Emotion Granularity and Mental Health

We now test if there are significant differences between the emotion granularities of each of the MHC groups and the control group, using t-tests.

We first limit the users in each group by placing thresholds on (a) the number of user tweets with a valid emotion score (set to a minimum of 50), and (b) the number of unique lexicon terms used in their tweets (set to a minimum of 25). These thresholds ensure that we are drawing inferences based on users with valid emotion arcs, with sufficient lexicon coverage and temporal information.

We performed independent t-tests to compare emotion granularities between each of the MHCs and the control group, for each emotion group, using the SciPy library [Virtanen et al.2020]. To correct for

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[6]We do not observe any major changes to our results based on these hyperparameter choices.

[7]We choose Spearman correlation as it is rank-based as compared to Pearson correlation which utilizes the raw-values.

[8]We choose to use Spearman correlation over ICC-based metrics because the emotion scores that we extract from textual utterances are a relative indicator of the intensity of the emotion, and not an absolute measure. Further, these scores cannot be directly compared across different emotions in terms of absolute intensity (a score of 0.9 for anger may not equate to the same level of anger as a score of 0.9 would for joy) due to differences in how overtly different emotions are expressed via language.

multiple comparisons (eight tests performed for each MHC per emotion granularity group), we used the Benjamini-Hochberg procedure in the statsmodels library [Seabold and Perktold2010]. Further details on the data assumptions for t-tests are in Appendix C.

5.1 Term Specificity as a Control

Lower emotion granularity occurs when, for a person, the concepts of the relevant emotions are so broad (and non-specific) that their meanings overlap substantially. This work is testing the hypothesis of whether people who have self-disclosed as having an MHC have lower emotion granularity than those that do not. However, another plausible hypothesis is that people in a particular group (e.g., MHC or the control) tend to use more specific words overall. Doing so would imply a higher specificity (i.e., a higher granularity) in their usage of all words, and that the high granularity of emotion words is simply a by-product of their general style of speaking (or posting online).

To ensure that the level of word specificity does not differ between MHCs and the control group and act as a confounder for our measure of emotion granularity, we performed a control experiment. We compute the average information content of the noun and verb terms in the posts of users in each group, and use this as a measure of the specificity of their language. We use the metric proposed in [Resnik1995], and implemented in the NLTK WordNet library,[9] which combines information about the depth of the term in the WordNet tree hierarchy and its frequency of occurrence in a large corpus (here, the Brown corpus) to compute an information content score [Miller1995].

We then compute the following measures of term specificity for each user:

- **IC(n):** The information content score for all nouns is averaged across all posts of each individual in each group.

- **IC(v):** The information content score for all verbs is averaged across all posts of each individual in each group.

Statistical tests for significant differences are similarly performed as described above (Section 5).

6 Results

In Table 13 we report the statistical results from the pairwise comparisons between each MHC and the control group, for the control experiment on general term specificity as well as emotion granularity, when scores are computed at the utterance-level.

All statistically significant differences between an MHC and the control group are described as either 'lower' or 'higher', and a dash (-) for no statistical difference. A 'lower' value in a cell indicates that the MHC (rows) has lower emotion granularity (or lower term specificity) than the control group, i.e., higher correlation between emotion pairs in that group (columns); 'higher' indicates the MHC has higher emotion granularity (or higher term specificity) than the control group (i.e., lower correlation between emotion pairs in that group).

In Table 11 in the Appendix, we also report the absolute Spearman correlation scores for each group.

Below we summarize the results for each column.

6.1 Emotion Granularity as an Indicator of MHCs

IC(n) and IC(v): We do not see any significant differences in the information content of noun and verb terms (IC(n) and IC(v)) between MHCs and the control group. This indicates that no group tends to use more specific or less specific language in general when posting on these platforms. Details on the statistical results are shown in Appendix H.

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[9]https://github.com/nltk/wordnet

EG(pos): All MHCs except for PPD had significantly lower positive emotion granularity than the control group (which had similar granularity compared to the control group). That is, tweeters in these MHC groups (ADHD, Anxiety, etc.) consistently expressed multiple positive emotions concurrently, more so than the control group.

EG(neg): All MHCs except MDD had significantly lower negative emotion granularity than the control group, in both datasets. Thus, tweeters in these MHCs were generally not differentiating between the negative emotions of anger, disgust, fear, and sadness, as well as the control group.

EG(var): Tweeters in the ADHD, Anxiety, Bipolar, OCD, PTSD, and Depression (Twitter-STMHD) had significantly lower variable emotion granularity than the control group (i.e., these groups generally differentiated between surprise and anticipation less than the control group).

EG(overall): All MHCs except PPD had significantly lower emotion granularity for emotion categories that express the same valence (the mixed valence emotions of surprise and anticipation are also included here). Tweeters in these groups are therefore expressing multiple close emotions frequently with one another—more so than the control group.

EG(cross): All MHCs except PPD had significantly lower granularity between emotion pairs that come from different valence groups. This indicates that positive and negative emotions are expressed together more frequently by tweeters in these groups compared to the control, as well as emotions like joy (positive valence) and surprise (variable valence).

Discussion: These results demonstrate that our measures of emotion granularity from text are consistently lower for users in the MHC groups compared to the control. The term specificity results also tell us that it is the specificity of emotion word usage in particular that is differentiating MHCs from the control group.

Aligning with self-report studies in psychology, the emotion granularity between negative-valence emotions is lower for most (7 out of 8) MHCs in our datasets with utterance-level operationalizations. Positive emotion granularity is also correlated with many of the MHCs (7 out of 8 disorders). In general, the granularity of emotional expression between within-group emotion pairs is lower for all MHC groups compared to the control in both datasets, except PPD. This is in line with both the theoretical and conceptual links established in the psychology literature on emotion granularity and mental health: the ability to better differentiate between emotion concepts that are close to one another leads to more adaptive health behaviour.

While emotion pairs from differently-valenced emotion groups are not usually operationalized in affective science experiments, we find that this measure is also significantly lower in many MHCs. Further investigations into what the concurrent expression of positive and negative emotions means, for emotion granularity and emotion dynamics in general, are interesting research directions.

Variation with hyperparameter choices: We observe only minor variations from the results reported in Table 13 when the hyperparameters described in Section 4.1 for emotion arc construction were changed—less than 10% of the cells differed in their values across all variations. We provide a more detailed report in Appendix F.

6.2 Additional Window Sizes

We also examined how the measures of differences in emotion granularity between MHCs and the control change when we compute emotion scores with larger window sizes.

Many of the utterance-level outcomes are replicated for negative, positive, and overall emotion granularity with window sizes 100 and 500. Some measures are no longer significantly different between certain MHCs and the control. We also find that EG(cross) is higher for certain MHCs (Anxiety, PPD, PTSD, Depression in Twitter-STMHD) when compared to the control, i.e., users in the control group are expressing negative and positive emotions together more frequently than those in the MHCs.

With larger window sizes, we end up capturing emotions expressed by the individual over longer time spans (tweets posted over the span of several hours or days), rather than co-endorsement at the same time. We hypothesize that these effects of dialecticism, where the control group has a higher

co-occurrence of cross-valence group emotions, are capturing the extent to which users balance negative emotions with positive emotions (and vice versa). The consistent effects with 100 and 500-word windows, and for several MHCs, makes this a promising area for future work. All emotion granularity measures with window sized 100 and 500 are reported in Appendix F.1.

6.3 Individual Emotion Pairs

In order to understand which emotion pairs are expressed together more frequently (resulting in lower emotion granularity), we performed the same significance tests as before between MHCs and the control for correlation scores between all individual emotion pairs. We found that:

- Seven out of the eight MHCs in the Twitter-STMHD dataset had a lower granularity (a higher correlation) for anger-disgust (except PPD) and anger-sadness (except MDD) in the negative valence group.

- All eight MHCs had a lower emotion granularity (higher correlation) between multiple cross-group emotion pairs, notably those involving the mixed-valence emotions of anticipation and trust.

- Contrary to trends, the Bipolar group had a higher emotion granularity (i.e., a lower correlation of emotion arcs) for the cross-group emotion pairs of anger-joy and fear-joy.

Detailed results for each of the emotion pairs and all MHCs are in Appendix G, Table 9.

Discussion: While lower granularity among certain emotion pairs consistently function as indicators of all MHCs, we also see a few instances where MHCs (specifically Bipolar disorder) have a higher granularity between the emotions when compared to the control. These findings are of interest to researchers studying the links between how emotions are expressed in text, and how they vary with different MHCs.

7 Conclusion

In this work, we operationalized for the first time a computational measure of emotion granularity that can be derived from the textual utterances of individuals. We applied this measure to two social media datasets of posts from individuals who have self-disclosed as having an MHC. Our findings showed that our measure of negative emotion granularity is significantly lower for 7 out of the 8 MHC groups under consideration when compared to a control group, at an aggregate-level. Also, all MHCs except for PPD had lower overall emotion granularity (and lower positive emotion granularity) compared to the control group. Our work makes an important contribution towards deriving aggregate-level indicators of emotional health from the large amounts of utterance data available on social media platforms. We hope this opens up an avenue of future work to explore emotional expression in text and mental health.

Limitations

Our work uses the social media utterances of individuals to derive measures of emotional expression that, at an aggregate level, are found to correlate with multiple mental health conditions. While we use datasets that were compiled by other researchers in the field, we stress that they may not be representative of the general population. Our methods therefore cannot be directly applied to make inferences on other datasets without a careful experimental validation first. The datasets we study rely on self-disclosures made on social media platforms; it is possible that users report only one such MHC but are diagnosed with others, or that they misrepresent their diagnoses. Further, the users in the control groups may include those who have chosen to simply not self-disclose on these platforms. This can occur due to many reasons, like social desirability [Latkin et al.2017] or impression management [Tedeschi2013]. Nonetheless, since we draw inferences at an aggregate level, the methods used can overcome some amount of noisy data.

The set of emotions that we have considered in our measurement of emotion granularity are also limited to those for which we can computationally obtain text-derived emotion scores. These eight emotions do not represent the wide range of emotion concepts that exist and are experienced and expressed by us with language, and future research can attempt to expand our operationalization to more emotion concepts. It should be noted though, that past psychology studies on emotion granularity have also tended to explore small sets of emotions, largely because it is cumbersome to ask users about how they feel for a large set of emotions.

The emotion lexicons that we use are some of the largest that exist with wide coverage and large number of annotators (thousands of people as opposed to just a handful). However, no lexicon can cover the full range of linguistic and cultural diversity in emotion expression. The lexicons are largely restricted to words that are most commonly used in Standard American English and they capture emotion associations as judged by American native speakers of English. See [Mohammad2023] for a discussion of the limitations and best-practises in the use of emotion lexicons.

Lastly, further work should explore if the relationships we found hold around various social factors such as age, region, language, etc. As we focus on English text, and the region of users is not known (some information could be extracted from user profiles in the Twitter-STMHD dataset however it is fairly noisy), conclusions should be drawn cautiously across various sociolinguistic factors.

Ethics Statement

Our approach, as with all data-driven models of determining indicators of mental health, should be considered as aggregate-level indicators, rather than biomarkers for individuals [Guntuku et al.2017]. We do not attempt to predict the presence of MHCs for individual users at any stage of the process. These measures should also not be taken as standalone indicators of mental health or mental wellness, even at the population level, but rather as an additional metric that can be used in conjunction with other population-level markers, and with the expertise of clinicians, psychologists, and public health experts.

Individuals vary considerably in how, and how well, they express their internal emotional states using language. Our method of assessing the emotional states of users based on their utterances may miss several linguistic cues of emotion expression, and may not account for individual variation or the extent to which these emotions are expressed on social media. The emotionality of one's language may also be conveying information about the emotions of the speaker, the listener, or something or someone else mentioned in the utterances. See further discussions of ethical considerations when using computational methods for affective science in [Mohammad2023, Mohammad2022].

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A Twitter-STMHD Dataset

Suhavi et al. (2022) created a regular expression pattern to identify posts which contained a self-disclosure of a diagnosis and the diagnosis name (using a lexicon of common synonyms, abbreviations,

etc.) such as 'diagnosed with X'. They collected a large set of tweets using the regex. This resulted in a preliminary dataset of users with potential MHC diagnoses. To handle false positives (e.g., 'my family member has been diagnosed with X', or 'I was not diagnosed with X'), the dataset was split into two non-overlapping parts, one of which was manually annotated, and the other using an updated and high-precision regex. In the part that was annotated by hand, each tweet was annotated by two members of the team. A user was only included in the dataset if both annotations were positive as self-disclosing for a particular class. A licensed clinical psychologist found the 500-tweet sample to be 99.2% accurate. The manual annotations were used to refine the regular expressions and diagnosis name lexicon. This updated search pattern was applied to the other dataset split. To verify the quality of the updated regex, the authors applied it to the manually annotated dataset split. When considering the manual annotations as correct, the regex was found to be 94% accurate.

B   Lexicon Words Removed

We considered the following sets of terms to be stop-words, which do not contribute to the emotion score of an utterance, for our analysis:

- **Common stopwords:** We remove common English stopwords, such as the, of, for, etc. We use the list of English stopwords from the Python NLTK library.

- **Domain-specific stopwords:** We remove terms (words and word pairs) whose dominant usage on social media platforms differs from their annotated sense (e.g., *like*, *chaotic evil*, *good morning*). The full list of these terms is in Table 2.

- **MHC-associated terms:** Finally, we filter out terms that are explicitly associated with the MHCs that we consider, such as *anxiety*, *mental health*, and *panic attack*. The full list of terms is in Table 3.

Table 2: Twitter-specific words and bigrams removed from the emotion lexicons.

love	christmas	birthday	pretty
vibe	vote	trump	like
flu shot	good day	good night	true crime
wholesome content	jump scares	fever dream	guilty pleasure
disability	psychosis	suicide	depressed
anxious	disabled	raptor	good morning
good afternoon	full time	slur word	hot chocolate
chaotic energy	chaotic neutral	discord	good evening
bloody murder	gut punch	life time	chaotic evil
chaotic good	hot mess		

Table 3: Mental health specific terms removed from the emotion lexicons.

ptsd
adhd
depressive disorder
mental health
mental illness
panic attack

C   Statistical Assumptions

Below we describe in more depth the requirements for performing an independent t-test, which was done in our analyses.

- The dependent variable must be measured using a continuous scale: emotion granularity is measured as the average of Spearman correlation between emotion arcs in the group, resulting in continuous values.

- The independent variable must have two categorical and independent groups: Our independent variable is diagnosis, which is either an MHC or the control group.

- Independence of observations: Since the text stream of utterances come from different people, we can assume these are independent observations.[10]

- Approximately normally distributed dependent variable for each group of independent variable: Given the large number of people and number of utterances per person in our dataset, we can assume that the means of the data for each group is approximately normally distributed according to the law of large numbers. Further, the t-test is robust to violations of normality.

- Homogeneity of variance: We performed Levene's test for homogeneity of variance to verify whether this assumption is met. Our data did not meet this assumption, therefore we performed t-tests with the unequal variance setting as True in SciPy.

D   Emotion Lexicons

In Table 4, we report statistics on the number of emotion terms in each lexicon for the eight emotions we consider in this work, and the number of terms common to and mutually-exclusive between each emotion pair.

E   Visualization of Emotion Arcs

In Figure 1, we plot the emotion arcs for the fear-sadness emotion pair, from the negative valence group, for a tweeter from an MHC group of the Twitter-STMHD dataset. Emotion scores are computed and plotted at the utterance-level, i.e., independently for each tweet by the user. Note that larger window sizes and overlapping windows will lead to smoother arcs.

Figure 1: Emotion arcs: Tweet-level emotion arcs for fear and sadness, for a sampled user from the Twitter-STMHD dataset.

F   Emotion Granularity: Hyperparameters

We report the results of the statistical analyses of emotion granularity when emotion arcs were generated using different choices of the hyperparameters described in Section 4.1. Table 5 reports the results when non-lexicon terms (and tweets) are assigned a score of 0, and only mutually-exclusive emotion terms are considered, similar to Table 13, but no user thresholds on number of tweets and unique emotion terms are applied. Table 6 reports the results when non-lexicon terms (and tweets) are not considered, and

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[10]In reality individuals are largely influenced by one another as we see, interact and engage with content from various communities, which can influence our emotional state and therefore utterances. However, for the purposes of our experiments since the utterances come from different people we can assume they are independent.

Table 4: Emotion Lexicons: For each emotion pair (emo1, emo2), the number of terms in each lexicon (e1-all, e2-all), the number of emotion terms common to the two lexicons (e12-comm), and the number of mutually-exclusive emotion terms (e1-excl, e2-excl).

emo1	emo2	e1-all	e2-all	e12-comm	e1-excl	e2-excl
anger	anticipation	1157	1157	43	1114	1114
anger	disgust	1157	782	407	750	375
anger	fear	1157	886	551	606	335
anger	joy	1157	1343	3	1154	1340
anger	sadness	1157	946	382	775	564
anger	surprise	1157	1014	102	1055	912
anger	trust	1157	454	6	1151	448
anticipation	disgust	1157	782	39	1118	743
anticipation	fear	1157	886	82	1075	804
anticipation	joy	1157	1343	283	874	1060
anticipation	sadness	1157	946	31	1126	915
anticipation	surprise	1157	1014	131	1026	883
anticipation	trust	1157	454	283	874	171
disgust	fear	782	886	400	382	486
disgust	joy	782	1343	1	781	1342
disgust	sadness	782	946	336	446	610
disgust	surprise	782	1014	56	726	958
disgust	trust	782	454	2	780	452
fear	joy	886	1343	545	341	798
fear	sadness	886	946	137	749	809
fear	surprise	886	1014	9	877	1005
fear	trust	886	454	0	886	454
joy	sadness	1343	946	113	1230	833
joy	surprise	1343	1014	308	1035	706
joy	trust	1343	454	73	1270	381
sadness	surprise	946	1014	3	943	1011
sadness	trust	946	454	56	890	398
surprise	trust	1014	454	111	903	343

user thresholds are set to 50 and 25 (similar to Table 13), and only mutually-exclusive emotion terms are considered (similar to Table 13). We find that largely the results do not change. However, when non-lexicon terms and tweets are ignored, this results in a smaller set of tweets to compute the emotion arc over, and fewer tweeters who meet the user thresholds for each group. This results in signals turning off for certain MHCs.

F.1 Various Window Sizes

We report the results of the statistical analyses of emotion granularity when emotion arcs were generated using two other window sizes: 100 (Table 7) and 500 (Table 8). All other hyperparameters are the same as for Table 13.

We find that largely the results do not change, however there are some differences in the scenario when the dataset was smaller (e.g., eRisk dataset or MHC such as MDD). In such cases, when the window size is increased, it is possible that several emotional experiences occurred, resulting in a weaker signal of emotion granularity.

Table 5: Emotion Granularity—hyperparameter variations: The difference in emotion granularity between each MHC group and the control. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference in granularity. Non-lexicon terms and tweets are assigned a score of zero; user tweet and unique term thresholds are both set to 0, and only mutually-exclusive emotion terms are considered.

MHC-Control	IC(n)	IC(v)	EG(pos)	EG(neg)	EG(var)	EG(cross)
ADHD-control	lower	lower	lower	lower	lower	lower
Anxiety-control	lower	lower	lower	lower	lower	lower
Bipolar-control	lower	lower	lower	lower	lower	lower
MDD-control	lower	lower	lower	-	lower	lower
OCD-control	lower	lower	lower	lower	lower	lower
PPD-control	lower	lower	-	lower	lower	lower
PTSD-control	lower	lower	lower	lower	lower	lower
Depression-control	lower	lower	lower	lower	lower	lower
Reddit eRisk Depression-control	lower	lower	lower	lower	-	lower

Table 6: Emotion Granularity—hyperparameter variations: The difference in emotion granularity between each MHC group and the control. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference in granularity. Non-lexicon terms and tweets are discarded; user tweet and unique term thresholds are set to 50 and 25, and only mutually-exclusive emotion terms are considered.

MHC-Control	IC(n)	IC(v)	EG(pos)	EG(neg)	EG(var)	EG(cross)
ADHD-control	lower	lower	lower	lower	lower	lower
Anxiety-control	lower	lower	lower	lower	lower	higher
Bipolar-control	lower	lower	lower	lower	lower	lower
MDD-control	lower	lower	lower	-	lower	lower
OCD-control	lower	lower	lower	lower	lower	lower
PPD-control	lower	lower	-	lower	lower	lower
PTSD-control	lower	lower	lower	lower	lower	lower
Depression-control	lower	lower	lower	lower	lower	lower
Reddit eRisk Depression-control	lower	lower	lower	lower	-	lower

G Emotion Granularity: Emotion Pairs

In Table 9 we report the pairwise emotion granularity results when testing for significant differences between MHCs and the control group.

H Term Specificity Results

Table 10 shows the results of the term specificity experiments described in Section 5.1 measuring information content. For both nouns and verbs, none of the diagnoses had significantly different term specificity levels compared to the control group in both the Twitter-STMHD and eRisk datasets. This verifies that the significant differences between the MHCs and the control group for emotion granularity is not due to varying word specificity levels in these groups.

Table 7: Emotion Granularity—using window 100: The difference in emotion granularity between each MHC group and the control. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference in granularity.

MHC-Control	IC(n)	IC(v)	EG(pos)	EG(neg)	EG(var)	EG(cross)
ADHD-control	lower	lower	lower	lower	lower	lower
Anxiety-control	lower	lower	lower	lower	lower	higher
Bipolar-control	lower	lower	lower	lower	lower	higher
MDD-control	lower	lower	lower	-	lower	higher
OCD-control	lower	lower	lower	lower	lower	higher
PPD-control	lower	lower	-	lower	lower	higher
PTSD-control	lower	lower	lower	lower	lower	higher
Depression-control	lower	lower	lower	lower	lower	higher
Reddit eRisk Depression-control	lower	lower	lower	lower	-	lower

Table 8: Emotion Granularity—using window 500: The difference in emotion granularity between each MHC group and the control. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference in granularity.

MHC-Control	IC(n)	IC(v)	EG(pos)	EG(neg)	EG(var)	EG(cross)
ADHD-control	lower	lower	lower	lower	lower	lower
Anxiety-control	lower	lower	lower	lower	lower	higher
Bipolar-control	lower	lower	lower	lower	lower	higher
MDD-control	lower	lower	lower	-	lower	higher
OCD-control	lower	lower	lower	lower	lower	higher
PPD-control	lower	lower	-	lower	lower	higher
PTSD-control	lower	lower	lower	lower	lower	higher
Depression-control	lower	lower	lower	lower	lower	higher
Reddit eRisk Depression-control	lower	lower	lower	lower	-	lower

I   Emotion Correlations

Table 11 shows the group-averaged Spearman correlations for emotion pairs in the positive, negative, mixed valence groups, and the within-group and cross-group averages, for the control groups, and the delta from these values for each MHC in both datasets.

Table 12 shows the Spearman correlation between emotion arcs for all pairs of emotions for the control group. These results indicate that as baselines largely emotions in the same group (e.g., positive, negative, mixed, overall) co-occur more often than emotions across groups.

Table 9: Emotion Granularity—emotion Pairs: The difference in emotion granularity between each emotion pair, for each MHC group and the control in the Twitter-STMHD dataset. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference.

Emotion Pair	ADHD	Anxiety	Bipolar	MDD	OCD	PPD	PTSD	Depression
anger-disgust	lower	lower	lower	lower	lower	-	lower	lower
anger-fear	lower	lower	lower	lower	lower	lower	lower	lower
anger-joy	lower	lower	higher	lower	lower	lower	lower	lower
anger-sadness	lower	lower	lower	-	lower	lower	lower	lower
anger-surprise	lower	lower	lower	lower	lower	lower	lower	lower
anger-trust	lower	lower	lower	lower	lower	lower	lower	lower
anticipation-disgust	lower	lower	lower	lower	-	lower	lower	lower
anticipation-fear	lower	lower	-	lower	lower	lower	lower	lower
anticipation-joy	lower	lower	lower	lower	lower	lower	lower	lower
anticipation-sadness	lower	lower	lower	lower	-	lower	lower	lower
anticipation-surprise	lower	lower	lower	lower	-	lower	lower	lower
anticipation-trust	lower	lower	lower	lower	lower	lower	lower	lower
disgust-fear	lower	lower	lower	lower	-	lower	lower	disgust
disgust-joy	lower	lower	lower	lower	lower	lower	lower	lower
disgust-sadness	lower	lower	lower	lower	lower	lower	lower	lower
disgust-surprise	lower	lower	lower	lower	lower	lower	lower	lower
fear-sadness	lower	lower	lower	lower	lower	lower	lower	lower
fear-surprise	lower	lower	lower	lower	lower	lower	lower	lower
fear-trust	lower	lower	lower	lower	lower	lower	lower	lower
joy-sadness	lower	lower	lower	lower	lower	lower	lower	lower
joy-surprise	lower	lower	lower	lower	lower	-	lower	lower
joy-trust	lower	lower	lower	lower	lower	lower	lower	lower
sadness-surprise	lower	lower	lower	lower	lower	lower	lower	lower
sadness-trust	lower	lower	lower	lower	lower	lower	lower	lower
surprise-trust	lower	lower	lower	lower	lower	lower	lower	lower

Table 10: Information Content: The degrees of freedom, t-statistic and p-value for the word specificity experiments described in Section 5.1.

Dataset, MHC	df	T-Statistic	P-value
Twitter-STMHD			
Noun ADHD-control	2368.64	-1.94	0.144
Anxiety-control	2233.36	-0.58	0.718
Bipolar-control	1726.26	-2.40	0.131
MDD-control	226.83	-0.52	0.718
OCD-control	1817.93	1.93	0.144
PPD-control	118.33	-0.49	0.718
PTSD-control	2237.82	-0.54	0.718
Depression-control	2245.64	-0.27	0.787
Reddit eRisk Depression-control	128.95	0.98	0.330
Verb ADHD-control	2235.85	1.12	0.420
Anxiety-control	1852.44	-2.10	0.096
Bipolar-control	213.0	1.36	0.354
MDD-control	1645.17	2.28	0.091
OCD-control	169.49	0.98	0.438
PPD-control	2351.2	2.53	0.091
PTSD-control	2274.59	0.54	0.589
Reddit eRisk Depression-control	110.40	1.59	0.116

Table 11: Emotion Granularity—Spearman correlations: Spearman correlation values between utterance-level emotion arcs for the Control group, and the delta for each MHC when compared to the Control group. Emotion granularity is defined as the negative of these correlations (i.e., higher correlations imply a lower granularity). Hyperparameters are the same as in Table 13.

Dataset, MHC	EG(pos)	EG(neg)	EG(var)	EG(cross)	EG(overall)
Twitter-STMHD					
Control	0.022	0.027	0.023	0.012	0.006
ADHD	-0.012*	-0.012*	-0.004*	-0.011*	-0.013*
Anxiety	-0.008*	-0.008*	-0.008*	-0.002	-0.009*
Bipolar	-0.005*	-0.005*	-0.004*	-0.001	-0.006*
MDD	-0.010*	-0.005	-0.002*	-0.005*	-0.009*
OCD	-0.010*	-0.010*	-0.006*	-0.005*	-0.009*
PPD	-0.003	-0.003*	-0.005*	-0.004	-0.003*
PTSD	-0.008*	-0.008*	-0.008*	-0.005*	-0.008*
Depression	-0.005*	-0.005*	-0.003*	-0.005*	-0.005*
Reddit eRisk					
Control	0.114	0.117	0.090	0.094	0.112
Depression	-0.016*	-0.021*	-0.012	-0.022*	-0.017*

Table 12: Emotion-Emotion Spearman correlations: Spearman correlation values between pairs of utterance-level emotion arcs for all users in the control group of the Twitter-STMHD dataset. Hyperparameters are the same as in Table 13.

	anger	anticipation	disgust	fear	joy	sadness	surprise	trust
anger	1.000	-0.003	0.020	-0.003	0.027	0.007	0.023	-0.010
anticipation	-0.003	1.000	0.021	-0.010	-0.003	0.024	0.004	0.021
disgust	0.020	0.021	1.000	0.021	-0.000	0.009	0.012	0.006
fear	-0.003	-0.010	0.021	1.000	0.012	0.008	0.012	0.007
joy	0.027	-0.003	-0.000	0.012	1.000	0.027	0.003	0.013
sadness	0.007	0.024	0.009	0.008	0.027	1.000	0.027	0.008
surprise	0.023	0.004	0.012	0.012	0.003	0.027	1.000	0.023
trust	-0.010	0.021	0.006	0.007	0.013	0.008	0.023	1.000

Table 13: The difference in emotion granularity between each MHC group and the control. A significant difference is indicated by the word 'lower' or 'higher', indicating the direction of the difference in granularity.

MHC-Control	IC(n)	IC(v)	EG(pos)	EG(neg)	EG(var)	EG(cross)
ADHD-control	-	-	lower	lower	lower	lower
Anxiety-control	-	-	lower	lower	lower	lower
Bipolar-control	-	-	lower	lower	lower	lower
MDD-control	-	-	lower	-	lower	lower
OCD-control	-	-	lower	lower	lower	lower
PPD-control	-	-	-	lower	lower	lower
PTSD-control	-	-	lower	lower	lower	lower
Depression-control	-	-	lower	lower	lower	lower
Reddit eRisk Depression-control	-	-	lower	lower	-	lower