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Article

Symptom Expression and Emotional Distress in Online Mental Health Narratives

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Abstract

Introduction: Online forums use as a source for mental health support has surged among individuals worldwide. Social media has become popular for sharing personal experiences and seeking information and support. Studies have analyzed posts on social media forums, focusing on frequency of engagement by users, why individuals engage, and how they engage on these web-based platforms. However, key questions about how mental illness is experienced, discussed and emotionally expressed from the user's perspective is needed to add important insight. **Objective:** This study aims to investigate how mental health related disorders and conditions are discussed, experienced, and emotionally framed in online discourse, specifically focusing on how mental health symptoms and distress language across mental health dialogues are expressed and examining the text-based communication beyond prevalence-based analyses and simplified sentiment analysis through symptom and experience-centered approach to uncover patterns in how symptoms are articulated and emotions expressed, and how distress is framed across multiple mental health conditions, by systematically analyzing digital textual data associated with various mental illnesses. **Methodology:** A retrospective observational design was conducted. The dataset used in this study was scrapped from YouTube between 11/2/2025 to 11/30/2025 by using a predefined keyword resulting in a total sample of 646 279 comments. The data was prepared and preprocessed using standard NLP procedures. Descriptive analysis of Disorder Representation, Symptom Expression Analysis, Emotional Tone and Distress Analysis, Cross-Disorder Statistical Comparisons and Crisis-Oriented Language Analysis was conducted. Kruskal–Wallis test a non-parametric analysis revealed no statistically significant differences in emotional proportion scores across mental health condition categories. Pearson's chi-squared test indicted a robust and statistically significant association between mental health disorder type and symptom category. **Result:** Among the mental health conditions discussed online, content related to anxiety made up the largest count of the dataset (n = 125,001; 19.3%), followed by depression (n = 100,281; 15.5%) mental breakdown (n = 93,836; 14.5%), and PTSD (n = 110,935; 14.2%). However, Obsessive-Compulsive Disorder exhibited a robust engagement (Eng = 158.5); and panic attack–related posts showed higher levels of engagement (Eng = 189). Mental health conditions such as panic attacks (0.1050), anxiety (0.0532), depression (0.0490), and mental illness (0.0497) demonstrated intense emotions. For the category Anxiety Terms, the most negative terminology was recorded with the most negative sentiment score (−62,667). Stigmatizing revealed a net negative sentiment (−7,787) while Self-Disclosure also revealed a net negative sentiment (−2,344). Empathy showed the highest positive sentiment score (50,432), followed by Supportive (24,867) and Advocacy (4,897) categories. No statistically significant differences in emotional proportion scores across mental health disorder categories were revealed (X^2 (6) = 0.118, p=1.000). However, a robust and statistically significant association between mental health disorder type and symptom category was identified (X^2(18) =11, 623, p<0.001), suggesting that each mental health condition presents different symptom profiles across cognitive, emotional, and somatic dimensions. **Conclusion:** In conclusion, this study makes several important contributions to mental health research and practice in understanding mental illness as a lived experience rather than solely a diagnostic category. This finding also provides empirical support for conceptualizing OCD as a cognitive-based disorder, where distress is often expressed through intrusive thought patterns and not solely emotional states.

Keywords: mental health condition; online discourse; sentiment analysis; online users; stigma; emotional tone; distress framing

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1. Introduction

Mental illness is a significant worldwide public health problem, globally reaching hundreds of millions of people [1–4]. According to a report by WHO in 2024[4] and 2025 [3], mental illness is a major crisis that drives widespread disability, leads to diminished quality of life and daily functioning, and contributes significantly to chronic morbidity and early deaths. Mental health conditions such as depression, anxiety disorders, bipolar disorder, post-traumatic stress disorder (PTSD), and obsessive–compulsive disorder (OCD) represent a significant share of global ill health. As a result, they are recognized as major priorities for health policy and focus areas for targeted intervention [5,6]. While there has been advancement in diagnosis, treatment and delivery of service, gaps persist specifically among low and middle-income communities and marginalized populations as mental illness remains severely untreated, undiagnosed and entrenched in stigma among these vulnerable individuals [7].

Traditionally, mental health has been looked at through clinical data and surveys. Although research using these tools have revealed pertinent information for understanding prevalence, risk factors and outcomes associated with mental health problems and have helped with advancing psychiatric knowledge, they failed to capture the human story of mental illness; the lived experiences, nuanced of emotions and how individuals perceive and describe their day-to-day symptoms and daily struggles in the real world [8–13]. Mental health symptoms are a spectrum of experiences, dimensional rather than binary. Thus, forcing complex experiences into rigid clinical diagnosis and categories may oversimplify the subjective nature of mental health illness and may distort individuals' unique everyday reality and experiences of living with a mental health condition [14–16].

In recent years, social media platforms and online communities have become major support groups and have changed the way people discuss health related issues including mental health conditions [17–20]. Social media has become an important space to share experiences that are deeply personal and unfiltered. Seeking mental health information has gained popularity as individuals seek out social media and other platforms to make sense of their emotions and behaviors, functioning, and symptoms either by sharing content or viewing information. People may find a sense of community among the other online users and content creators with common experiences [20,21]. Further, the rise of social media provides opportunities to seek support and share emotions and struggles in ways that may not be possible in clinical settings by providing a rich source of data for understanding mental health and the way it is felt, shared, and conceptualized by the public in everyday life.

1.1. Online Mental Health Discourse and Its Significance

Digital mental health dialogues have surged as individuals increasingly seek validation, information, and peer support [22,23]. Unlike standard clinical assessments which are constrained by rigid and traditional diagnostic approaches, narratives shared via online communities are unfiltered, emotionally expressive, and typically spontaneous [24,25]. Consequently, these social media conversations provide nuanced insight into distress as they evolve in real time, and coping mechanisms adopted by individuals experiencing early warning signs of mental health conditions [26,27].

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1.2. Symptom Manifestation and Lived Experienced

Mental health is lived as a multifaceted experience of emotional, cognitive, behavioral, and somatic symptoms beyond a formal diagnosis. While labels are used by doctors, individuals may frequently express and describe their symptoms using non-clinical terms such as fear, feeling stuck, hollow, exhaustion, hopelessness, or loss of control [28,29]. These expressions can vary significantly across disorders and individuals, reflecting a unique difference in symptom profiles, illness trajectories, and how different people navigate their own personal symptoms and ways of coping [30].

1.3. Emotional Tone and Distress Framing

Emotional tone is just as critical as symptom expression in analyzing how mental illness is discussed online. Emotional tone encompasses both general and specific sentiments of emotional states such as fear, sadness, anger, shame, and emotional exhaustion [31–33]. These emotions shape how individuals interpret their experiences, seek help, and engage with others.

Distress framing refers to a specific language that is constructed to express psychological suffering and spans a spectrum from slight discomfort to severe crisis. Often the expressed language illuminates' themes of long-term fatigue, urgent and overwhelming feelings of helplessness, while other narratives express the experiences as enduring resulting in loss of control [34–37]. Recognizing these patterns is critical for identifying high risk individuals and development of online mental health support interventions. in high-risk discourse and informing mental health support interventions in digital communities.

Previous research has demonstrated that online mental health discourse can provide valuable insights into demographic shifts, emotional states, and key indicators [38]. Researchers have evaluated what people share online to track depression, anxiety trends and suicide risk, and how individuals respond to major societal stressors. Keeping a pulse on mental health by looking at what people share online has reliably gauged mental health trends, suggesting that digital text analysis can potentially complement traditional mental health data collection to create early intervention strategies and provide better and faster ways to offer support [39].

However, much of the existing literature remains limited in scope. Many studies focus on a single disorder, most commonly depression or anxiety; neglecting the broader spectrum of mental illnesses. Others rely on simplified measures of sentiment polarity using a basic three level categorization, positive, negative and neutral, which is inadequate to capture complex emotional and symptomatic language that characterizes mental illness narratives. The emphasis is on defining mental health in a clinical or institutional context whereas the viewpoints of how individuals themselves describe mental illness is insufficiently represented. As such, statistical comparison of symptoms and emotional patterns across disorders is present in only a few studies.

This study aim to investigate how mental illness is discussed, experienced, and emotionally framed in online dialogues specifically focusing on how mental health symptoms expression and distress language across mental health conditions adopting beyond prevalence-based analyses and simplified sentiment analysis a symptom and experience-centered approach while uncovering patterns in how symptoms are articulated and emotions expressed, and how distress is framed across multiple mental health conditions, by systematically analyzing digital textual data associated with various mental illnesses.

1.4. Research Questions

To achieve these aims, the study addresses the following research questions:

RQ1: How are different mental health conditions represented in online narratives in terms of prevalence and prominence?

RQ2: What types of symptom-related language dominate online discussions of mental illness, and how do these patterns vary across mental health conditions?

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RQ3: What emotional tones characterize mental illness narratives, and how are distress and psychological suffering are expressed?

RQ4: Are there statistically significant differences in symptom expression and emotional framing across mental health conditions?

2. Methods

2.1. Study Design

This study investigated mental health symptoms and emotional framing expressed through user generated online content associated with multiple health conditions using a retrospective observational design [40]. A mixed methodology was employed, combining natural language processing (NLP) techniques with quantitative statistical analysis [41–44]. This study evaluates how individuals frame emotions and manifest symptoms related to mental health conditions. It tracks the shift in mental health trends progressing from descriptive characterization to inferential comparison across mental health conditions.

2.2. Data Collection

The dataset used in this study was scrapped from the video-sharing platform YouTube between 11/2/2025 to 11/302025 by using a predefined keyword (See supplementary file 1) with an automated web scraping approach implemented in Python (See supplementary file 2). The data collection process was conducted in two main stages: (1) retrieval of video links based on a predefined search query (See supplementary file 2), and (2) extraction of user-generated comments and associated metadata from each video (See supplementary file 2). A custom script utilizing the Selenium WebDriver library was developed to simulate user interaction with the YouTube search interface. The script programmatically accessed the YouTube search results page and performed repeated scrolling actions to dynamically load additional results. To ensure a sufficiently large and diverse dataset, the page was scrolled multiple times (n = 60), allowing more videos to load beyond the initial results. The HTML content of the fully loaded page was then parsed using regular expressions to extract unique video identifiers.

2.3. Sample Size

A total sample of 646279 comments were collected (See supplementary file 3). The dataset consisted of amassed publicly available data that represents diverse mental health condition, including anxiety, depression, bipolar disorder, obsessive–compulsive disorder (OCD), post-traumatic stress disorder (PTSD), stress-related conditions, and broader mental illness discussions containing a text-based information expressed by users, along with associated metadata (Video title ,Comment text ,Author username , Number of likes, Associated video URL).

2.4. Data Preparation and Preprocessing

Text entries were standardized using duplicate detection and normalization procedures to uphold validity of frequency-based analysis and avoid bias and redundancy. After exact text matching and normalization, only a unique instance was retained [45]. Using standard NLP procedures, the data set was cleaned for lexical and statistical analysis by converting all text to lowercase to ensure case-insensitive matching and removing hyperlinks and non-informative such as excessive whitespace and non-linguistic terms. Common stop words (e.g., "the," "and" "is") were also removed. To preserve the original linguistic expression and preserve the integrity of it, stemming or lemmatization was excluded. This ensured that subtle variations in the original narratives remained intact, which is crucial for experiential analysis of mental health narratives.

2.5. Descriptive Analysis of Disorder Representation

Descriptive analysis was conducted to address Research Question 1, which examined how different mental health conditions are represented in online discussions in terms of frequency and prominence. Each category was computed using number of text entries and word count total to provide an overview of the relative visibility and textual intensity of each condition within the dataset.

2.6. Symptom Expression Analysis

To capture core essential indicators of mental health illnesses, a symptom lexicon was created and guided by combined existing psychiatric literature and NLP studies [45,46] (See supplementary file 4). Symptoms were organized into three broad categories (cognitive symptoms. emotional symptoms, somatic). Lexical variants and non-clinical, colloquial expressions were included to ensure wide coverage and everyday language use.

Each text entry was analyzed to detect terminology related to mental health symptoms. For each entry, absolute frequency of symptom terms, category-specific symptom counts (cognitive, emotional, somatic), symptom density, defined as the number of symptom-related terms per total word count were computed. These measures ensured a cross mental health condition comparison of symptoms mental health conditions while controlling for variation in text length.

2.7. Emotional Tone and Distress Analysis

To adequately capture and analyze the specific emotional dimensions within the textual data, the study employed established lexicons-based approaches such as the NRC Emotion Lexicon, AFINN, AFINN, Bing, Loughran–McDonald, NRC, Syuzhet, VADER [47]. The following emotional dimensions were examined: Fear, Sadness, Anger, Anxiety, and Hopelessness. Emotion scores based on the frequency of emotion-related terms were assigned to each text entry based on text length to normalize emotion counts and allow comparison across entries. Aggregating normalized emotion scores within each category resulted in the creation of disorder-level emotion profiles. It is important to note that lexicon-based sentiment methods such as AFINN are sensitive to emotional valence but not contextual nuance. Consequently, negatively scored categories may represent legitimate expressions of suffering rather than harmful intent. Therefore, sentiment scores were interpreted as indicators of emotional tone, not moral or communicative quality.

2.8. Cross-Disorder Statistical Comparisons

To determine the statistical significance of observed differences in symptom expression and emotional framing across disorders, inferential statistics were used. Kruskal–Wallis tests were used for comparing continuous emotion scores across multiple groups and Chi-square tests of independence for categorical symptom frequencies [48]. The stability of the rule-based classification and cross-classification tables were generated comparing initial category assignments with the final refined labels. Proportional agreement was examined across all discourse categories, and discrepancies were primarily attributable to negation of handling and contextual refinement (See supplementary file 5). This process demonstrates that the final classification preserves the semantic intent of initial labels while reducing misclassification.

2.9. Crisis-Oriented Language Analysis

For Crisis language with a focus on the prevalence of high-intensity distress expressions across mental health conditions. Terms related to emotional overwhelm, acute distress, or loss of coping capacity (e.g., “breakdown,” “can’t cope,” “overwhelmed”) were used to construct a crisis lexicon (See supplementary file 4) [47]. To exclude explicit self-harm instructions or graphic content, care was considered in handling textual data. Crisis term frequency and density were computed for each mental health category. Comparative analyses were conducted to identify conditions more strongly associated with crisis-oriented narratives.

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2.10. Ethical Considerations

All data analyzed in this study were publicly available and anonymized. No attempts were made to identify individual users. The study followed ethical guidelines for digital research and the responsible use of online data. Given the sensitive nature of mental health content, analyses were conducted and conclusions drawn only at a group level; no individual-level conclusions were drawn.

3. Result

3.1. Overview of Online Mental Health Discourse

Table 1 shows the distribution of online discussions across 8 mental health conditions. Content related to anxiety made up the largest count of the dataset (*n* = 125,001; 19.3%), suggesting that anxiety is the most widely discussed mental health condition in online narratives. Followed by depression (*n* = 100,281; 15.5%) and mental breakdown (*n* = 93,836; 14.5%), PTSD (*n* = 110,935; 14.2%), and general references to mental illness (*n* = 90,241; 14.0%). In contrast, disorders such as obsessive–compulsive disorder (OCD) (*n* = 52,051), bipolar disorder (*n* = 53,436; 8.3%), and panic attacks (*n* = 20,498; 3.2%) were less frequently discussed.

Engagement patterns revealed a considerable divergence. Despite its low prevalence, *obsessive compulsive disorder* exhibited a robust engagement (Eng = 158.5), indicating that online posts that explicitly made reference to this diagnosis elicited significantly higher interaction. Similarly, panic attack–related posts showed higher levels of engagement (Eng = 189), than the more prevalent categories such as PTSD (Eng = 99.4) and bipolar disorder (Eng = 81). Likewise, post related to depression-related resulted in a sizeable engagement (Eng = 228), underscoring its significance in user responsiveness.

Table 1. Distribution of mental health conditions across the dataset.

Mental Health Condition	Number of Posts (n)	Mean Engagement (Eng)	Proportion (Per)
Anxiety	125,001	173.0	0.193
Depression	100,281	228.0	0.155
Mental breakdown	93,836	146.0	0.145
Post-traumatic stress disorder	110,935	99.4	0.172
Mental illness	90,241	166.0	0.140
Bipolar disorder	53,436	81.0	0.083
Obsessive-compulsive disorder	52,051	158.5	0.081
Panic attacks	20,498	189.0	0.032

3.2. Symptom-Related Language Across Disorders Conditions

Language that highlighted emotional symptom was the most prominent category of expression across nearly all mental health conditions that were investigated (Table 2). Mental health conditions such as panic attacks (0.1050), anxiety (0.0532), depression (0.0490), and mental illness (0.0497) demonstrated intense emotions, indicating that individuals generally frame their experiences using affective terminology such as fear, distress, sadness, and emotional overwhelm.

When compared to most mental health conditions, obsessive–compulsive disorder (OCD) written using complete diagnostic form, exhibited higher density of cognitive symptom (0.1139, 3,027). In conditions characterized by physiological bodily discomfort and arousal, somatic

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symptoms were highly expressed in the narratives. The highest somatic symptom density was evident in panic attack language (0.0672), followed by PTSD (0.0628).

Table 2. Distribution of Symptom-Related Language.

Mental Health Condition	Cognitive	Emotional	Somatic
Anxiety	0.0056 (700)	0.0532 (6,645)	0.0244 (3,053)
Bipolar disorder	0.0029 (154)	0.0294 (1,569)	0.0169 (901)
Depression	0.0028 (285)	0.0490 (4,914)	0.0251 (2,522)
Mental breakdown	0.0006 (59)	0.0196 (1,842)	0.0084 (787)
Mental illness	0.0043 (387)	0.0497 (4,481)	0.0209 (1,886)
Obsessive-compulsive disorder	0.1139 (3,027)	0.0927 (2,441)	0.0316(786)
Panic attacks	0.0056 (114)	0.1050 (2,152)	0.0672 (1,378)
Post-traumatic stress disorder	0.0080 (389)	0.0746 (4,046)	0.0628 (3,496)

3.3. Emotional Framing of Mental Illness

For the category Anxiety Terms (Table 3, Figure 1), the most negative terminology was recorded with the most negative sentiment score (−62,667). Of significance, the use of those negative expressions does not suggest harmful discussions but rather reflects the articulation of their emotional burden and severity of their lived experiences.

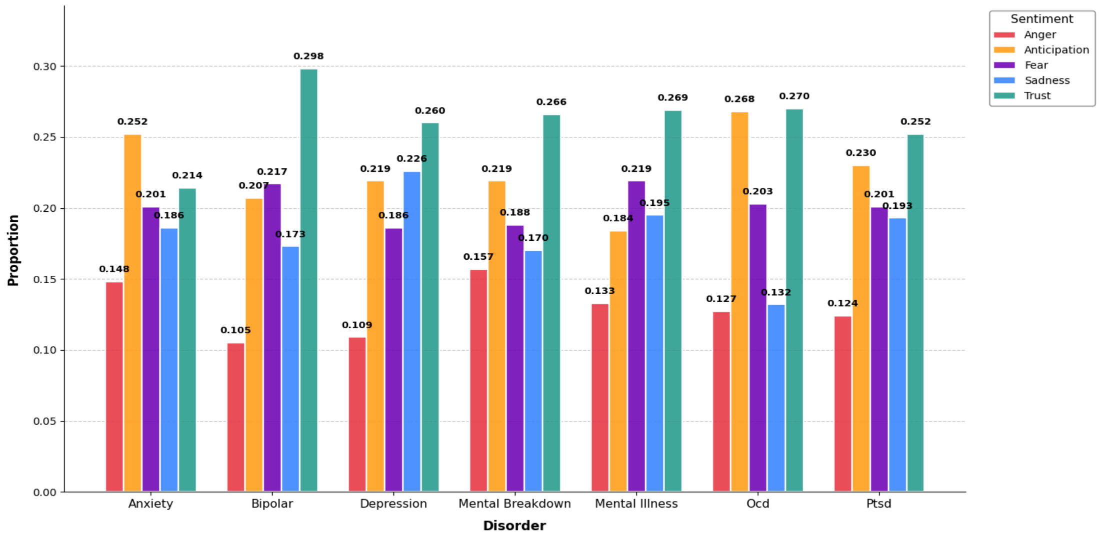

Figure 1. Emotion score proportions by Mental health disorder.

Similarly, stigmatizing revealed a net negative sentiment (−7,787) while self-Disclosure category showed a modest negative score (−2,344), indicating that online discourse continues to be laden with dismissive, judgmental, or harmful rhetoric toward mental health conditions. In contrast, Empathy showed the highest positive sentiment score (50,432), followed by Supportive (24,867) and Advocacy (4,897). This suggests that despite the prevalence of distress-oriented content, online spaces also function as an environment of support for users as they actively offer reassurance, understanding, and empathetic support.

Table 3. Aggregate sentiment scores across thematic categories.

Category Final	Total AFINN Score

Anxiety	−62,667
Empathy	50,432
Self-Disclosure	−2,344
Advocacy	4,897
Stigmatizing	−7,787
Supportive	24,867

Across all lexicons, Distress vocabulary pertaining to negative sentiment (Table 4), consistently appear with negative counts ranging from 44,247 (Loughran–McDonald) to 116,283 (Bing), compared with positive counts between 25,052 and 83,678 polarity ratios consistently below unity (e.g., NRC = 0.45; AFINN = 0.72; Bing = 0.71; VADER = 0.74; Syuzhet = 0.72; Loughran–McDonald = 0.56) reflecting the intrinsically distress-laden and symptom-focused nature of clinical and therapeutic language.

Table 4. Distribution of Negative (−) and Positive (+) Sentiment Counts Across Discourse Categories.

Category	AFINN (– / +)	Bing (– / +)	Syuzhet (– / +)	Loughran–McD (– / +)	NRC (– / +)	VADER (– / +)
Distress	115,043 / 83,279	116,283 / 82,051	114,691 / 82,311	44,247 / 25,052	91,348 / 41,275	113,859 / 83,678
Empathy	30,336 / 48,531	30,856 / 48,017	29,967 / 47,991	11,313 / 14,011	24,015 / 24,904	29,944 / 48,651
Disclosure	8,144 / 6,288	8,200 / 6,232	8,114 / 6,209	2,099 / 1,793	6,977 / 3,312	8,071 / 6,306
Advocacy	4,070 / 5,793	4,140 / 5,727	4,023 / 5,752	1,554 / 1,537	3,287 / 2,831	4,005 / 5,810
Stigma	12,485 / 7,813	12,613 / 7,685	12,418 / 7,702	3,060 / 2,300	10,695 / 3,880	12,357 / 7,884
Support	13,181 / 22,340	13,351 / 22,172	12,985 / 22,108	5,152 / 6,919	10,308 / 13,127	13,051 / 22,398

In contrast, Empathy consistently displays positive emotional dominance across all lexicons with positive counts reaching 48,531 (AFINN) and 48,651 (VADER), compared to negative values of approximately 30,000 with a polarity ratios for Empathy exceed 1.0 in every case (e.g., NRC = 1.04; AFINN = 1.60; Bing = 1.56; VADER = 1.62; Syuzhet = 1.60; Loughran–McDonald = 1.21) (Table 5).

This trend is more pronounced for Supportive which show the highest polarity ratios observed in the dataset (e.g., NRC = 1.27; AFINN = 1.69; Bing = 1.66; VADER = 1.72; Syuzhet = 1.70; Loughran–McDonald = 1.31), with positive language ranging from 22,108 (Syuzhet) to 22,398 (VADER), substantially exceeding negative counts, which remain around 13,000.

Table 5. Positive-to-Negative Sentiment Ratio Across Discourse Categories.

Category	AFINN	Bing	Syuzhet	Loughran–McD	NRC	VADER
Distress	0.72	0.71	0.72	0.56	0.45	0.74
Empathy	1.60	1.56	1.60	1.21	1.04	1.62
Disclosure	0.77	0.76	0.77	0.84	0.48	0.78
Advocacy	1.42	1.38	1.43	0.97	0.86	1.45
Stigma	0.63	0.61	0.62	0.73	0.36	0.64
Support	1.69	1.66	1.70	1.31	1.27	1.72

Additionally, Advocacy Language contributes to this positive emotional climate with lower counts with positive counts ranging from 5,727 (Bing) to 5,810 (VADER), compared with negative counts between 4,005 and 4,140 and polarity ratios are consistently above or near unity across lexicons (e.g., NRC = 0.86; AFINN = 1.42; Bing = 1.38; VADER = 1.45; Syuzhet = 1.43; Loughran–McDonald = 0.97).

By comparison, Self-Disclosure category revealed a more balanced but mildly negative sentiment profile with polarity ratios below 1.0 across all lexicons (e.g., NRC = 0.48; AFINN = 0.77;

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Bing = 0.76; VADER = 0.78; Syuzhet = 0.77; Loughran–McDonald = 0.84) consistently exceed positive values, indicating that personal narratives are often expressed as challenges, likely reflecting vulnerability, distress, and lived experiences of mental health challenges.

Conversely, Stigmatizing consistently exhibits strong negative dominance across all lexicons, with some of the lowest polarity ratios in the dataset (e.g., NRC = 0.36; AFINN = 0.63; Bing = 0.61; VADER = 0.64; Syuzhet = 0.62; Loughran–McDonald = 0.73) with a count for negative sentiments range from 12,357 (VADER) to 12,613 (Bing), substantially exceeding positive counts, which remain below 8,000.

The normalized negative (Table 6) scores exceed positive scores for AFINN (61.6 vs. 44.6), Bing (62.2 vs. 43.9), Syuzhet (61.4 vs. 44.0), and NRC (50.2 vs. 22.7). In contrast, Empathy displays a consistent dominance of positive sentiment across all lexicons. Positive scores are notably higher than negative scores for AFINN (29.8 vs. 18.7), Bing (29.5 vs. 19.0), Syuzhet (29.5 vs. 18.4), and VADER (0.642 vs. 0.354). NRC results show near parity (16.5 vs. 15.9), reflecting its broader emotional categorization, yet still do not contradict the overall positive orientation.

Table 6. Mean Normalized Sentiment Scores (+/−) Across Discourse Categories by Lexicon Method.

Discourse Category	AFINN (+/−)	Bing (+/−)	Syuzhet (+/−)	Loughran–McD (+/−)	NRC (+/−)	VADER (+/−)
Anxiety	44.60 / 61.60	43.90 / 62.20	44.00 / 61.40	14.80 / 26.50	22.70 / 50.20	0.470 / 0.527
Empathy	29.80 / 18.70	29.50 / 19.00	29.50 / 18.40	10.00 / 8.27	16.50 / 15.90	0.642 / 0.354
Self-Disclosure	6.56 / 8.49	6.50 / 8.55	6.48 / 8.47	2.49 / 2.96	3.53 / 7.45	0.411 / 0.585
Advocacy	6.61 / 4.65	6.54 / 4.73	6.57 / 4.60	2.38 / 2.45	3.57 / 4.15	0.607 / 0.388
Stigma	7.00 / 11.20	6.89 / 11.30	6.90 / 11.10	2.69 / 3.68	3.59 / 9.88	0.376 / 0.623
Supportive	16.70 / 9.85	16.60 / 9.98	16.60 / 9.73	6.13 / 4.67	10.40 / 8.16	0.630 / 0.369

A similar but slightly weaker positive dominance is observed in Supportive, where positive sentiment exceeds negative sentiment across lexicons (e.g., AFINN: 16.7 vs. 9.85; Bing: 16.6 vs .98; NRC: 10.4 vs. 8.16; VADER: 0.630 vs. 0.369). Advocacy also exhibits a positive sentiment orientation, though with more modest magnitudes. Positive scores are slightly higher than negative scores for AFINN (6.61 vs. 4.65), Bing (6.54 vs. 4.73), Syuzhet (6.57 vs. 4.60), and VADER (0.607 vs. 0.388).

In contrast, stigmatizing language shows a consistent and explicit dominance of expressed negative sentiment with negativity scores exceeding positive scores across all analyzed lexicons (e.g., AFINN: 11.2 vs. 7.00; Bing: 11.3 vs. 6.89; NRC: 9.88 vs. 3.59; VADER: 0.623 vs. 0.376). Self-Disclosure sentiment intensity was relatively low, however most lexicon shows a negative skew across most lexicon (e.g., AFINN: 8.49 vs. 6.56; Bing: 8.55 vs. 6.50; NRC: 7.45 vs. 3.53; VADER: 0.585 vs. 0.411).

3.4. Comparisons Between Symptom and Emotional Expression Across Disorders

Kruskal–Wallis test a non-parametric analysis (Table 7) revealed no statistically significant differences in emotional proportion scores across mental health disorder categories (X^2 (6) = 0.118, p=1.000), indicating that overall emotional expression did not vary significantly between disorders. In contrast, Pearson's chi-squared test (Table 8) indicted a robust and statistically significant association between mental health disorder type and symptom category (X^2(18) =11, 623, p<0.001), suggesting that each mental health disorder presents different symptom profiles across cognitive, emotional, and somatic dimensions.

Table 7. Kruskal–Wallis Test Comparing Emotional Proportions Across Disorders.

Test	Outcome Variable	Grouping Variable	Chi-square (χ^2)	df	p-value
Kruskal–Wallis	Emotional proportion	Disorder	0.1181	6	1.000

Table 8. Chi-Squared Test of Association Between Disorder and Symptom Category.

Test	Variables Compared	Chi-square (χ^2)	df	p-value
Pearson Chi-square	Disorder × Symptom category	11,623	18	< 0.001

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4. Discussion

In summary, the high prevalence of somatic symptoms observed in panic narratives reinforces the association between mental distress and physiological symptoms. Similarly, the heightened somatic symptom density in PTSD-related discussions aligns with mounting evidence that trauma-related conditions reflect ongoing nervous system instability and procedural body imprints, may be more readily expressed as a story rather than abstract affective labelling [49,50].

This pattern is consistent with previous digital mental health research suggesting that emotional pain and distress is often the most direct and visible form of psychological distress in online communities [51,52]. However, panic attacks showed a significantly higher emotional symptom density exceeding that of other conditions, highlighting the affect-driven nature of panic-related experiences. This finding validates clinical description of sudden surges in intense emotional distress evident in self-expressed narratives of individuals [50,51].

This finding also provides empirical support for conceptualizing OCD as a cognitive-based disorder, where distress is often expressed through intrusive thought patterns and not solely emotional states. This pattern is consistent across both abbreviated and full diagnostic labels, suggesting robustness and more importantly how individuals conceptualize and describe their experiences related to OCD-related regardless of how it is named [53]. Thus, reiterating the significance of symptom-level analysis for understanding specific disorders. An importance that is often lost through reliance on broad sentiment-based approaches [54].

On one hand, when users expressed psychological distress and lived experiences of mental health challenges there is strong a presence of empathy, support, and advocacy within the communication that helps to mitigate the negative and emotional tone of distress narratives [55–57].

Theoretically, the results align with social support and emotional transfer frameworks, where negative emotions expressed through self-disclosure can elicit empathetic and supportive responses from others underscore the importance and potential of online platforms as informal mental health support systems, while at the same time illuminating the need for interventions aimed at reducing or eliminating stigma [56].

Mental health-related discussions and clinical terminology are characterized by a substantially higher negative emotional load, while discourse driven by empathy and support is predominantly positive which reflects that mental health discussions are frequently expressed as significant affective distress, emotional overwhelm, and psychological vulnerability [55,58]. Negative tone prevalence across lexicons, as indicated by the robustness of this finding, confirms that negative sentiments are not merely a linguistic artifact but an embedded characteristic of mental health discourse [54].

The sentiment analysis demonstrates that mental health discourse is both emotionally intense and deeply supportive. Narratives that focus on experiences with distress are also expressed alongside strong expressions of empathy, support, and advocacy, suggesting that while mental health discussions remain emotionally heavy, they also foster meaningful social connections and collective coping within digital communities [59,60]

Taken together, these results reveal that digital narratives were expressed in terms of experiencing two seemingly contradictory emotions such that intense negative sentiment concentrated in mental health related discussions coexists with strong positive sentiment in empathetic, supportive, and advocacy-oriented responses [54]. The consistent results validate the sentiment analysis and strengthen the study, underscoring that mental health related discussions fluctuates based on intent and shifts to reflect specific communicative purpose, including seeking help or support, distress, advocacy or stigma [59–61]

Ultimately the heterogeneity in symptom expression provides evidence that underscores the limitations of diagnosis-centric approaches that treat mental illness as a homogeneous category and supports a for symptom-centered frameworks that recognize variability in lived experience.

These findings indicate that frequency is not the only determinant of discourse prominence. Although anxiety and depression were experienced in greater quantity, they were less frequently discussed specifically when framed using specific diagnostic or language related to crisis [60].

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However, they tend to generate higher levels of engagement. This suggests that online users may respond with greater intensity to narratives perceived as intense, severe, or diagnostically explicit.

In conclusion, this study makes several important contributions to mental health research and practice. Theoretically, it advances understanding of mental illness as a lived experience rather than solely a diagnostic category. It demonstrates the value of combining natural language processing techniques with statistical inference to analyze complex mental health narratives at scale. Practically, the findings have implications for monitoring mental health, detecting early risk, public health communication, and the development of digital mental health interventions; it provides actionable insight. By shifting the focus on symptom expression and emotional framing, this research provides a more human centered perspective on mental illness, one that aligns more closely with the experiences of those affected.

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Data Availability Statement: The synthesized data and all other data are available upon reasonable request.

Conflicts of Interest: Declared None.

List of Abbreviations

OCD: obsessive–compulsive disorder (OCD)
PTSD: post-traumatic stress disorder (PTSD)
NLP: Natural Language Processing
NRC: National Research Council Canada Emotion Lexicon
AFINN: AFINN Sentiment Lexicon (developed by Finn Årup Nielsen)
Bing: Bing Liu Sentiment Lexicon (Opinion Lexicon)
VADER: Valence Aware Dictionary and sEntiment Reasoner
Syuzhet: Syuzhet Sentiment Lexicon (from the Syuzhet R package)
Loughran–McDonald: Loughran–McDonald Financial Sentiment Lexicon

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