

Reshaping of Mental Health Discourse on Reddit: The Rise of Neurodivergence

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Abstract

Public discourse about mental health is changing rapidly, and these changes are increasingly playing out online. Previous research has explored how specific mental health conditions are represented on social media, but little is known about representations of the wider mental health domain or how these representations have evolved over time. Analyzing posts and comments from 14 mental health subreddits (2015–2022), we characterize shifts in affinities among subreddits based on language and user activity. We also examine whether changes in mental health discourse reflect changes in attention (salience) to different conditions. Reddit mental health discourse was substantially reshaped over the study period, with autism and ADHD becoming more central within the network. Moreover, rises in a condition’s centrality within the network were associated with increases in its salience. Our findings indicate that public understandings may be changing not only for individual conditions but also in how mental health and disorder are understood more broadly. These shifts may be contributing to discrepancies between public and professional understandings of mental health problems and have implications for help-seeking behaviors, overdiagnosis, and misdiagnosis. As public attention to mental health grows, understanding these dynamics is becoming increasingly important.

Introduction

Rates of mental ill health are rising globally (Richter et al. 2019) and roughly one in eight people worldwide are now living with a mental disorder (WHO 2022). The classification of mental disorders is also in a state of flux. Diagnostic systems such as the Diagnostic and Statistical Manual of Mental Disorders (DSM) and the International Classification of Diseases (ICD) have been criticized for drawing questionable distinctions between disorders (Borsboom et al. 2011; Forbes et al. 2024) and between pathology and normality (Fried and Nesse 2015; Galatzer-Levy and Bryant 2013), and have undergone multiple revisions. Radically

new approaches to classification and diagnosis have been proposed (e.g., Cuthbert & Insel, 2013; Kotov et al., 2017).

While there has been substantial work on the conceptualization and classification of mental disorder by professionals, less attention has been paid to changes in how the public understand it. Public awareness of mental health has grown substantially, as the proliferation of mental health discourse on social media demonstrates. Twitter posts mentioning ‘mental health’ increased nearly 100-fold between 2012–2018 (Stupinski et al. 2022) and the hashtag #mentalhealth has amassed over 26 million posts on the video-based social media platform TikTok. This growing awareness has led to important benefits such as reducing stigma (e.g., Ahad et al. 2023), but there is increasing recognition of the potential risks. Increases in mental health discourse on social media are linked to greater utilization of healthcare services (Booth et al. 2018). Increased exposure to harmful content on social media can induce or exacerbate mental disorders, as research on eating disorders attests (Hinojo-Lucena et al. 2019; Pruccoli et al. 2022). Mental health discourse on social media has also been implicated in the sociogenic spread of symptoms, such as the rise in adolescents presenting with tic-like behaviors attributable to exposure to tic-related content (Olvera et al. 2021). Similar trends have also been documented with respect to dissociative identity disorder (DID) and the rise in content related to switching self-states (Salter et al. 2025; Haltigan et al. 2023; Christensen 2022). Clinicians have also reported increases in self-diagnosed cases of ADHD and autism (Hartnett and Cummings 2024; Weigle and Shafi 2024), and there is evidence that holding inaccurately expansive definitions of mental illness is associated with self-diagnosis (Tse and Haslam, 2024). Although self-diagnosis can promote appropriate help-seeking, it can also lead to unwarranted, ineffective or even harmful treatment (Allison et al. 2023). Together, these studies highlight the consequential implications of mental health discourse on social media.

As most mental health-related content is created by non-professionals (Basch et al. 2022), it often contains inaccurate information. An analysis of the 100 most popular TikTok videos about ADHD (attention-deficit/hyperactivity disorder) found over half (52%) were misleading (Yeung et al. 2022). Similarly, an analysis of the top 133 TikTok videos tagged #autism reported 27% were accurate, 41% were inaccurate, and 32% contained potentially misleading over-generalizations (Aragon-Guevara et al. 2023). Similar concerns have been raised about discourse related to obsessive-compulsive disorder (OCD; Tan et al., 2021) and DID (Munoz et al., 2024). In this content, these conditions are often presented in a sympathetic and strengths-focused but simplistic way, with users finding a sense of identity and self-understanding that propels further engagement (Corzine and Roy 2024; Haltigan et al. 2023). The algorithmic design of these platforms then reinforces this pattern by prioritizing similar content (Avella 2024), which can amplify and perpetuate the spread of misleading or inaccurate information over time.

Related Work

Advances in machine learning (ML) and natural language processing (NLP), including large language model (LLM) methods (Xu et al. 2024), have enabled the large-scale analysis of social media discourse. A substantial focus of this work has been detecting the presence of mental health conditions such as depression (De Choudhury et al. 2013; Eichstaedt et al. 2018), generalized anxiety disorder (Shen and Rudzicz 2017), schizophrenia (Mitchell et al. 2015), post-traumatic stress disorder (PTSD; Coppersmith et al. 2014), suicide risk (O’Dea et al. 2015), anorexia nervosa (Wang et al. 2017), and ADHD (Guntuku et al. 2017), utilizing data from platforms such as Twitter, Facebook, and Reddit. These studies typically focus on identifying linguistic markers of specific conditions.

Researchers have paid far less attention to how these conditions are represented or conceptualized within social media discourse. Most of the studies that have done so have been restricted to single conditions. Three exceptions have explored relationships among multiple conditions using Reddit data. Kalantari et al. (2023) identified overlapping topics and themes in autism and ADHD communities. Park et al. (2018) found that anxiety and PTSD subreddits were more similar to each other than to the depression subreddit. Ringwald et al. (2025) compared the hierarchical structure of 27 mental health-related subreddits with the structure proposed by a popular system of psychiatric classification, revealing overlaps between the two.

Most existing work on social media mental health discourse has focused on a single time point rather than examining patterns of temporal change (Owen et al. 2024). However, studies using large historical text corpora have shown

that mental health-related concepts have undergone significant semantic shifts over time (Baes et al. 2024; Haslam et al. 2020; Xiao et al. 2023). For example, Haslam et al. (2021) found that the concept of “trauma” broadened its meaning in academic psychology texts from the 1970s to the 2010s, which coincided with increases in the concept’s cultural salience. To our knowledge, only one study has examined shifts in the relationship between two mental health conditions; using Reddit data from the two largest ADHD- and autism-related communities over a ten-year period, Kang et al. (2025) found that the conditions became increasingly interconnected in terms of co-mention frequency, semantic similarity, and thematic content. No research to date has examined broader patterns of change in mental health discourse on social media.

Our Contributions

Given the rising public attention to mental health and the paucity of work examining how public mental health discourse has evolved, the present study examines how affinities among mental health subreddits have reconfigured over time. It aims to characterize how relationships among conditions have changed and how these changes are related to shifts in public attention to them. One such shift is the rise of the neurodiversity movement. Emerging as a call to embrace neurological differences, this movement is reframing how neurodevelopmental conditions are understood by shifting narratives around causes, presentations, and appropriate support (Grummt 2024). It challenges diagnostic categories and emphasizes that such conditions exist on a spectrum, with neurodivergent individuals often presenting with symptoms spanning multiple conditions (Miranda-Ojeda et al. 2025). Despite its impact, the concept of neurodiversity is inconsistently defined, partly because it has been shaped by diverse and sometimes contradictory interpretations (Doyle 2020; Botha et al. 2024; Dwyer et al. 2024). As such, the concept is dynamic and has a family resemblance structure rather than one based on necessary and sufficient conditions (Wittgenstein 1953). Autism and ADHD are central to the concept. However, the concept is often extended to conditions such as dyspraxia, dyslexia, and Tourette syndrome (Clouder et al. 2020; Doyle 2020), and sometimes neurodiversity is extended to other mental health conditions such as bipolar disorder (Miranda-Ojeda et al. 2025).

We expect neurodiversity-related conditions (particularly autism and ADHD) to become more salient (i.e., receive greater attention) and more central within Reddit’s mental health discourse. We use posts and comments from 14 mental health-related subreddits over a seven-year period to examine their similarities using linguistic and user-based representations and explore the following questions:

- **RQ1:** How have the pairwise similarities among mental health-related subreddits shifted over time?

- **RQ2:** Which subreddits have become increasingly similar (central) to the overall network over time?
- **RQ3:** Are these shifts in network position associated with changes in public attention to particular conditions (salience)?

We find that Reddit mental health discourse was substantially reshaped over the study period, with autism and ADHD becoming more central to the broader mental health network. Moreover, rising similarity to the network was also associated with increases in a condition’s salience. These findings suggest that relationships among mental health subreddits have changed over time, signaling potential shifts in public understanding not only of particular conditions but also of mental health and disorder more generally.

Method

Data

Reddit is a prominent platform for studying online mental health-related discourse, because of its large volume of user-generated content. Reddit is a forum-style social media platform organized around communities focused on specific topics of interests, known as subreddits. Subreddit names are prefixed by “r/” (e.g., r/funny, r/worldnews, and r/gaming). As such, Reddit is a suitable platform for our study as this community-based structure allows us to investigate discourse related to specific mental health conditions and easily observe user posting activity across subreddits.

Our dataset was incrementally collected from Pushshift.io until the beginning of 2023. The dataset covered the years of 2015 to 2022. We focused on 14 mental health-related subreddits: *r/ADHD*, *r/autism*, *r/Anxiety*, *r/bipolar*, *r/BPD* (borderline personality disorder), *r/OCD*, *r/ptsd*, *r/Dyslexia*, *r/dyspraxia*, *r/DID*, *r/schizophrenia*, *r/socialanxiety*, *r/Tourettes*, and *r/depression*. These were selected to represent a diverse collection of the most popular mental health-related subreddits, as they included sufficient posts and comments across years. There was also a deliberate attempt to include neurodiversity-related conditions given our expectation that these conditions have become especially salient in recent years. Specifically, we consider these to be ADHD, autism, dyslexia, dyspraxia, and Tourette syndrome as these are the conditions most associated with the neurodiversity movement (Clouder et al. 2020; LeFevre-Levy et al. 2023; Stening and Rosqvist 2021; Masataka 2017) compared to other conditions such as OCD, which is less often associated with the concept of neurodiversity (Doyle 2020). We avoided overrepresenting any single broad diagnostic grouping (e.g., anxiety disorders) from the DSM to avoid topical skew. Furthermore, we selected only one subreddit per condition, excluding more specific communities such as *r/adhdwomen* or *r/anxiety*. This approach was intended to capture the

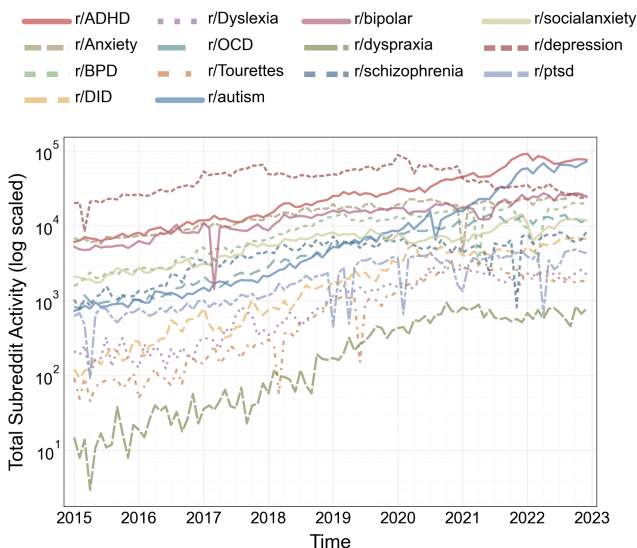


Figure 1. Log scaled total number of posts and comments per month for each subreddit from 2015 to 2022.

most general discourse related to each condition on Reddit. This selection was not intended to be comprehensive.

We retained original posts and top-level comments (i.e., direct responses to posts) under the assumption that these better reflect a community’s focus, as opposed to lower-level replies (i.e., any comment that replies to another comment), which may be more conversational and tend to drift from the main topic of the original post (Zhang et al. 2017). The filtered dataset included 11.08M comments and 3.37M posts. The total posts and comments per month for each subreddit are shown below in Figure 1.

Ethical Statement

This study was approved by the University of Melbourne Human Research Ethics Committee (2024-30416-58642-3). We analyzed publicly available social media data in accordance with institutional ethical guidelines. Because the data were public and non-identifiable, the ethics committee granted a waiver of informed consent. Although the data analyzed in this study are publicly available, we recognize that they concern sensitive and potentially vulnerable discussions related to mental health. Engagement with such data therefore raises important ethical considerations, including the risk that findings could be misinterpreted, taken out of context, or used in ways that could enable monitoring of individuals or communities. Consistent with the guidelines proposed by Benton et al. (2017), we use appropriate protections for this sensitive data. We analyze and report only aggregated data, do not include any personally identifiable information, and do not use verbatim quotations. Data are stored on a secure server, with access limited to researchers involved in the project.

We caution against using these results to guide clinical or policy decisions that could potentially stigmatize specific groups or communities.

Analysis

We applied standard preprocessing measures to all text, which included lowercasing, punctuation and URL removal, and lemmatization. Following Lucy and Mendelsohn (2019), we removed tokens that appeared in only one subreddit or in all subreddits so that extremely rare words and stop words were removed, as well as users who appeared in one or all subreddits to filter out rare users and bots. From the cleaned text we extracted unigrams, bigrams, and trigrams.

Text and User Pairwise Similarity

To assess the similarity between subreddits, for each year we computed the term frequency-inverse document frequency (TF-IDF; Sparck Jones 1972) vectors for each subreddit using user and n-gram frequencies. The TF-IDF vectors were calculated using the following equation:

$$w_{t,d} = (1 + \log t f_{t,d}) \log \left(\frac{N}{d f_t} \right)$$

All posts and top-level comments from each subreddit and each year were concatenated and treated as a single document. For both text- and user-based vectors, TF was computed using the frequency of t (n-gram or user) in d (subreddit). IDF represents the number of subreddits in which t appears, and N is the total number of subreddits.

We then applied truncated singular value decomposition (SVD) to reduce the dimensionality of the TF-IDF matrix to 100 components. The resulting vectors were normalized to unit length. Cosine similarity, the cosine angle between vectors, was calculated between pairs of subreddit vectors to quantify text and user similarity for each year.

Last, we computed the change in similarity between all pairs of subreddits across years. To do so, a simple linear regression model was fitted using year as the independent variable and cosine similarity as the dependent variable. This was computed separately for text and user similarity. The resulting regression slope coefficient quantifies the average annual rate of change in similarity for a given pair. A positive slope indicates increasing similarity over time, whereas a negative slope reflects decreasing similarity.

Although alternative representations (e.g., word embeddings or topic models) can be used to assess subreddit similarity, we adopt TF-IDF because it is transparent, does not require tuning, and allows for simple comparison across years. It can also be applied to text and user activity, allowing the use of a single similarity metric (cosine) across both dimensions. This choice aligns with prior work that has

compared subreddit similarity in language and/or user activity (Datta et al. 2017; Kumar et al. 2018; Lucy and Mendelsohn 2019; TeBlunthuis et al. 2022).

Text and User Similarity to the Network

To assess the similarity of each subreddit to the broader network of mental health communities, we computed for each year a composite TF-IDF vector representing all subreddits except the target. To calculate the composite vector, we first calculated log-normalized term frequency (TF) scores for each subreddit, then summed these TF vectors across all mental health subreddits (not including the given target subreddit). We then applied the globally calculated inverse document frequency (IDF) weights to this composite TF vector to obtain the final TF-IDF representation. For each target subreddit and year, we reused the text- and user-based TF-IDF vectors from the pairwise analysis and then calculated the cosine similarity between the target subreddit's vector and the corresponding composite vector. This method captured how similar each subreddit was to the broader discourse or user base of all other mental health communities.

To quantify change over time, we fitted a simple linear regression model for each subreddit, with year as the independent variable and cosine similarity as the dependent variable. This was computed for both text- and user-based similarity. A positive slope indicates a subreddit is becoming more central to the broader network over time.

Condition Salience Change

We calculated the average annual growth rate of activity within each subreddit using the compound annual growth rate:

$$\text{Growth Rate} = \left(\frac{V_{\text{end}}}{V_{\text{start}}} \right)^{\frac{1}{n}} - 1$$

Here, V_{start} and V_{end} represent the number of posts and top-level comments (i.e., direct responses to posts) in the first and last years of the dataset, respectively, with $n = 7$ years. This metric captures the yearly change rate in subreddit activity, used here as a proxy for shifts in the attention to or salience of specific mental health conditions, assuming that higher user activity reflects greater attention. We examined whether changes in salience were related to changes in a subreddit's similarity to the network by correlating each subreddit's growth rate with its network similarity slope coefficient.

Finally, we repeated the pairwise and network similarity analyses with a set of control subreddits drawn from prior mental health-related research (Morini et al. 2025). In this work, the authors curated a list of subreddits intended to include communities both similar to and distinct from mental health subreddits: r/Advice, r/RealEstate, r/eczema, r/communism, r/modelmakers, and r/dankchristianmemes.

Results

Text and User Pairwise Similarity

Below we present heatmaps of slope coefficients, reflecting the average annual change in similarity between subreddit pairs, based on TF-IDF representations of text and user activity. Darker cells indicate greater change in affinity between subreddits. Blue cells represent increasing similarity, indicating growing convergence over time, whereas red cells represent decreasing similarity, indicating growing divergence.

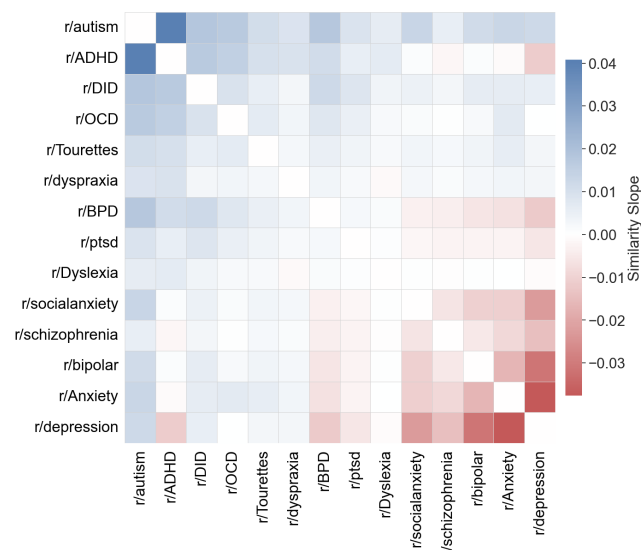


Figure 2. Heatmap of average annual rate of change in text similarity between pairs of subreddits.

Figure 2 presents a heatmap of slope coefficients for text similarity (see Table 1 in Appendix for full list of slope coefficients). The strongest increase was observed between r/ADHD and r/autism ($B = 0.04$, $p = 0.003$). Furthermore, over time r/ADHD and r/autism became increasingly similar to the other conditions commonly associated with neurodiversity, r/Tourettes (r/autism: $B = 0.01$, $p < 0.001$, r/ADHD: $B = 0.01$, $p = 0.002$), r/dyspraxia (r/autism: $B = 0.01$, $p < 0.001$, r/ADHD: $B = 0.01$, $p < 0.001$), and r/Dyslexia (r/autism: $B = 0.01$, $p < 0.001$, r/ADHD: $B = 0.01$, $p = 0.003$). These findings indicate that over time the language in neurodiversity-related subreddits have become more similar to each other.

Notably, r/autism became increasingly similar to all other mental health subreddits, particularly r/DID ($B = 0.02$, $p < 0.001$), r/BPD ($B = 0.02$, $p < 0.001$), and r/OCD ($B = 0.02$, $p = 0.002$). Comparatively, r/ADHD also showed the strongest increases in similarity with r/DID ($B = 0.02$, $p < 0.001$), r/OCD ($B = 0.02$, $p < 0.001$), and r/BPD ($B = 0.01$, $p =$

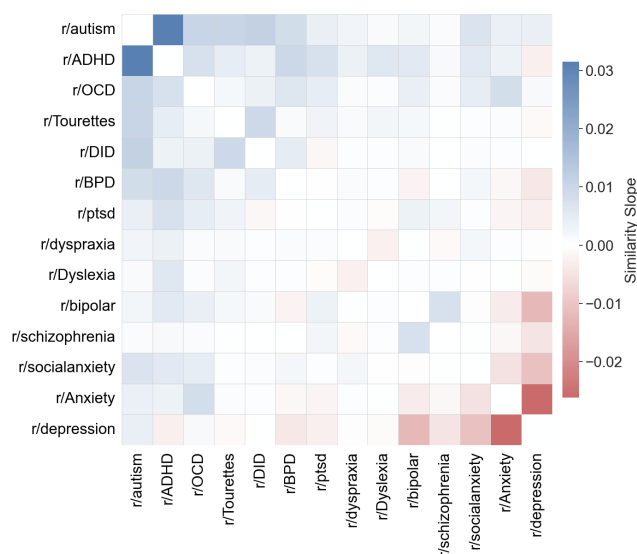


Figure 3. Heatmap of average annual rate of change in user similarity between pairs of subreddits.

0.002) but decreased in similarity with r/depression ($B = -0.01$, $p = 0.008$). Additionally, r/OCD, r/Tourettes, and r/DID exhibited widespread increases in similarity.

The greatest decrease in similarity occurred between r/Anxiety and r/depression ($B = -0.04$, $p < 0.001$). Additionally, the subreddits related to bipolar, schizophrenia, social anxiety, anxiety, and depression decreased in similarity with each other (B s -0.01 to -0.03 , all p s < 0.05 except for the bipolar and schizophrenia comparison where $p > 0.05$).

Mean slopes for pairwise comparisons between control subreddits (r/RealEstate, r/eczema, r/communism, r/modelmakers, r/dankchristianmemes), and mental health subreddits were approximately $B \approx 0.00$, except r/Advice ($B = 0.01$).

Figure 3 presents a heatmap of slope coefficients for user similarity (see Table 2 in Appendix for full list of slope coefficients). Consistent with the text similarity results, r/ADHD and r/autism showed the largest increase in user similarity ($B = 0.03$, $p = 0.002$) and they also both became more similar to the neurodiversity-related subreddits, r/Tourettes (r/autism: $B = 0.01$, $p = 0.003$, r/ADHD: $B = 0.005$, $p = 0.013$) and, r/dyspraxia (r/autism: $B = 0.003$, $p = 0.012$, r/ADHD: $B = 0.004$, $p = 0.002$). Additionally, r/ADHD became more similar to r/Dyslexia ($B = 0.01$, $p = 0.008$). Again, these findings indicate that over time the user bases in neurodiversity-related subreddits have become more similar to each other.

Among all subreddits, r/autism experienced the most widespread increase in user similarity, particularly with r/DID ($B = 0.01$, $p = 0.001$), r/BPD ($B = 0.01$, $p = 0.001$), and r/OCD ($B = 0.01$, $p < 0.001$).

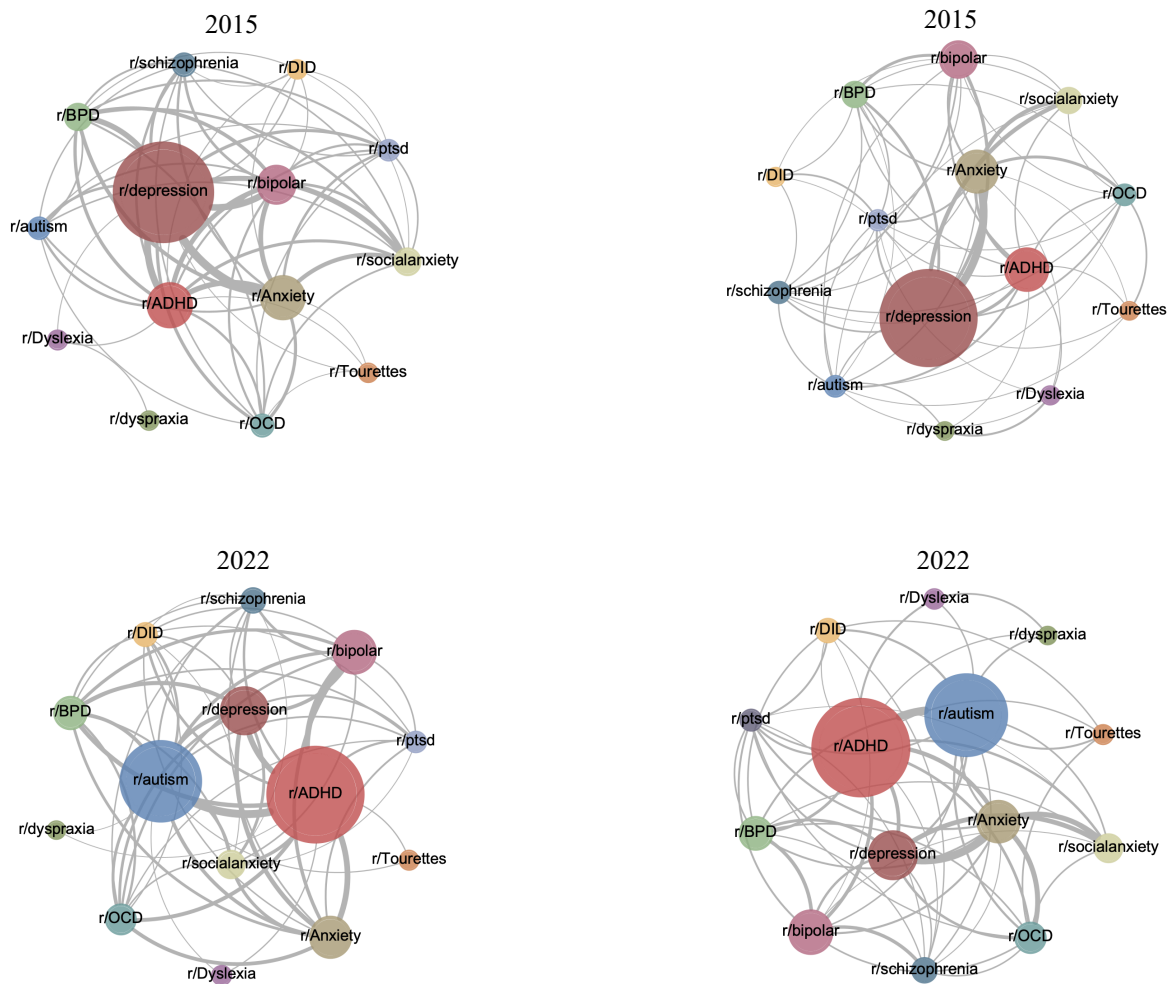


Figure 4. Network graph showing text similarity (left) and user similarity (right) between subreddits for 2015 (top) and 2022 (bottom). Edge thickness reflects the strength of similarity and node size represents total post and comment volume per subreddit. Only the top 65% of edges by similarity strength are displayed.

Similarly, *r/ADHD* became more similar to most other subreddits, particularly with *r/ptsd* ($B = 0.01, p < 0.001$), *r/OCD* ($B = 0.01, p = 0.002$), and *r/BPD* ($B = 0.01, p < 0.001$). Widespread increases in similarity were also observed for *r/OCD*.

The largest decline in pairwise similarity was between *r/Anxiety* and *r/depression* ($B = -0.03, p < 0.001$). Both communities also became less similar to *r/socialanxiety* (*r/Anxiety*: $B = -0.01, p = 0.005$, *r/depression*: $B = -0.01, p = 0.043$) and *r/bipolar* (*r/Anxiety*: $B = -0.004, p = 0.004$, *r/depression*: $B = -0.01, p < 0.001$), with smaller declines relative to *r/schizophrenia* (*r/Anxiety*: $B = -0.001, p = 0.019$, *r/depression*: $B = -0.005, p = 0.014$), *r/ptsd* (*r/Anxiety*: $B = -0.002, p = 0.024$, *r/depression*: $B = -0.003, p = 0.021$), and *r/BPD* (*r/depression* only: $B = -0.004, p = 0.023$).

The mean slopes of the user similarity pairwise comparisons between control subreddits and the mental health-related subreddits were all $B \approx 0.00$ (*r/Advice*, *r/RealEstate*,

r/eczema, *r/communism*, *r/modelmakers*, *r/dankchristianmemes*).

Overall, changes in user similarity over time were less pronounced than those observed in the text similarity results. However, there was a strong, positive association between user similarity slopes and text similarity slopes across subreddit pairs (Pearson's $r = 0.86, p < .001$), suggesting that subreddit pairs that became more similar in user activity over time also tended to become more similar in language.

The network graphs in Figure 4 show affinities among mental health subreddits in 2015 and 2022. We visualized the graphs in Gephi (Bastian et al. 2009). Nodes are scaled by each subreddit's total number of posts plus top-level comments in the given year. Edges are weighted by cosine similarity between subreddit pairs, for both user activity (right) and text (left) TF-IDF representations. We used the Fruchterman–Reingold layout to display the overall configuration of the mental health subreddit network. The left side

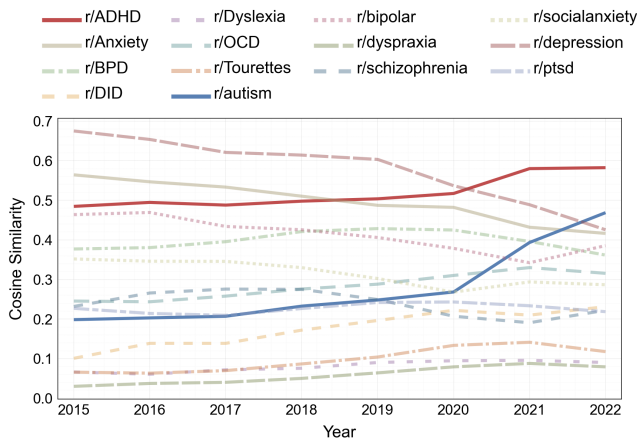


Figure 5. Text similarity per year between each subreddit and the whole network of mental health-related subreddits

of Figure 4 demonstrates the growing text similarity between r/ADHD and r/autism and the substantial expansion in their activity levels, as indicated by the larger node sizes. It also illustrates the shifting affinities with various other subreddits. For example, when comparing 2015 to 2022 the link between r/autism and r/ADHD with r/OCD, r/DID, and r/Tourettes, became notably stronger. By implication, the affinities among multiple subreddits have shifted over the study period in tandem with changes in the relative salience of the subreddits.

The right side of Figure 4 illustrates the user similarity among the network of mental health-related subreddits in 2015 and 2022. It highlights the growing affinity between the r/ADHD and r/autism, and the substantial expansion in their activity levels, as indicated by the larger node sizes. Furthermore, it shows the increased affinities among r/autism and r/ADHD with r/DID, r/BPD, and r/ptsd over time.

Text and User Similarity to the Network

Figures 5 and 6 illustrate changes in each subreddit’s similarity to the rest of the network, measured as yearly cosine similarity between each subreddit and the composite network vector. Figure 5 shows shifts in text-based similarity: r/depression and r/Anxiety were most similar to the overall network until r/ADHD surpassed them after 2020. Meanwhile, r/autism maintained a relatively stable similarity until a sharp increase after 2020, becoming the second most similar subreddit to the rest of the network by 2022, behind r/ADHD. These findings indicate that r/ADHD and r/autism have become more typical of or central to the overall mental health-related subreddit network over time.

The slope coefficients, representing the average annual change in text similarity between the control subreddits and

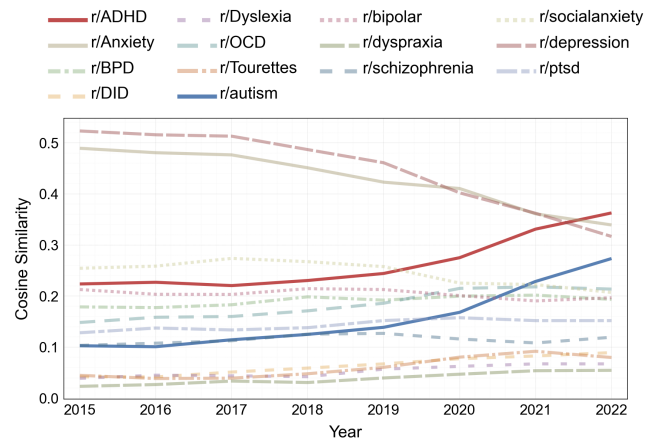


Figure 6. User similarity per year between each subreddit and the whole network of mental health-related subreddits.

the mental health subreddit network were all $B \approx 0.00$ (r/RealEstate, r/eczema, r/Advice, r/modelmakers, r/dankchristianmemes), except r/communism ($B = -0.01$).

Figure 6 presents comparable findings to Figure 5 but employing user- rather than text-based similarity. Until 2019, user similarity between r/ADHD and the rest of the subreddit network remained relatively stable, ranking below r/depression, r/Anxiety, and r/socialanxiety. However, after 2020, r/ADHD rose steadily until it ranked highest in user similarity by 2022. A similar pattern is observed in r/autism: it remained stable until a steady increase after 2020 and became the fourth highest in user similarity with the rest of the subreddit network by 2022. These findings replicate that r/ADHD and r/autism have become more central in the overall mental health subreddit network, consistent with the text-based similarity results in Figure 5.

The slope coefficients, representing the average annual change in user similarity between the control subreddits and the mental health subreddit network were all $B \approx 0.00$ (r/RealEstate, r/eczema, r/Advice, r/modelmakers, r/dankchristianmemes, r/communism).

Condition Salience Change

Finally, we observed strong positive correlations between yearly change rate in subreddit activity and changes in both text-based (Spearman’s $\rho = 0.92, p < .001$) and user-based (Spearman’s $\rho = 0.87, p < .001$) subreddit similarity to the network. In other words, subreddits showing larger increases in attention or salience over time also tended to become more similar to the overall mental health subreddit network in both language use and user base. Note that the composite vectors used to calculate similarity in each case excluded the target community, meaning that the community size is not a confounding factor in the comparison. The

results indicate that greater attention to a mental health condition on Reddit is associated with the condition becoming more central in mental health discourse.

Discussion

Public discourse about mental health is changing rapidly, and much of this change is now happening online. Previous research has explored how specific conditions are represented on social media, but few have examined how representations of the broader mental health domain have altered over time. This study is the first to examine how social media discourse on mental health has been reconfigured, in terms of patterns of shifting affinities among subreddits, and how that reshaping reflects changes in attention to different mental health conditions. Analyzing posts and comments from 14 mental health subreddits (2015–2022), we characterized changes in their linguistic and user similarity. Furthermore, we examined whether these shifts were associated with changes in their salience. We found evidence of consistent patterned changes that reflect a substantial reconfiguration of mental health subreddits. Autism and ADHD have become increasingly central to the network of mental health communities. We also found that, conditions that have attracted greater attention have become more central. It is important to note that some of the observed shifts were relatively modest in magnitude. However, our interpretations prioritize the direction and consistency of trends across the user- and text- based similarity measures, rather than relying on the size of trends alone.

Pairwise similarities between mental health subreddits clarify how relationships have changed over time. Across language and user similarity, the largest increase was between r/ADHD and r/autism. Based on a qualitative analysis of posts and comments in the two communities, discussions in later years increasingly centered on overlapping traits such as social difficulties, sensory sensitivities, and restricted or fixed interests. In contrast, some earlier discussions emphasized their distinctive underlying causes. For example, posts distinguished between ADHD-related hyperfocus and the restricted interests characteristic of autism, noting that although these behaviors may appear similar, they arise from different mechanisms. Both r/ADHD and r/autism also showed notable increases in similarity with r/DID, r/BPD, r/OCD, and r/ptsd. The growing salience of social media discourse related to these conditions (and for PTSD, discourse centered on trauma) has been widely discussed (Aragon-Guevara et al. 2023; Corzine and Roy 2024; O'Connor et al. 2024; Pavelko and Myrick 2016; Salter et al. 2025; Yeung et al. 2022). Some of this work shows that social media discourse is oversimplifying or expanding diagnostic concepts. These dynamics may be contributing to a blurring of boundaries between conditions that increases the

similarity of discourse about them. Additionally, r/ADHD and r/autism became more similar to other neurodiversity-related subreddits (r/Dyslexia, r/dyspraxia, and r/Tourettes) in text and users, with the sole exception being user similarity between r/autism and r/Dyslexia. This pattern could be attributed to the rising salience of the neurodiversity movement, which has grouped these conditions together and emphasized that such conditions exist on a spectrum rather than as distinct diagnostic categories (Miranda-Ojeda et al. 2025). Our findings extend those of Kang et al. (2025) by demonstrating that ADHD and autism have not only converged with one another in social media discourse, but also with a wider set of conditions.

There were also some notable decreases in text and user similarity between conditions, with the strongest decrease observed between r/Anxiety and r/depression. Qualitative examination of posts and comments in r/depression and r/Anxiety reveal that earlier discussions tended to focus on overlapping symptoms, such as distorted thinking, lethargy, and irritability, as well as the challenges associated with experiencing both conditions. In later years, while these difficulties continued to be acknowledged, conversations increasingly emphasized the distinct qualities of each condition. For example, depression was often described as “pulling people into the past,” whereas anxiety was characterized as causing “fear of the future”. The bipolar disorder, schizophrenia, social anxiety, anxiety and depression subreddits also decreased in text and user similarity with each other, based on the pairwise comparisons. This pattern diverges from what would be expected based on professional understandings, given high rates of comorbidity between mood and anxiety disorders (Huppert 2009; Kalin 2020) and high levels of symptom overlap (Baldessarini et al. 2020). The observed divergence in the discourse among these conditions suggests that shifts in public understandings of mental ill health may not mirror clinical frameworks, which emphasize their underlying similarities and frequent co-occurrence.

The text- and user-based network graphs illustrate that affinities among multiple subreddits have shifted over the study period in tandem with changes in the relative salience of the subreddits. Node size and edge strength increased most for r/ADHD and r/autism, whereas r/depression showed the most pronounced decline in node size and weakening of connections. The graphs depicting changes in subreddit similarity to the broader network likewise indicate that the ADHD and autism communities increasingly converged with the network as a whole, particularly around 2020, whereas r/Anxiety and r/depression became less central. Moreover, these shifts were associated with changes in condition salience, suggesting that as conditions attracted greater attention, their language and users aligned more closely with other mental health communities. Previous

work has shown concepts that have received increased cultural attention have broadened their meanings (Haslam et al. 2021). The early 2020s has also been noted as an inflection point of neurodiversity discourse on social media, coinciding with increased social media usage and isolation associated during the COVID-19 pandemic (Alper et al. 2025). As ADHD and autism are central to the neurodiversity movement, their meanings may have expanded as the movement itself grew in prominence, increasing their similarity to the broader mental health network.

Our findings have important implications. Scholarly interest in the representation of mental ill health on social media is growing, alongside concerns about misinformation (e.g., Starvaggi et al., 2024). We show that affinities among mental health subreddits have shifted over time, suggesting that public understandings may be changing not only for individual conditions but also for the wider mental health domain. These shifts may be contributing to discrepancies between public and professional understandings of mental health problems and to altered patterns of help-seeking and self-diagnosis (Corzine & Roy 2024). For example, the rising affinity between the ADHD- and autism-related subreddits is likely to lead people who have only one condition to seek diagnosis and treatment for both (Russell et al. 2022). This development might result in inappropriate dual or "comorbid" diagnosis, unwarranted service use and treatment, and unnecessary complication of treatment planning. More generally, the rising interconnectedness and similarity of several conditions, including BPD, Tourette syndrome, and DID as well as ADHD and autism, risks blurring important distinctions among them. This blurring could foster misdiagnosis (i.e., assigning an incorrect diagnosis) and over-diagnosis (i.e., assigning multiple diagnoses when only one applies).

In addition, the rising salience of conditions such as ADHD and autism that we observed would be expected to promote unwarranted self-diagnosis or "overinterpretation" (Foulkes & Andrews 2023) of each condition independently. Studies have found that a condition's increasing salience tends to drive the broadening of its definition (Xiao et al. 2023) and that holding broad concepts of illness is associated with self-diagnosis, holding constant levels of distress and disability (Tse & Haslam 2024). There is a risk that as some conditions become more culturally salient and central to the domain of mental health, people will come to incorrectly identify symptoms of less prominent conditions as features of the more salient ones. Forms of emotional distress that are typical of depression and anxiety, for example, may be viewed through the lens of ADHD or autism, with further implications for misdiagnosis. These findings highlight the need for evidence-based awareness strategies and better-informed public discourse led by mental health professionals that delineate important distinctions among conditions to reduce such potential risks.

Limitations

To our knowledge, this study is the first to systematically investigate shifts in the configuration of mental health discourse on social media. Future work should broaden the set of conditions studied to capture a more expansive map of psychopathology (e.g., adding eating disorders and substance-use disorders) or, alternatively, increase the number of conditions within categories (e.g., panic disorder, agoraphobia) to examine shifts in higher-order diagnostic groupings.

Despite its novel focus, this study has limitations. Reddit's user base is heterogeneous, including people seeking support, sharing lived experiences, or simply curious, and although it is likely to reflect wider public discourse related to mental health it is not representative of the general population or generalizable to it. This limitation is further compounded by the demographic skew of Reddit data. For example, Reddit users in the United States tend to skew male, younger (18–29 years old), and identify as politically left-leaning. They also tend to have higher income levels, be college-educated, and reside in urban or suburban areas. Racially, they are more likely to identify as Asian, followed by Hispanic, White, and Black (Barthel et al. 2016). Future studies could extend similar methodologies to offline contexts or other platforms such as X, Facebook, or TikTok to determine whether the observed trends hold across platforms. Given that numerous studies have documented mental health misinformation on TikTok (Starvaggi et al. 2024), replication in this context could be especially informative. Finally, the seven-year window we examined extends only until 2022, omitting more recent developments. While the dataset spans a period of rising public attention to mental health, future work should use datasets with more recent data. Nevertheless, our findings demonstrate important and novel insight into shifting public discourse about mental ill health on social media.

Conclusion

Our study demonstrates that mental health discourse on social media has been reshaped over time, with autism and ADHD becoming increasingly central to the network. Additionally, our findings show that changes in salience of particular mental health conditions are linked to these shifts. Previous work has documented the consequential implications of social media discourse on mental health, and although a growing literature examines how individual conditions are portrayed online, the organization of mental disorder more broadly has been largely overlooked. Our results indicate that relationships among conditions are dynamic and diverge from professional diagnostic frameworks. As public attention to mental health grows, it is vital for future

work to monitor these shifts and clarify their impacts on clinical practice and the broader public.

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Paper Checklist

1. For most authors...

- (a) Would answering this research question advance science without violating social contracts, such as violating privacy norms, perpetuating unfair profiling, exacerbating the socioeconomic divide, or implying disrespect to societies or cultures? **Yes**.
- (b) Do your main claims in the abstract and introduction accurately reflect the paper's contributions and scope? **Yes**.
- (c) Do you clarify how the proposed methodological approach is appropriate for the claims made? **Yes, see the Methods section**.
- (d) Do you clarify what are possible artifacts in the data used, given population-specific distributions? **Yes, see the Data section where we provide information about the dataset e.g., the subreddits that were selected, number of posts and comments, and time period**.
- (e) Did you describe the limitations of your work? **Yes, in the Limitations section**.
- (f) Did you discuss any potential negative societal impacts of your work? **Yes, in the Ethical Statement section**.
- (g) Did you discuss any potential misuse of your work? **Yes, in the Ethical Statement section**.
- (h) Did you describe steps taken to prevent or mitigate potential negative outcomes of the research, such as data and model documentation, data anonymization, responsible release, access control, and the reproducibility of findings? **Yes, see the Ethical Statement section. We adhered to ethical guidelines for analyzing publicly available social media data. All analyses used aggregated data, and no personally identifiable information was collected or reported**.
- (i) Have you read the ethics review guidelines and ensured that your paper conforms to them? **Yes**.

2. Additionally, if your study involves hypotheses testing...

- (a) Did you clearly state the assumptions underlying all theoretical results? **NA**
- (b) Have you provided justifications for all theoretical results? **NA**
- (c) Did you discuss competing hypotheses or theories that might challenge or complement your theoretical results? **NA**
- (d) Have you considered alternative mechanisms or explanations that might account for the same outcomes observed in your study? **NA**
- (e) Did you address potential biases or limitations in your theoretical framework? **NA**
- (f) Have you related your theoretical results to the existing literature in social science? **NA**
- (g) Did you discuss the implications of your theoretical results for policy, practice, or further research in the social science domain? **NA**

3. Additionally, if you are including theoretical proofs...

- (a) Did you state the full set of assumptions of all theoretical results? **NA**

- (b) Did you include complete proofs of all theoretical results? **NA**

4. Additionally, if you ran machine learning experiments...

- (a) Did you include the code, data, and instructions needed to reproduce the main experimental results (either in the supplemental material or as a URL)? **NA**
- (b) Did you specify all the training details (e.g., data splits, hyperparameters, how they were chosen)? **NA**
- (c) Did you report error bars (e.g., with respect to the random seed after running experiments multiple times)? **NA**
- (d) Did you include the total amount of compute and the type of resources used (e.g., type of GPUs, internal cluster, or cloud provider)? **NA**
- (e) Do you justify how the proposed evaluation is sufficient and appropriate to the claims made? **NA**
- (f) Do you discuss what is "the cost" of misclassification and fault (in)tolerance? **NA**

5. Additionally, if you are using existing assets (e.g., code, data, models) or curating/releasing new assets, **without compromising anonymity**...

- (a) If your work uses existing assets, did you cite the creators? **NA**
- (b) Did you mention the license of the assets? **NA**
- (c) Did you include any new assets in the supplemental material or as a URL? **NA**
- (d) Did you discuss whether and how consent was obtained from people whose data you're using/curating? **NA**. Because the data were public and non-identifiable, the ethics committee granted a waiver of informed consent.
- (e) Did you discuss whether the data you are using/curating contains personally identifiable information or offensive content? **Yes, in the Ethical Statement section**.
- (f) If you are curating or releasing new datasets, did you discuss how you intend to make your datasets **FAIR**? **NA**
- (g) If you are curating or releasing new datasets, did you create a Datasheet for the Dataset? **NA**

6. Additionally, if you used crowdsourcing or conducted research with human subjects, **without compromising anonymity**...

- (a) Did you include the full text of instructions given to participants and screenshots? **NA**
- (b) Did you describe any potential participant risks, with mentions of Institutional Review Board (IRB) approvals? **Yes, in the Ethical Statement section**
- (c) Did you include the estimated hourly wage paid to participants and the total amount spent on participant compensation? **NA**
- (d) Did you discuss how data is stored, shared, and deidentified? **NA**

Appendix

Subreddit 1	Subreddit 2	<i>B</i>	<i>p</i>
ADHD	DID	0.017	0.000
ADHD	OCD	0.015	0.000
ADHD	dyspraxia	0.009	0.000
ADHD	Tourettes	0.010	0.002
ADHD	BPD	0.011	0.002
ADHD	ptsd	0.006	0.002
ADHD	Dyslexia	0.007	0.003
ADHD	autism	0.041	0.003
ADHD	depression	-0.011	0.008
ADHD	Anxiety	-0.001	0.386
ADHD	schizophrenia	-0.002	0.439
ADHD	socialanxiety	0.001	0.539
ADHD	bipolar	0.001	0.712
Anxiety	depression	-0.038	0.000
Anxiety	socialanxiety	-0.011	0.000
Anxiety	bipolar	-0.017	0.000
Anxiety	autism	0.013	0.002
Anxiety	OCD	0.007	0.005
Anxiety	dyspraxia	0.003	0.006
Anxiety	Tourettes	0.006	0.011
Anxiety	DID	0.006	0.017
Anxiety	schizophrenia	-0.009	0.021
Anxiety	BPD	-0.007	0.075
Anxiety	ptsd	-0.003	0.141
Anxiety	Dyslexia	0.000	0.854
autism	dyspraxia	0.009	0.000
autism	ptsd	0.009	0.002
autism	depression	0.012	0.004
autism	socialanxiety	0.013	0.008
autism	bipolar	0.012	0.015
autism	schizophrenia	0.005	0.037
bipolar	depression	-0.031	0.000
bipolar	socialanxiety	-0.011	0.001
bipolar	dyspraxia	0.003	0.001
bipolar	ptsd	-0.003	0.025
bipolar	schizophrenia	-0.005	0.146
BPD	autism	0.018	0.000
BPD	DID	0.012	0.001
BPD	OCD	0.008	0.005
BPD	dyspraxia	0.003	0.005
BPD	Tourettes	0.005	0.014
BPD	socialanxiety	-0.003	0.029
BPD	bipolar	-0.006	0.053
BPD	depression	-0.012	0.091
BPD	Dyslexia	0.001	0.095
BPD	schizophrenia	-0.004	0.154
BPD	ptsd	0.002	0.367
depression	socialanxiety	-0.023	0.000
depression	schizophrenia	-0.015	0.012
depression	dyspraxia	0.003	0.033
depression	ptsd	-0.006	0.045
DID	OCD	0.010	0.000
DID	autism	0.018	0.000
DID	dyspraxia	0.003	0.000
DID	Dyslexia	0.003	0.001
DID	socialanxiety	0.004	0.001
DID	Tourettes	0.006	0.001
DID	ptsd	0.008	0.002
DID	bipolar	0.006	0.006
DID	depression	0.006	0.111
DID	schizophrenia	0.003	0.119
Dyslexia	autism	0.006	0.000
Dyslexia	Tourettes	0.002	0.005
Dyslexia	OCD	0.002	0.009
Dyslexia	ptsd	0.001	0.087
Dyslexia	socialanxiety	0.001	0.180
Dyslexia	bipolar	0.000	0.303
Dyslexia	schizophrenia	0.000	0.545
Dyslexia	depression	-0.001	0.553
Dyslexia	dyspraxia	-0.001	0.661
dyspraxia	socialanxiety	0.003	0.000
dyspraxia	ptsd	0.002	0.003
dyspraxia	schizophrenia	0.001	0.004
OCD	dyspraxia	0.003	0.001
OCD	autism	0.017	0.002
OCD	ptsd	0.005	0.005
OCD	Tourettes	0.007	0.008
OCD	bipolar	0.002	0.012

OCD	socialanxiety	0.001	0.188	autism	dyspraxia	0.003	0.012
OCD	schizophrenia	0.000	0.763	autism	ptsd	0.004	0.048
OCD	depression	0.000	0.964	autism	bipolar	0.002	0.100
ptsd	socialanxiety	-0.002	0.004	autism	schizophrenia	0.001	0.391
ptsd	schizophrenia	-0.002	0.070	bipolar	depression	-0.012	0.000
schizophrenia	socialanxiety	-0.006	0.017	bipolar	ptsd	0.003	0.020
Tourettes	autism	0.011	0.000	bipolar	schizophrenia	0.008	0.037
Tourettes	dyspraxia	0.003	0.002	bipolar	dyspraxia	0.000	0.229
Tourettes	socialanxiety	0.003	0.006	BPD	socialanxiety	-0.001	0.487
Tourettes	bipolar	0.004	0.007	BPD	autism	0.008	0.001
Tourettes	schizophrenia	0.002	0.007	BPD	OCD	0.006	0.001
Tourettes	ptsd	0.003	0.010	BPD	socialanxiety	0.002	0.008
Tourettes	depression	0.003	0.151	BPD	DID	0.005	0.009

Table 1. Slope coefficients reflecting the average annual change in similarity (2015-2022) between subreddit pairs using text-based TF-IDF representations.

Subreddit 1	Subreddit 2	<i>B</i>	<i>p</i>
ADHD	BPD	0.010	0.000
ADHD	ptsd	0.008	0.000
ADHD	socialanxiety	0.006	0.000
ADHD	DID	0.003	0.001
ADHD	autism	0.031	0.002
ADHD	OCD	0.007	0.002
ADHD	dyspraxia	0.004	0.002
ADHD	bipolar	0.005	0.008
ADHD	Dyslexia	0.006	0.008
ADHD	schizophrenia	0.002	0.012
ADHD	Tourettes	0.005	0.013
ADHD	Anxiety	0.003	0.059
ADHD	depression	-0.003	0.071
Anxiety	depression	-0.026	0.000
Anxiety	autism	0.004	0.001
Anxiety	bipolar	-0.004	0.004
Anxiety	socialanxiety	-0.005	0.005
Anxiety	OCD	0.008	0.005
Anxiety	schizophrenia	-0.001	0.019
Anxiety	ptsd	-0.002	0.024
Anxiety	dyspraxia	0.001	0.094
Anxiety	BPD	-0.001	0.105
Anxiety	Tourettes	0.001	0.174
Anxiety	DID	0.001	0.362
Anxiety	Dyslexia	0.000	0.611
autism	socialanxiety	0.007	0.000
autism	depression	0.004	0.002

depression	schizophrenia	-0.005	0.014
depression	ptsd	-0.003	0.021
depression	socialanxiety	-0.011	0.043
depression	dyspraxia	0.000	0.660
DID	Tourettes	0.010	0.001
DID	autism	0.011	0.001
DID	socialanxiety	0.001	0.002
DID	OCD	0.004	0.005
DID	Dyslexia	0.001	0.016
DID	dyspraxia	0.001	0.048
DID	bipolar	0.002	0.286
DID	ptsd	-0.001	0.303
DID	depression	0.000	0.958
DID	schizophrenia	0.000	0.963
Dyslexia	Tourettes	0.002	0.013
Dyslexia	OCD	0.001	0.201
Dyslexia	depression	-0.001	0.229
Dyslexia	dyspraxia	-0.003	0.253
Dyslexia	bipolar	0.000	0.297
Dyslexia	ptsd	-0.001	0.392
Dyslexia	socialanxiety	0.000	0.466
Dyslexia	schizophrenia	0.000	0.482
Dyslexia	autism	0.002	0.526
dyspraxia	socialanxiety	0.002	0.004
dyspraxia	ptsd	0.001	0.067
dyspraxia	schizophrenia	-0.001	0.088
OCD	socialanxiety	0.005	0.000
OCD	autism	0.010	0.000
OCD	ptsd	0.004	0.006

OCD	dyspraxia	0.001	0.009
OCD	bipolar	0.004	0.012
OCD	schizophrenia	0.001	0.082
OCD	depression	0.002	0.259
OCD	Tourettes	0.002	0.604
ptsd	schizophrenia	0.002	0.050
ptsd	socialanxiety	0.001	0.238
schizo- phrenia	socialanxiety	0.000	0.458
Tourettes	autism	0.011	0.003
Tourettes	bipolar	0.002	0.008
Tourettes	ptsd	0.003	0.011
Tourettes	dyspraxia	0.001	0.018
Tourettes	socialanxiety	0.001	0.264
Tourettes	depression	-0.001	0.290
Tourettes	schizophrenia	0.000	0.756

Table 2. Slope coefficients reflecting the average annual change in similarity (2015-2022) between subreddit pairs using user-based TF-IDF representations.