Public perception and changing attitudes toward antidepressants over a decade in social media: lessons learned from online discussion using artificial intelligence

Min Ho An, Min Kyu Kim, Jueon Kim, Seheon Chang, Dong Yun Lee, Rae Woong Park

Table of Contents

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Abstract

Background: Antidepressants play a crucial role in treating mental health disorders such as depression and anxiety. Understanding of patients' perspective on antidepressants is essential for improving treatment outcomes; however, year-to-year change in the public's perception of antidepressants remain unclear.

Objective: This study aimed to analyze changes in public sentiments and predominant perceptions regarding antidepressants over the past 14 years using artificial intelligence pipeline.

Methods: This study analyzed online discussions related to antidepressants on Reddit from January 1, 2009, to December 31, 2022. Antidepressant-associated communities were explored to collect a list of discussions relevant to antidepressant therapy. Discussion topics on antidepressants were identified using BERTopic, and the sentiments were analyzed using a RoBERTa model. Trends were assessed using the Mann–Kendall test to evaluate shifts in sentiments over time.

Results: We analyzed 429,510 antidepressant-related from 204,035 unique authors over 14 years, with negative sentiments predominating (mean negative score: >0.5 across all groups). The most frequently mentioned medications were Lexapro (13.4%), Zoloft (13.0%), and Prozac (10.9%). Analysis revealed three key discussion clusters: (1) benefits and side effects of antidepressants, (2) drug switching experiences, and (3) bupropion-specific concerns. Trend analyses showed a significant decrease in negative sentiments (Mann-Kendall score: -71, z=0.2, p<0.05) and an increase in neutral sentiments (Mann-Kendall score: 57, z=3.5, p<0.05) over time. This trend corresponded with a significant decline in side effect-related topics (Mann-Kendall score: -71, z:-3.8, p<0.05) within the clusters.

Conclusions: Negative perceptions toward antidepressants are prevalent on social media, mainly focusing on efficacy and side effects. However, a decade-long analysis shows a decline in negative sentiments, with an increase in neutral sentiments with downturn in yearly proportion of side-effected related topics within each cluster. These trends and information may help improve strategies to address barriers to antidepressant use and adherence.

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Abstract

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Conclusions. Negative perceptions toward antidepressants are prevalent on social media, mainly focusing on efficacy and side effects. However, a decade-long analysis shows a decline in negative sentiments, with an increase in neutral sentiments with downturn in yearly proportion of side-effected related topics within each cluster. These trends and information may help improve strategies to address barriers to antidepressant use and adherence.

Introduction

Antidepressants are essential for managing and treating various mental health conditions, such as depression and anxiety, which are prevalent globally [34,35]. They are among the most frequently prescribed medications in the United States (US) from the age of 20 to 59 years [21]. Luo et al [20] have also documented a rise in the prevalence of major depressive disorder (MDD) among patients in the US, accompanied with an increase in the prescription of antidepressant medications [27].

Owing to their proven efficacy and large availability, antidepressants are crucial in the clinical management of MDD [6,7]. Despite the potential therapeutic benefits, many patients often hesitate in initiating or adhering to antidepressant therapy [5]. Adherence to long-term antidepressant therapy is crucial for symptom remission and relapse prevention in MDD [22]. Consequently, a comprehensive understanding of patient-level perspectives on antidepressants is essential for improving treatment outcomes and developing public health strategies involving antidepressant use. Additionally, physicians' education in preventing the early discontinuation of antidepressants is important [9] and has been integrated into clinical practice. Nonetheless, evidence regarding how public sentiment on antidepressants has changed over time is lacking.

Social media platforms have become valuable in acquiring public health perceptions beyond the clinic, [12,31] often used for sharing experiences, seeking advice, or sparking debates on health topics. For instance, prior research has harnessed social media as a data source to explore the public's perspective on statins [13,32]. In recent years, Reddit, a popular social media platform, has become a significant hub for health-related discussions. In 2022, the platform recorded an upload of over 490 million posts and 2 billion comments [30]. It provides an extensive dataset of public opinions, experiences, and concerns about various health topics, including antidepressants [23.33]. When analyzing social media, it has been reported that leveraging artificial intelligence techniques such as natural language processing (NLP) can efficiently process, interpret, and extract insights from large

amounts of textual data [24,32,36].

Therefore, we hypothesized that social media data analysis using artificial intelligence could reveal trends in public sentiment, common perceptions, and potential misconceptions about antidepressant therapy. This study aimed to analyze trends in public perceptions and concerns regarding antidepressants over the past 14 years by examining a substantial corpus of discussions in Reddit.

Methods

Ethics approval

Analyses were approved by local scientific and ethics committees (Ajou University Medical Center Institutional Review Board: AJOUIRB-EX-2024-258). Also, this study conformed to the guidelines of the Standards for Reporting Qualitative Research [26].

Data Sources

This study used Reddit as the data source. This platform consists of various communities, each designated by an "r/" prefix. Users can engage with Reddit by posting to start a new discussion thread or by adding comments on others' posts within these discussions. Most of these communities, including all the posts and comments within them, are open to public viewing and access.

To curate a dataset of antidepressant-related discussions on Reddit, we employed the methodology delineated by Somani et al [32]. Initially, we identified appropriate communities by querying the terms "depression" and "antidepressant" in the platform's search engine, subsequently selecting those communities recommended by the engine for both queries. All posts and comments including author information, name of subreddit, title, body of text, created time within these identified communities were systematically collected using the Pushshift Application Programming Interface (API). We collected data from 2009 to 2022. This search was conducted for case-insensitive occurrences of the term "antidepressant" and for both the generic and brand names of specific

antidepressants **(Multimedia Appendix 1, Table S1)** [4].

Data Preprocessing and Cleansing for the Text Analysis of Social Media Posts

In the preprocessing of 832,359 collected raw text data, several steps were undertaken to ensure data quality and relevance (**Multimedia Appendix 1, Figure S1**). Initially, we identified and removed duplicate entries, resulting in the exclusion of 12,587 rows. Next, we eliminated rows containing null values (n = 15). Subsequently, instances of text indicating post or comment deletion, characterized by placeholders such as "[deleted]" or attributes such as "NA," were replaced with empty spaces. Furthermore, any text comprising fewer than five characters was removed from the dataset (n = 18). The final stage of preprocessing involved converting all texts into lowercase for consistency. Ultimately, the dataset comprised 819,739 posts and comments.

Topic Modeling

For analyzing trends that reflect public perception, we first clustered users' topics. Specifically, we employed BERTopic, [14] an advanced NLP method that uses the capabilities of bidirectional encoder representations from transformers (BERT) models for topic modeling. Various discussion topics surrounding antidepressants were identified using BERTopic. We first used sentence-BERT and then the uniform manifold approximation and projection (UMAP) technique to simplify this representation by dimensionality reduction. The all-MiniLM-L6-v2 pretrained model was used for the sentence-BERT and for a vast array of trained data including more than 700 million Reddit comments and trained with a dataset called the Semantic Scholar Open Research Corpus, which contains more than 100 million abstracts[10]. Next, we used HDBScan to find clusters of documents that corresponded to specific topics. Thereafter, we used class-based term frequency inverse document frequency (c-TF-IDF) techniques to identify keyword expressions for each topic based on the documents presented.

Given that the topics generated by BERTopic are highly granular, we conducted another

clustering to select large topics, as applied in previous study [32]. Before additional clustering, each generated topic was manually reviewed by a psychiatrist to ensure accurate and appropriate large topic clustering. This process involved the examination of at least five documents, which were randomly selected from within each topic to warrant the relevance and consistency of the topic categorization. Subsequently, UMAP and spectral clustering were conducted on the c-TF-IDF representation of each topic to group these topics. To measure clustering performance and determine the final number of clusters, we used silhouette coefficient measures[28] and the Davies–Bouldin index [8].

Sentiment and Trend Analyses

After topic clustering, we analyzed public's sentiments from all documents and topics and their trends. Sentiment analysis techniques are designed to identify and assess the underlying tone or attitude present in relation to a specific topic within a document's context [18]. The sentiment of each post was evaluated using a pretrained BERT model, specifically a version of RoBERTa fine-tuned on a dataset for sentiment analysis [19]. RoBERTa can assign multiclass labels to text, categorizing it as positive, neutral, or negative. This model has gained recognition in recent research focused on healthcare issues, particularly in studies that analyze data derived from social media platforms [3,17,32]. For each discussion, RoBERTa calculated a positive, neutral, and negative score and ensured that the sum of the three scores equaled 1. Thus, each discussion was represented by a ratio of positive, neutral, and negative sentiments. The sentiment with the most dominant score was then labeled.

We evaluated trends in sentiments over time by using the Mann–Kendall test, which assesses whether a monotonic increasing or decreasing trend occurred over time. We also analyzed the trends by drug, evaluated the score within each label (e.g., negative scores for negative labels), and the yearly proportion of topics within each cluster.

Statistical Analysis

All statistical data were analyzed using Python, version 3.8.8 (Python Software Foundation), alongside several essential libraries, including scikit-learn, version 1.3.1; BERTopic, version 0.15.0; transformers, version 4.33.2; and matplotlib, version 3.7.3. The characteristics of the posts and comments were quantitatively described using mean values and standard deviations. Trends were analyzed through the original Mann–Kendall tests using the PyMannKendall package, version 1.4.3. A p-value of 0.05 was considered statistically significant. To enhance the statistical power of the analyses, we used annual mean values. Codes are available on [37].

Results

Data Characteristics and Topic Clustering

AI driven topic clustering and trend analysis workflow for this study is depicted **(Multimedia Appendix 1, Figure S1)**. After searching for "depression" and "antidepressant" within the platform's search engine, we identified 29 subedits relevant to both queries. In 819,739 discussions, subsequent topic and group clustering, excluding off-topic discussions, resulted in a refined dataset of 429,510 discussions (**Table 1**). Within the generic and brand names of specific antidepressants, the largest single-word search terms were selective serotonin reuptake inhibitors (SSRIs), including "Lexapro", "zoloft," and "prozac", which accounted for 13.4%, 13.0%, and 10.9% of the search queries, respectively. The subreddits "Anxiety" (15.3%) and "AskReddit" (14.6%) were the most active in discussions containing prespecified keywords, followed by "ADHD" (12.5%) and "depression" (11.9%). Furthermore, descriptive analysis identified 204,035 unique authors.

Table 1. Discussion Summary Statistics

Characteristic, category	All discussions	Comments	Posts
No. of discussions scraped	429510	344478	85032
No. of characters, mean (SD)	512.7 (748.5)	432.3 (557.8)	838.5 (1198.9)
Unique authors	204035	169906	52618
Search words			
lexapro	57597 (13.4%)	44608 (12.9%)	12989 (15.3%)
zoloft	55922 (13.0%)	45236 (13.1%)	10686 (12.6%)
prozac	46956 (10.9%)	38049 (11.0%)	8907 (10.5%)
effexor	28921 (6.7%)	23523 (6.8%)	5398 (6.3%)
paxil	15132 (3.5%)	12159 (3.5%)	2973 (3.5%)
cymbalta	14894 (3.5%)	11722 (3.4%)	3172 (3.7%)
Subreddit			
Anxiety	65669 (15.3%)	49699 (14.4%)	15970 (18.8%)
AskReddit	62774 (14.6%)	60825 (17.7%)	1949 (2.3%)
ADHD	53675 (12.5%)	41698 (12.1%)	11977 (14.1%)
depression	51202 (11.9%)	34090 (9.9%)	17112 (20.1%)
depressionregimens	28637(6.7%)	24576 (7.1%)	4061 (4.8%)
Nootropics	25698 (6.0%)	21760 (6.3%)	3938 (4.6%)
bipolar	20608 (4.8%)	17513 (5.1%)	3095 (3.6%)
AskDocs	19814 (4.6%)	11029 (3.2%)	8785 (10.3%)
shrooms	12206 (2.8%)	9626 (2.8%)	2580 (3.0%)
mentalhealth	10935 (2.5%)	7216 (2.1%)	3719 (4.4%)
microdosing	10224 (2.4%)	8314 (2.4%)	1910 (2.2%)
BipolarReddit	8352 (1.9%)	7221 (2.1%)	1131 (1.3%)
BabyBumps	7738 (1.8%)	6933 (2.0%)	805 (0.9%)
science	7184 (1.7%)	6982 (2.0%)	202 (0.2%)
bipolar2	6766 (1.6%)	5895 (1.7%)	871 (1.0%)
AskPsychiatry	6064 (1.4%)	3555 (1.0%)	2509 (3.0%)
stopdrinking	6018 (1.4%)	4733 (1.4%)	1285 (1.5%)
SuicideWatch	5050 (1.2%)	3729 (1.1%)	1321 (1.6%)
relationship_adivce	4450 (1.0%)	4014 (1.2%)	436 (0.5%)
todayilearned	4407 (1.0%)	4336 (1.3%)	71 (0.1%)
trees	4184 (1.0%)	3792 (1.1%)	392 (0.5%)
depression_help	1877 (0.4%)	1304 (0.4%)	573 (0.7%)

The volume of online discussions related to antidepressants demonstrated a increase over 14 years (**Multimedia Appendix 1, Figure S2A**). The frequency of antidepressant-related discussions dynamically increased in certain communities, such as "ADHD" and "Anxiety" in 2020–2022 (**Multimedia Appendix 1, Figure S2B and S2C**). In addition, the annual count of antidepressant-related posts and comments increased over time after clustering (**Multimedia Appendix 1, Figure S2D**).

Initially, topic clustering yielded 98 distinct antidepressant-related discussion topics from the final dataset. (**Multimedia Appendix 1, Figure S3)** presents a hierarchical representation of these topics. From the 98 topics, irrelevant topics (e.g., antidepressants were only mentioned, and the topic was about something else) were excluded through a manual review by a psychiatrist, resulting in a final dataset of 73 topics (429,510 discussions). From the 73 topics categorized, three primary groups emerged according to clustering performance (**Table 2, Figure 1A, Multimedia Appendix 1 Figure S4**): (1) "Benefits and side effects of antidepressants," (2) "Drug switch, augmentation, alcohol, sertraline, escitalopram," and (3) "Bupropion, effect, seizure, weight, augmentation."

Table 2. Overview of groups of topics with example text

Group	No. Posts	Comments	Description	Sentiment	Example text
1 [a]	6143 5	240938	Benefits and side effects of antidepressants	Positive	"Cymbalta and citalopram are what worked for me in combo with amitriptyline for migraines. Antidepressants were the answer for me."
				Negative	"I was on Paxil for about 10 years and started having the brain fog symptoms about 5-6 years being on it. it got worse so I was thinking maybe Paxil caused the brain fog"
				Negative	"started taking lexapro for my anxiety, need help I'm experiencing one of the side effects of the medicine, it makes me unable to ejaculate. is this temporary? or should I just stop taking it. I started it yesterday."
				Negative	"recently, I've been reading a lot about how antidepressants are beginning to be recognized as not being effective. if this is true, biochemically speaking, why don't they work? I have read that a series

9

					of pivotal studies determining the effectiveness of antidepressants have resulted in the conclusion that their effect is not clinically significant. it has been claimed that any benefit from taking these drugs is merely just a placebo effect."
2 [b]	2038 2	83158	Drug switch, augmentation, alcohol, sertraline, escitalopram	Negative	"Switching Zoloft to Lexapro? I've been on Zoloft for over 4 years now (50mg right now, but I've been up to 100mg) and I think it may be losing its effectiveness, as in the last year I've had a pretty major resurgence of symptoms that come and go."
				Negative	"zoloft cocktail so, I've realized that I drink as a way to cope with my anxiety and depression. I'm on zoloft for both, and when I drink it intensifies the effects of my medication."
				Negative	"I know the thing I really need to walk away from is the alcohol. I've been on a medication for it, and mixing that with therapy now (only 2 weeks in)."
				Positive	"naltrexone and lexapro helped me with my relationship with alcohol and my husband"
3 [c]	3409	20382	Bupropion, effect, seizure, weight, augmentation	Neutral	"Does anyone have experience with bupropion? I was diagnosed with major depression, and my doctor prescribed me bupropion.
				Negative	"I took too many wellbutrin. purposely overdosed on wellbutrin 2 days ago. My stupid decision resulted in 2 seizures within a 4 hour time span."
				Negative	"Sudden weight loss on wellbutrin? I know I have to mention this to my psychiatrist the next time I see him at the end of september, I'm just wondering if it's common."
				Negative	"wellbutrin and excessive sex drive ever since being on wellbutrin, I've had an overly excessive sex drive to the point where I become almost angry when my day lacks intimacy with my partner. has anyone else noticed this? any suggestions? this is a cross post of something I submitted at /r/sex

[a] Topic number of Group1: 1, 4, 6, 7, 8, 9, 12, 13, 14, 15, 16, 18, 19, 24, 25, 26, 27, 30, 31, 32, 33, 36, 37, 39, 41, 44, 46, 48, 51, 53, 57, 60, 61, 62, 68, 69, 70, 74, 76, 81, 85, 86, 87, 91, 92, 93, 96, 97

[b] Topic number of Group2: 3, 5, 10, 11, 21, 29, 59, 65, 66, 71, 77, 80, 82, 90

[c] Topic number of Group3: 22, 23, 47, 49, 50, 55, 58, 67, 75, 78,

After reviewing the texts categorized into distinct topic clusters, we found a considerable number of discussions predominantly featuring personal experiences associated with antidepressant administration. Also, there were 5 or fewer dicussions per author (**Multimedia Appendix 1, Figure S5)**. The first topic cluster encompasses queries about antidepressant use, with individuals sharing their personal stories, including the perceived benefits and side effects. In the second topic, the discourse shifts to experiences related to switching between different antidepressants, along with inquiries and anecdotes about the implications of consuming alcohol while on these medications. The third topic is specifically focused on bupropion, highlighting its effects and side effects, especially the risk of seizures and the potential for weight loss.

Sentiment Analysis Results

In the 429,510 online discussions, we categorized sentiments into positive, neutral, and negative. Sentiments were analyzed both by topic groups and by antidepressant types (**Table 2, Multimedia Appendix 1 Table S1 and S2**). An example of a comment with negative sentiments from Topic Cluster 1 is as follows: "I was on Paxil for about 10 years and started experiencing brain fog symptoms after 5–6 years. It worsened over time, leading me to suspect Paxil as the cause." Conversely, a positive sentiment can be exemplified by the following comment: "Cymbalta and citalopram are what worked for me in combination with amitriptyline for migraines. Antidepressants were the answer for me." However, negative sentiments were the most prevalent among all the sentiment categories; **Figure 1B** illustrates their distribution. Furthermore, the mean negative scores for each group were consistently above 0.5 (**Multimedia Appendix 1, Table S3**). We also provided the mean negative sentiment score for each topic in (**Multimedia Appendix 1, Table S4)**.

We measured the fluctuations in sentiment proportions over time to analyze the

11

temporal changes in sentiment trends across all the antidepressants discussed (**Figure 2A, Multimedia Appendix 1 Table S5**). The negative sentiments remained to be the most frequent during the observation period, followed by the neutral sentiments and then the positive sentiments. Regarding the annual trend analysis of these sentiments over time, the proportion of negative sentiments (Mann–Kendall score: −71, z = 0.2, p < 0.05) steadily decreased, whereas those of neutral sentiments (Mann–Kendall score: 57, z = 3.5, p < 0.05) and positive sentiments (Mann–Kendall score: 61, z = 3.8, p < 0.05) steadily increased (**Multimedia Appendix 1, Table S6**). However, when trends were analyzed starting from 2013, no significant uptrend in positive sentiments (Mann-Kendall score: 32, z= 0.4, p = 1.56) was observed, while the significance of trends for neutral (Mann-Kendall score:32, z=3.23, p<0.05) and negative sentiments (Mann-Kendall score:-34, z=-3.44, p<0.05 was maintained (**Multimedia Appendix 1, Table S7**).

Moreover, an additional sensitivity analysis was conducted to evaluate changes in sentiment trends over time for individual antidepressants (**Multimedia Appendix 1, Table S8**). Interestingly, among all the drugs analyzed for trend, SSRIs and serotonin and norepinephrine reuptake inhibitors (SNRIs) showed a significant decline in negative sentiments alongside an increase in neutral sentiments. Overall, for each drug, negative sentiments exhibited either a stable pattern or a downward trend, whereas neutral and positive sentiments displayed either a stable pattern or an upward trend. No significant upward trends in negative sentiments or downward trends in positive or neutral sentiments were observed.

Next, we analyzed the change in the strength of the probability of classifying sentiments into their designated labels over time (**Figure 2B**). For instance, we examined the trend of how dominant the proportion of negatives was within the group classified as negative over the years. The probability of sentiment classification within the neutral sentiments (Mann–Kendall score: 65, z = 3.5, p < 0.05) and positive sentiments (Mann–Kendall score:

12

71, z = 3.8, p < 0.05) also showed significant rise (**Multimedia Appendix 1, Table S9**).

Temporal Changes in Topics and Sentiments

To better understand the observed trends, we conducted a further analysis of the annual changes in topic proportions within each cluster, focusing specifically on topics that constituted at least 3% of the discussions within cluster per year (**Figure 3**). Then, two example text from given topic is randomly selected and provided in (**Multimedia Appendix 1, Table S10)**. In cluster 1, we observed a notable increase in the proportion of discussions (Mann-Kendall score: 75, z= 4.05, p <0.05) related to ADHD (topic 1), involving terms such as "ADHD," "ADHD medication," and "antidepressant effect" A case from the discussions illustrates patient's inquiry about the use of antidepressant and ADHD medication together. Concurrently, there was a decrease in discussions concerning the side effects of antidepressants, including Prozac (Mann-Kendall score: -71, z:-3.8, p < 0.05, topic 4), sexual side effects (Mann-Kendall score:-41, z:-2.19, p<0.05, topic 7), and Effexor (Mann-Kendall score: -69, z:-3.72, p<0.05, topic 8). In cluster 2, a decline in Topic 5(Man-Kendall score:-79, z:-4.27, p<0.05) is observed, which is characterized by terms such as "stop," "dose," "side effect," and "withdrawal from Zoloft.". An illustrative example from this topic is: "I stopped taking my zoloft for a solid week. I had a constant headache and cried all the time." Conversely, Topic 10, which includes terms like "switch," "augmentation," and "stop from sertraline," exhibited an increase (Mann-Kendall score:87, z: 4.71, p<0.05). For cluster 3, there was an increase in discussions pertaining to the benefits of bupropion (Mann-Kendall score: 57, z: 3.06, p<0.05, topic22) A representative example from these discussions is: "I'm very happy you found meds that work. (bupropion)." In contrast, the seizure related topics with bupropion decreased (Mann-Kendall score: -59, z:-3.18,p<0.05, topic 55).

Lastly, the yearly change in sentiment proportion within represented topics in (**Multimedia Appendix 1, Figure S6)** to show the annual sentiment composition difference

13

among the topics and proportional change of each sentiment within the topic.

4. Discussion

Principal Results

Our study examined 429,510 online discussions from 204,035 unique authors across various subreddits from 2009 to 2022. This dataset, obtained from an initial pool of over 800,000 discussions, provides both public perception and individual experiences with antidepressant use, providing a unique perspective on real-world concerns and sentiments toward antidepressants.

Among the discussions about antidepressants over 14 years, medications such as Lexapro and Zoloft were most frequently mentioned, aligning with their prevalent use in clinical settings. The subreddit "Anxiety" appeared as one of the leading platforms for these discussions, suggesting that concerns and inquiries related to antidepressants are highly frequent within communities engaged in anxiety-related topics.

Through topic modeling, we identified 73 distinct discussion themes. The topics were grouped into (1) the benefits and side effects of antidepressants, (2) drug switching and the interaction with alcohol, and (3) specific discussions around bupropion. This categorization underlines the community's interest in realistic, experience-based information beyond what is typically available through a clinical context.

The cluster 1, which encompasses the largest number of topics compared to other clusters, primarily addresses the benefits and side effects associated with antidepressants, indicating the major concern for antidepressant among patients. Topics related to side effects or specific circumstances include changes in sex drive (topic 7), pregnancy (topic 18), nausea (topic 37,97), weight gain (topic 27), brain zaps, fog (topic 44, 96), memory loss (topic 51), No effect in anhedonia (topic 60), hair loss (topic 92), and diarrhea (topic 93) These aspects

14

are likely subjects of interest among individuals and may require comprehensive explanation within clinical settings.

While the cluster 1 primarily focused on the side effects and benefits of antidepressants, the cluster 2 addressed concerns for switching, augmenting, or discontinuing antidepressant. Among the topics in the cluster, particularly extracted medications as a topic keyword were sertraline (Zoloft), escitalopram (Lexapro), and trazodone (for insomnia). This may indicate that patient may have many worries or concerns whether to switch, augment or stop from these medications. In addition, we found that a patient's significant focus was on medication interactions, particularly with alcohol. Patients may not be informed about the interaction of alcohol consumption with antidepressants, or they may hesitate to ask their physicians about alcohol intake because of anticipated negative responses from healthcare providers, [25] indicating a barrier to open communication.

The cluster 3 addressed issues with the use of bupropion, a medication categorized as a norepinephrine and dopamine reuptake inhibitor (NDRI). It finds application not only in smoking cessation but also off-label for conditions such as ADHD[16] and weight loss [15]. This unique classification, owing to its diverse therapeutic utility compared to conventional antidepressants, implies its categorization into a distinct cluster.

The sentiment analysis further enriches our understanding of patient perception. Negative sentiments were the most predominant among the three sentiments, indicating its possible link with medication adherence, considering that the clustered groups contained topics about the antidepressants' side effects and drug switching. Therefore, the importance of in-depth explanations about the drugs' effects and potential side effects should be further emphasized [2].

The sentiment trends related to antidepressant use have also revealed the public perception of these medications over time. The consistent predominance of negative

15

sentiments throughout the observation period highlights the challenges and concerns associated with antidepressant use. However, our annual trend analysis showed a gradual shift, with a steady decrease in negative sentiments and an increase in neutral sentiments. This trend was also consistent in the sensitivity analyses of SSRIs and SNRIs. This shift may reflect greater acceptance and understanding of mental health challenges and the role of medication in managing these conditions [29]. It may also indicate improved experiences with antidepressants, perhaps because of better patient education, more effective treatment approaches, or advancements in the development of these drugs.

Furthermore, the observed increase in the certainty of sentiment classification over time, especially within the neutral and positive sentiment categories, suggests that public opinions on antidepressants are becoming more pronounced and definitive. This trend may reflect a growing body of shared experiences and knowledge among users, fostering a community of informed individuals who can confidently articulate their perspectives.

To further elucidate the observed shift in sentiment, additional analyses were conducted to assess changes in the annual proportions of major topics within clusters. In the cluster 1, there has been an increasing trend in the discussion of topics related to ADHD and antidepressants, encompassing terms such as 'ADHD,' 'ADHD medications' and 'antidepressants effects'. This trend may align with previous studies indicating an increase in ADHD diagnoses,[11] and findings suggesting that a concomitant diagnosis of ADHD with depression is prevalent[11]. Moreover, while discussions about the side effects of antidepressants have diminished in Cluster 1 (topics 4, 7, 8), Cluster 2 (topic 5), and Cluster 3 (topic 55), there has been an increase in discussions on the benefits of bupropion within Cluster 3 (topic 22).This shift could indicate that patients are becoming more aware of the effects and side effects of antidepressants as their use accumulates over time, which may correspond with a decrease in negative sentiment and an increase in neutral sentiment."

16

Limitations

Although this study offers significant findings on public perceptions and trends in sentiment change, its inherent limitations should also be acknowledged. First, the data represent self-selected individuals willing to share their experiences on a public platform; thus, such data may not fully represent the broader population. Additionally, the inherent anonymity of users on the employed social media platform constrained us from identifying the demographic characteristics of individuals who posted and commented on the platform. Furthermore, social media user demographics are generally skewed toward a younger population, mostly ranging from 18 to 29 years;[30] this characteristic could influence the nature and context of the discussions analyzed. Additionally, the dataset for this study was obtained from prespecified communities identified as having the highest association with antidepressant-related discussions. Consequently, this approach may have excluded relevant posts and comments from other areas of the social media platform not encompassed within these specified communities. Lastly, spelling inaccuracies may result in the erroneous categorization of discussions, thereby attributing a false-positive sentiment related to antidepressant use.

Conclusions

In summary, the negative perceptions of antidepressants remain high on social media, with topics about drug effectiveness and side effects being the dominant topics. However, negative sentiments gradually decreased, while neutral sentiments increased over 10 years. This shift may align with a decrease in yearly proportion of side effect related topics within each cluster and an increase in discussions highlighting the benefits of antidepressants, particularly bupropion. These trends and information may help improve strategies to address barriers to antidepressant use and adherence.

17

18

Acknowledgments

Data availability

The data that support the findings of this study are available from the corresponding author upon reasonable request.

Author's Contributions

DY Lee and MH An conceptualized the study design. MH An and MK Kim were responsible for data curation, and together with DY Lee, conducted the formal analysis and developed the methodology. DY Lee led the project administration, while RW Park provided essential resources. The research was funded through grants acquired by DY Lee and RW Park. MH An drafted the original manuscript, which was critically reviewed and edited by J Kim, DY Lee, RW Park, and S Chang. All authors have read and approved the final version of the manuscript.

Conflicts of interest

The authors have nothing to report.

Abbreviations

ADHD: Attention Deficit Hyperactivity Disorder

API: Application Programming Interface

BERT: Bidirectional Encoder Representations from Transformers

c-TF-IDF: Class-based Term Frequency Inverse Document Frequency

MDD: Major Depressive Disorder

NDRI: Norepinephrine and Dopamine Reuptake Inhibitor

NLP: Natural Language Processing

SNRIs: Serotonin and Norepinephrine Reuptake Inhibitors

SSRIs: Selective Serotonin Reuptake Inhibitors

UMAP: Uniform Manifold Approximation and Projection

References

1. Reddit. URL: https://www.reddit.com [accessed 2023-03-26]

2. Alfian SD, Annisa N, Perwitasari DA, Coelho A, Abdulah R. The role of illness perceptions on medication nonadherence among patients with hypertension: a multicenter study in indonesia. Front Pharmacol 2022;13:985293. doi:10.3389/fphar.2022.985293

3. Baker W, Colditz JB, Dobbs PD, Mai H, Visweswaran S, Zhan J, et al. Classification of Twitter vaping discourse using BERTweet: comparative deep learning study. JMIR Med Inform 2022;10(7):e33678. doi:10.2196/33678

4. Baumgartner J, Zannettou S, Keegan B, Squire M, Blackburn J. The pushshift Reddit dataset. Proc Int AAAI Conf Web Soc Media 2020;14(1):830-839. doi:10.1609/icwsm.v14i1.7347

5. Bull SA, Hu XH, Hunkeler EM, Lee JY, Ming EE, Markson LE, et al. Discontinuation of use and switching of antidepressants: influence of patient-physician communication. JAMA 2002;288(11):1403-1409. doi:10.1001/jama.288.11.1403

6. Cipriani A, Furukawa TA, Salanti G, Chaimani A, Atkinson LZ, Ogawa Y, et al. Comparative efficacy and acceptability of 21 antidepressant drugs for the acute treatment of adults with major depressive disorder: a systematic review and network meta-analysis. Lancet 2018;391(10128):1357-1366. doi:10.1016/s0140-6736(17)32802-7

7. Cipriani A, Furukawa TA, Salanti G, Geddes J R, Higgins J P, Churchill R, et al. Comparative efficacy and acceptability of 12 new-generation antidepressants: a multiple-treatments meta-analysis. Lancet 2009;373(9665):746-758. doi:10.1016/s0140-6736(09)60046-5

8. Davies DL, Bouldin DW. A cluster separation measure. IEEE Trans Pattern Anal Mach Intell 1979;1(2):224-227. doi:10.1109/TPAMI.1979.4766909

21

9. Elizabeth HB, Von Korff M, Katon W, Bush T, Simon GE, Walker E, et al. The role of the primary care physician in patients' adherence to antidepressant therapy. Med Care 1995;33(1):67-74. doi:10.1097/00005650-199501000-00006

10. Face H. sentence-transformers/all-MiniLM-L6-v2. URL: https://huggingface.co/sentence-transformers/all-MiniLM-L6-v2 [accessed 2023-05-02]

11. Fairman KA, Peckham AM, Sclar DA. Diagnosis and treatment of ADHD in the United States: update by gender and race. J Atten Disord 2017;24(1):10-19. doi:10.1177/1087054716688534

12. Forgie EME, Lai H, Cao B, Stroulia E, Greenshaw AJ, Goez H. Social media and the transformation of the physician-patient relationship: viewpoint. J Med Internet Res 2021;23(4):e25230. doi:10.2196/25230

13. Golder S, O'Connor K, Hennessy S, Gross R, Gonzalez-Hernandez G. Assessment of beliefs and attitudes about statins posted on Twitter: a qualitative study. JAMA Netw Open 2020;3(6):e208953. doi:10.1001/jamanetworkopen.2020.8953

14. Grootendorst MR. BERTopic: neural topic modeling with a class-based TF-IDF procedure. arXiv 2022. URL: https://arxiv.org/abs/2203.05794

15. Hendricks EJ. Off-label drugs for weight management. Diabetes Metab Syndr Obes 2017;10:223-234. doi:10.2147/dmso.S95299

16. Huecker MR, Smiley A, Saadabadi A. Bupropion. In: StatPearls [Internet]. Treasure Island (FL): StatPearls Publishing 2024. ISBN:9781234567890

17. Kolluri N, Liu Y, Murthy D. COVID-19 misinformation detection: machine-learned solutions to the infodemic. JMIR Infodemiology 2022;2(1):e38756. doi:10.2196/38756

18. Liu B. Sentiment analysis and opinion mining. Springer Nature Switzerland AG 2022. ISBN:9783031025761

22

19. Liu Y, Ott M, Goyal N, Du J, Joshi M, Chen D, et al. Roberta: a robustly optimized bert pretraining approach. arXiv 2019. URL: https://arxiv.org/abs/1907.11692

20. Luo Y, Kataoka Y, Ostinelli EG, Cipriani A, Furukawa TA. National prescription patterns of antidepressants in the treatment of adults with major depression in the US between 1996 and 2015: a population representative survey based analysis. Front Psychiatry 2020;11:35. doi:10.3389/fpsyt.2020.00035

21. Martin CB, Hales CM, Gu Q, Ogden CL. Prescription drug use in the United States, 2015-2016. NCHS Data Brief 2019;346:1-8. PMID:31158240

22. Masand PS. Tolerability and adherence issues in antidepressant therapy. Clin Ther 2003;25(8):2289-2304. doi:10.1016/S0149-2918(03)80220-5

23. Melton CA, Olusanya OA, Ammar N, Shaban-Nejad A. Public sentiment analysis and topic modeling regarding COVID-19 vaccines on the Reddit social media platform: a call to action for strengthening vaccine confidence. J Infect Public Health 2021;14(10):1505-1512. doi:10.1016/j.jiph.2021.08.010

24. Melton CA, White BM, Davis RL, Bednarczyk RA, Shaban-Nejad A. Fine-tuned sentiment analysis of COVID-19 vaccine-related social media data: comparative study. J Med Internet Res 2022;24(8):e40408. doi:10.2196/40408

25. O'Donnell A, Abidi L, Brown J, Karlsson N, Nilsen P, Roback K, et al. Beliefs and attitudes about addressing alcohol consumption in health care: a population survey in England. BMC Public Health 2018;18(1):391. doi:10.1186/s12889-018-5275-2

26. O'Brien BC, Harris IB, Beckman TJ, Reed DA, Cook DA. Standards for reporting qualitative research: a synthesis of recommendations. Acad Med 2014;89(9):1245-1251. doi:10.1097/ACM.0000000000000388

27. Pratt LA, Brody DJ, Gu Q. Antidepressant use among persons aged 12 and over: United States, 2011-2014. NCHS Data Brief 2017;283:1-8. PMID:29155679

23

28. Rousseeuw PJ. Silhouettes: a graphical aid to the interpretation and validation of cluster analysis. J Comput Appl Math 1987;20:53-65. doi:10.1016/0377-0427(87)90125-7

29. Schomerus G, Schwahn C, Holzinger A, Corrigan PW, Grabe HJ, Carta MG, et al. Evolution of public attitudes about mental illness: a systematic review and meta-analysis. Acta Psychiatr Scand 2012;125(6):440-452. doi:10.1111/j.1600-0447.2012.01826.x

30. Shewale R. 14+ Reddit statistics for 2024 (eye-opening facts & data). URL: https://www.demandsage.com/reddit-statistics/ [accessed 2024-01-20]

31. Smailhodzic E, Hooijsma W, Boonstra A, Langley DJ. Social media use in healthcare: a systematic review of effects on patients and on their relationship with healthcare professionals. BMC Health Serv Res 2016;16:442. doi:10.1186/s12913-016-1691-0

32. Somani S, van Buchem MM, Sarraju A, Hernandez-Boussard T, Rodriguez F. Artificial intelligence-enabled analysis of statin-related topics and sentiments on social media. JAMA Netw Open 2023;6(7):e239747. doi:10.1001/jamanetworkopen.2023.9747

33. Song M, Xie Q. Characterizing the psychiatric drug responses of Reddit users from a socialomics perspective. J Informetr 2020;14(3):101056. doi:10.1016/j.joi.2020.101056

34. World Health Organization. Anxiety disorders [Internet]. Geneva: WHO 2023. URL: https://www.who.int/news-room/fact-sheets/detail/anxiety-disorders [accessed 2024-01-20]

35. World Health Organization. Depressive disorder (depression) [Internet]. Geneva: WHO 2023. URL: https://www.who.int/news-room/fact-sheets/detail/depression [accessed 2024-01-20]

36. Yan T, Liu F. COVID-19 sentiment analysis using college subreddit data. PLoS One 2022;17(8):e0275862. doi:10.1371/journal.pone.0275862

37. ABMI. Reddit psychiatry. GitHub 2024. URL: https://github.com/ABMI/reddit-psychiatry/tree/main [accessed 2024-01-20]

24

Supplementary Files

Figures

Groups of clustered topics and sentiment. (A) Representation of the clustering analysis results applied to various topics. Each cluster is denoted by a unique color; shades of blue, red, and green denote groups 1, 2, and 3, respectively. The size of each circle is proportional to the number of discussions encapsulated within that topic. The two-dimensional scatterplot positions topics according to their respective scores on Features 1 and 2, which are derived from a dimensionality reduction process using the uniform manifold approximation and projection (UMAP) technique. (B) Analysis of sentiments on clustered topic , where the color intensity corresponds to the mean negative sentiment score associated with each topic. Sentiment scores are scaled between 0 and 1, with the stronger sentiment indicated by darker hues and the weaker sentiment indicated by lighter hues.
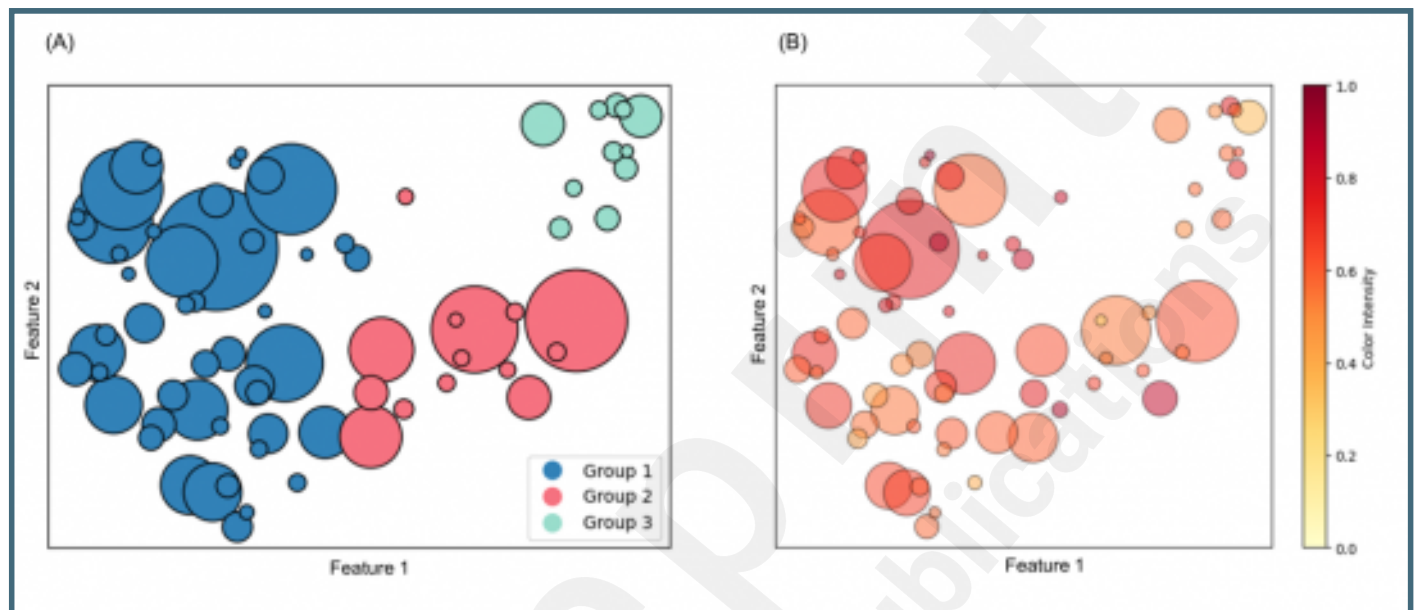
Sentiment Trends in Antidepressant. (A) Representation of proportional changes in antidepressant-related sentiments over time, showing the prevalence of negative ((A)-1), neutral ((A)-2), and positive ((A)-3) discussions. (B) Illustration of annual change in mean sentiment scores within online discussions about antidepressants.
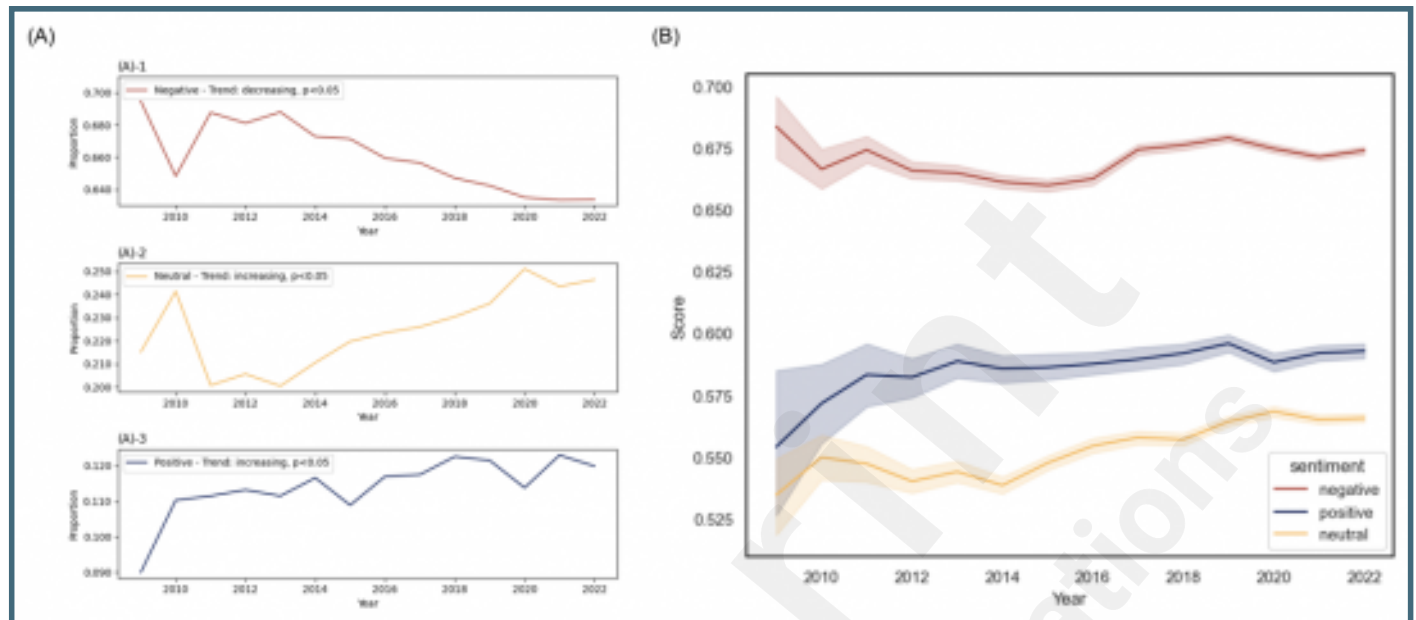
Yearly Change in Topic Proportions Related to Antidepressant Discussions Across Three Clusters. Each topic is assigned a specific number that corresponds to a particular discussion theme as summarized in the topic summary section. *p-value less than 0.05 in Mann-Kendall trend test.

Topic Summary:
1: ADHD, ADHD medications, antidepressants effect*
3: Switch, augmentation, stop from Lexapro
4: Prozac side effects*
5: Stop, dose, side effect, and withdrawal from Zoloft*
6: SSRI side effects
7: Sexual side effects*
8: Effexor side effects*
10: Switch, augmentation, stop from Sertraline*
11: Augmentation of trazodone, insomnia
21: Alcohol drinking, augmentation with alcohol and antidepressants*
22: Benefits from bupropion, switch to Bupropion*
23: Benefits of Wellbutrin, recommending Wellbutrin as an antidepressant
47: Side effects, switch from bupropion, no benefit from both Lexapro and Wellbutrin
49: Seizure risk of Bupropion*
55: Adding bupropion to Zoloft, Adding Zoloft to Bupropion*
58: Bupropion for depression, No effects

Multimedia Appendixes

Supplementary_materials.
URL: http://asset.jmir.pub/assets/552a0882de93a908fe0f3a8cc533193e.docx

SRQR Guidelines Checklist.
URL: http://asset.jmir.pub/assets/6c264915f49cfa6d71520e1fdfd41e9f.doc