Deciphering psycho-social effects of Eating Disorder : Analysis of Reddit Posts using Large Language Model(LLM)s and Topic Modeling

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Abstract

Eating disorders are a global health concern as they manifest in increasing numbers across all sections of society. Social network platforms have emerged as a dependable source of information about the disease, its effect, and its prevalence among different sections. This work lays the foundation for large-scale analysis of social media data using large language models (LLMs). We show that using LLMs can drastically reduce the time and resource requirements for garnering insights from large data repositories. With respect to ED, this work focuses on understanding its psychological impacts on both patients and those who live in their proximity. Social scientists can utilize the proposed approach to design more focused studies with better representative groups.

1 Introduction

Eating disorders (ED) are an area of increasing concern even as it continues to be under-reported and under-researched. Eating disorders are recognized by signs and symptoms which are published in the fifth edition of the Diagnostic and Statistical Manual of Mental Disorders (DSM-5). Clinical symptoms of ED most often manifest as Anorexia Nervosa, Bulimia Nervosa, Binge Eating Disorder, or ARFID which is defined as an eating or feeding disturbance so pervasive that the person is unable to meet appropriate nutritional needs, resulting in significant weight loss, nutritional deficiency, dependency on nutritional supplements, or interference in social functioning.

In (Silén and Keski-Rahkonen, 2022), it was reported that there is an alarming rise in ED across the world. According to the paper, an estimated 5.5–17.9% of young women and 0.6-2.4% of young men have experienced a DSM-5 eating disorder by early adulthood in the Western world. Studies from other parts of the world also show similar trends. A study conducted by NIMHANS in India in 2018 reported that Eating Disorders (ED) affect 6.5% of adolescent girls in India and an estimated 2-3% of the population as a whole. National Eating Disorders Association[1] reinforces this and states that though eating disorders impact people of all genders, ages, races, religions, ethnicities, sexual orientations, body shapes, and weights, the diversity is not represented in published research, which has most often relied on surveys of targeted groups. This lack of inclusion implies that the true impact of ED is still not well understood.

With the advent of hyper-specific online communities, those suffering from eating disorders (EDs) have access to social network platforms where they can share their experiences anonymously and seek support from each other as well as from therapists, counselors, and caregivers. Reddit, a popular online forum, hosts many such communities centered around eating disorders, with the largest one being r/EatingDisorders. These platforms are good sources of data since they are used by patients as well as those who live in proximity. Hence unlike targeted surveys which analyze information from affected individuals only, social media platforms also give insights into the psychological stress and trauma experienced by other groups of people like parents, partners, siblings, and friends of affected individuals.

In this paper, we present a study that exploits large language models (LLM) and topic modeling for analyzing large volumes of Reddit posts, to obtain insights about ED and its impact on social relationships. While traditional topic modeling techniques like Latent Dirichlet Allocation (LDA) perform a global analysis of large repositories, LLMs are good at generating summaries and answering questions through contextual analysis of individual articles, like posts. However, being gen-

[1] https://www.nationaleatingdisorders.org/resource-center/

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erative in nature, the answers to different questions have to be further semantically analyzed to identify global patterns. Most of the earlier work on analyzing social networks for similar purposes has been done on much smaller datasets. The research contributes to the growing body of literature on the intersection of mental health, social media, and Natural Language Processing. Since the posts are made available publicly after anonymization and careful removal of all sensitive information, these kinds of studies do not violate any ethical norms. It reinforces the potential of online platforms as a resource for studying Eating Disorders. It also establishes the role of LLMs in facilitating large-scale automated analysis in social science as stated in (Ziems et al., 2024).

The focus of our work is on analyzing the psychological state of people suffering from ED and those who live in proximity, using both statistical technical techniques like LDA and LLMs. Consequently, the key research questions were formulated as follows:

- Q1: What are topics that come up in the discussions on subreddit forums? Are there any new insights that can be obtained about the causes of ED and its effects on the physical and mental health of subjects? How do traditional methods like LDA compare with LLM-identified themes?

- Q2: Who are the common speakers in these posts, what are their relationships with people suffering from ED and what is the effect of this relationship on both? By doing so, we aim to understand not only what is being discussed, but how these discussions are framed and influence interpersonal dynamics.

- Q3: What could be a typical pipeline for analyzing large volumes of social media posts using LLM-generated insights? Besides giving directions on formulating the right prompts, we have also performed manual evaluations for parts of the content. This was done by identifying the original texts using linguistic phrases extracted, along with the LLM-generated inferences, evaluating the answers to questions on dominant emotions, and validating the mentioned interpersonal relationships, and their contexts from the text. From a computational point of view, this question helps to establish the effectiveness of using LLMs for such research.

The rest of the paper is organized as follows. Section 2 presents an overview of earlier work in the area. Section 3 presents statistics about the data. Section 4 presents the analytical pipeline, along with details of each module. This is followed by results and discussions.

2 Related Work

Eating disorders (EDs) are complex psychiatric disorders with a range of associated mental and physical health symptoms. A meta-review article published in 2021 (Qian et al., 2021) analyzed thirty-three studies published across the world and concluded that the prevalence of eating disorders might have been underestimated thus far. Combined analyses showed that the lifetime prevalence of EDs in Western countries was 1.89%, and was high at 2.58% in females. Most of these studies did not use the DSM-5 criteria for their analyses. It also proposed that new diagnostic criteria should be used to comprehensively assess all types of eating disorders. In a study from Finland (Silén et al., 2020), the prevalence of lifetime DSM-5 eating disorders among the Finnish population was estimated to be 17.9% for females and 2.4% for males, and 10.5% across genders. A meta-review on ED-related research in India was presented in (Vaidyanathan et al., 2019), and also states that cultural context should be included in the analysis, with the help of culturally sensitive instruments used for diagnosis, and generating locally relevant epidemiological data about eating disorders from community as well as hospital settings.

The role played by social network platforms in the health and wellness pursuits of people was comprehensively analyzed in (Marks et al., 2020). The article states that social networking sites (SNSs) have evolved into an informal source of health education which influences peoples' health choices. Analysis revealed that the discussion majorly focuses on the promotion of idealized bodies, healthy foods, diets, and exercise. While this raises concern about the influence of social media on mental health, especially promoting body image concerns, eating disorders, and psychological distress, it is also acknowledged that social media can be alternately used to encourage wellness through promoting self-acceptance, intuitive eating, and life-enhancing movements. This work critically evaluates both the positive and negative role of social networks concerning health and wellness content. Prior to this, a small sample study on content analysis from a pro-ED community on Reddit was presented in (Sowles et al., 2018). This study delved into the task of identifying the expression of behaviors aligned with ED symptoms and support for these behaviors within the social network discussion. The paper presented results based on an analysis of four weeks of topic-specific discussion threads on a small dataset of 125 threads created for the purpose. It reported statistics on behaviors consistent with ED, and how the platforms provided support. Topic modeling using Latent Dirichlet Allocation (LDA) was employed to identify topics in eating disorder-specific social media content in (Moessner et al., 2018). The paper employed social network analysis using a linear network autocorrelation model to analyze communication patterns and the most influential users.

Twitter, another popular social network platform was studied by (Zhou et al., 2020) to assess social media engagement among individuals with ED. The focus of this was to develop an automatic approach to assess public perceptions about ED and ED-related behaviors. A machine learning approach was developed to identify ED-relevant tweets, and content analysis using topic modeling was implemented to unearth potential ED-related factors including behaviors, thoughts, and mental status.

3 Dataset Details and Data Preparation

We scraped data from three Reddit communities: r/EatingDisorders, r/EatingDisordersOver30, and r/EDAnonymous, spanning from 2020 to 2023, among which the most prolific one was r/EatingDisorders. A total of 20,918 posts and 58,228 comments posted from 2021 to 2023 were collected from this site. Upon generating a time-based chart with the number of monthly posts, we found a significant increase in the numbers over this period. The most substantial spike occurred between 2021 and 2022 as shown in Figure 1, and continued consistently into 2023. For this paper, we have presented insights extracted from the posts that appeared in the years 2022 and 2023, since these would present the most contemporary issues. The results presented are based on an analysis of more than 16.5 K posts, with 6700 from 2022 and 10450 posted in 2023. Text cleaning and preprocessing included the removal of HTML tags, URLs, special symbols, etc. The title and text were merged into one body for analysis.

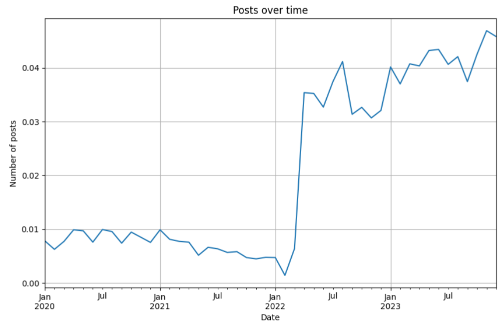

Figure 1: Number of Posts in subreddit community Eating Disorders

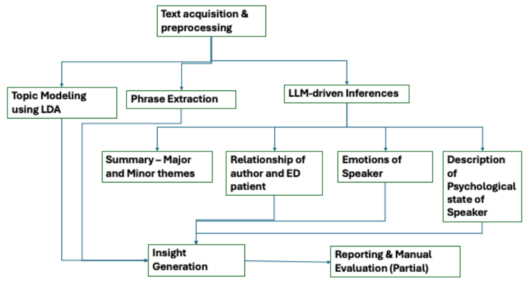

Figure 2: Unsupervised Content Processing Pipeline using traditional NLP techniques and LLMs

4 Methodology

Figure 2 describes the processing pipeline, which is generic and can be applied for analysis of any large-scale repository. Starting with an aggregate analysis of content, we move towards an analysis of individual posts. The first step towards aggregate analysis is topic modeling. Statistical topic modeling techniques like Latent Dirichlet Allocation (LDA) leverage an unsupervised statistical approach to discover hidden semantic patterns from a large text collection to automatically identify topics that exist inside it. Topics are represented by clusters of similar words within a body of text.

Though topic modeling is effective in obtaining a bird's eye view of content from a large repository, the words assigned to topics by themselves do not obtain much semantic information. To alleviate the problem, we have exploited the generative powers of an LLM to generate a semantically coherent description of the topic from the representation words. This step is referred to as Topic naming.

The topic summaries generated at this step can be used to compare topics against each other. This has been utilized later to compute topic trends based on the percentage presence of similar topics across the years.

The aggregate analysis is followed by an individual analysis of posts. Since the intent of analyzing any repository is to obtain statistics about certain key concepts present in the repository, the objective of this step is to establish the presence or absence of the concepts in each post. This step is akin to "coding" in the social sciences, which is an analytical process by which data elements are "categorized" to facilitate analysis. Traditionally this is an expensive knowledge-intensive task. In recent times, there have been efforts to use the Large Language Models (LLMs) for this task, as these are capable of performing various language processing tasks without additional task-specific training. These models, termed as zero-shot LLMs, can also reliably classify and explain certain social phenomena (Ziems et al., 2024). It is this aspect of a large language model, that we have exploited to use it as a computational social science tool. Details for each of these sub-tasks are presented in the following subsections.

4.1 Obtaining Topical Insights from Post repositories

To explore the nature of conversations and the content of discourse in r/EatingDisorders, we implemented Latent Dirichlet Allocation (LDA) for topic modeling. This technique identifies hidden topics in text data by grouping words that frequently occur together. We conducted separate topic modeling for 2022 and 2023 data, to obtain insights about the temporality of topics, including the emergence, persistence, and disappearance of topics over this time. The optimal number of topics was decided based on coherence, inclusivity, and perplexity scores, and was found to be 16 for each year. On average, we achieved a perplexity score of -22 and a coherence score of 0.40, indicating a reasonably well-fitted model.

LDA assigns a topic distribution for each of the 16 topics to each post, where the total topic strength sums up to 1. Each post may contain a significant presence of more than one topic. To determine how good the topic assignments are, we performed skew analysis for the entire sets of each year. Skewness is a statistical measure that reveals whether a distribution is symmetric or asymmetric. For asymmetric

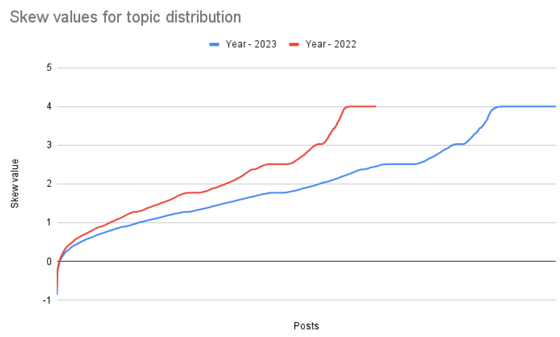

Figure 3: Skew Values for topic Distribution: Positive values indicate the presence of a dominant topic

distributions, the skew values reveal whether there is a sharp trend towards either end of the normal curve. For topic assignments, a zero skew value would indicate that all topics are present in equal measure thereby revealing the absence of any significant topic in the text. A positive skew value on the other end would indicate the presence of dominant topics. Figure 3 shows that the skew values are majorly positive, indicating that the topic distributions can be used to find the dominant topics of the posts. To analyze the topics and their relative presence in the discussions, each post was assigned a “dominant topic” which was the topic with the maximum strength for it. The red line is shorter because 2022 had fewer posts than 2023.

For each topic identified, LDA returns the probability distribution of the words to the topics. Using the top 30 words for each topic, a one-line description and a short name were generated for it, with the help of `gpt-3.5-turbo-1106`. The summaries for each topic thus obtained were compared with each other within and across the years to identify similar topics, if any. BERT-based embeddings were generated for each summary, and then cosine similarity measures were computed between the topic summaries identified for 2022 and 2023. To compute the topic strength for a year, we computed the percentage of posts that had the corresponding topic as the dominant topic in that year. This analysis allowed us to plot the relative strengths of topics each year, revealing shifts in focus across the two years. The results were further contextualized through consultations with a psychologist to understand the emotional and psychological dynamics of these communities.

4.2 Analysis of Posts using Large Language Model

After obtaining the aggregate views on topics in the posts, analysis of individual posts was done by employing prompt engineering to generate structured summaries of posts. The process was designed in a way that helps distill complex discussions into manageable insights. First, a set of intent was created, based on the analytical insights required. For each intent thereafter, a prompt was designed to extract relevant information from the post. The intent and the corresponding prompts used for this work are as follows:

- Intent - Summarize
  Prompt 1: Write a 1 sentence summary of the post text and identify the major and secondary themes
- Intent - Identify emotions expressed in post
  Prompt 2: What are the major emotions conveyed in the post?
- Intent - Establish a relationship between author and subject suffering from ED
  Prompt 3: Identify whether the author of the post is writing about their own experience or discussing the issues concerning someone else. What is the relationship between the author of the post and the person whose ED-related disorders are discussed?
- Intent - Understand the psychological impact of ED
  Prompt 4: What can you infer about the impact of ED on the psychological state of the author?
- Intent - Identify the presence of DSM 5 Eating Disorder symptoms in post
  Prompt 5: What are the physical, physiological, or psychological impacts of ED mentioned in the text?

We used the OpenAI `gpt-3.5-turbo-1106` model, with the parameters `temperature` set to 0 and `maxtokens` set to 150. Temperature is used to control the randomness in the response generated; when the temperature is low, it chooses only the most likely next word based on the context. We kept it at 0 to ensure minimum randomness in the responses generated. The *maxtoken* parameter defines the limit on the number of tokens the model can generate. The prompts were executed with each post given as the context for generating the answers. For clarity of presentation, we have segregated the prompts, though they were all executed together. Prompt 5 could be broken into more atomic-level prompts, one for each disorder. However, it would have incurred more computational cost. There were further instructions to restrict the prompts to generate answers in very few words, and repeat words for similar interpretation. Though posing multiple choice-type questions could be a way to alleviate the problem, we refrained from doing so since there are reports that LLMs assign the choices quite randomly, rather than logically, whereby the answers on the top are returned most often. In contrast, the generative approach allows it to generate a more plausible answer (Li et al., 2024).

It was observed that though there was substantial repetition in the answers, there were some syntactic variations within semantically similar answers. For example, for Prompt 2, while the most common answer was "the speaker is referring to themselves", similar answers were "the speaker is likely referring to themselves", "self-referential" etc. In case the author is not talking about self, common answers were "the speaker is in a romantic relationship with the person being referred to" or "the speaker is the parent of the child they are referring to" etc. Some additional effort was required to aggregate the answers under different categories, for which string-matching codes were written.

5 Results: Findings and Discussion

We first present an aggregated analysis of the content obtained in terms of topics and topic trends using LDA. A short description of each topic was generated by feeding the top 10 topic words to LLM. To compare the topic strengths for two years, topic alignment was done using BERT-based similarity scores among the short descriptions across the years. The unique topics, their names, and trends across the years found by LDA are presented in Figure 4. While the most dominant topic of 2022 was "weight gain and image-related issues", the conversation around this substantially dropped in 2023. The topics rather shift towards those which are about "seeking help", sharing experiences on "relapse and recovery", "disordered eating", and "eating patterns and appetite" along with a discussion on handling "relationship issues" and advice on handling "social interactions". There are also

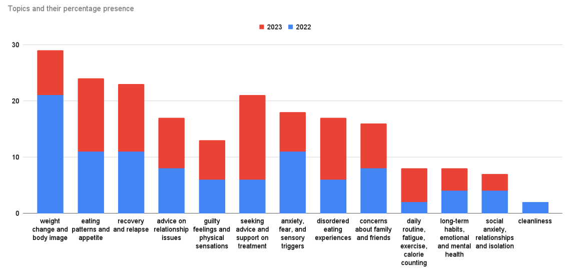

Figure 4: Topic Presence in percentage of posts for 2022 and 2023

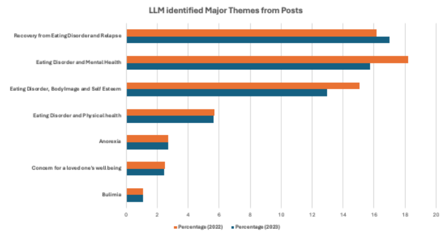

Figure 5: Post Themes identified by LLM and their percentage presence in 2022 and 2023

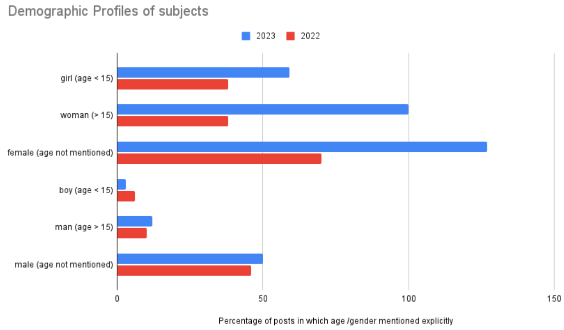

Figure 6: Demographic Profiles of users who explicitly mention age. gender - indicates trends and not estimates

topics centered around extreme feelings of guilt, shame, concern, and fear which appear as a major topic. These emotions will be discussed in more detail later. A topic centering around "cleanliness" discussing changes in personal cleanliness routines and organizational approaches to cleanliness featured in 2022, but not in 2023. This could be due to the immediate aftermath of the pandemic. The changes in topic trends indicate that the platform is indeed emerging as a forum where ED patients form a mutual support group.

Figure 5 presents the most frequently occurring topics in the posts as identified by the LLM using prompt 1. Comparing these with figure 4 shows that while both the results show similar trends, the LLM-identified topics are broader in nature, more like themes rather than topics. An issue faced with LLM themes was the wording differences in the answers generated for the posts. These themes had to be combined based on the words that appeared in them.

The similarity of the topics and themes obtained by two different unsupervised methods increases confidence in the results obtained. The most commonly occurring theme is that of personal struggle faced by patients of ED, especially during recovery, as they frequently get into relapse. This is followed by concerns about body image which is at the center of triggering ED in people. Impact on mental and physical health is also a recurring theme. The topics reveal finer nuances of these topics as weight-related issues for body image, guilty feelings along with anger, fear, and anxiety as chief mental health problems.

Few posts had explicit mentions of the age and gender of the author or the patient of ED as "x/G" where x indicated age and G indicated gender. 208 posts in 2022 and 351 posts in 2023 had such mentions. Figure 6 shows their relative distributions. There was a much higher mention of woman/female/girl than man/male/boy across both years. This is consistent with the findings in past literature where women are reported as more susceptible to eating disorders than men. However, this also shows the spread or acknowledgment of ED across demographics. These results establish that monitoring social media platforms could provide a good understanding of trends and thereby help clinical experts choose their subjects in a more informed manner for deeper studies. We also found that a significantly higher number of mentions came from the teenage group, peaked at around 25, and then started decreasing, with the higher mentions of age, going up to 50+. The lowest age mentioned is 10, which also aligns with the literature. All results were manually verified and found to be correct.

Emotion analysis results were obtained from the output of Prompt 2. Analysis shows that the emotions present in the posts are predominantly negative, with concern, frustration, confusion, fear, and desperation dominating over others. Figure 7 shows that the relative presence of these emotions is fairly consistent over time. Such a high presence of negative emotions is consistent with the DSM 5

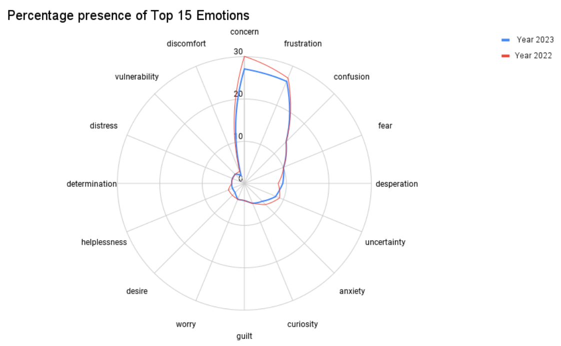

Figure 7: Emotion distribution across posts for 2022 and 2023

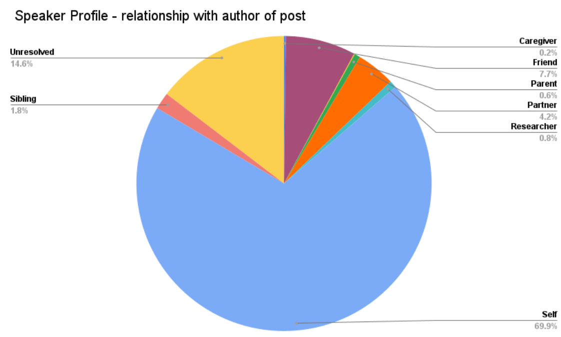

Figure 8: LLM-inferred relationship between author of post and subject of ED

diagnostic disorders which mention that individuals who develop eating disorders are at increased risk of developing various co-occurring mental health concerns, including anxiety, depression, obsessive-compulsive disorder (OCD), and Post-traumatic stress disorder (PTSD).

A manual evaluation of the LLM-assigned emotion was done for 100 posts, 50 from among those tagged with *frustration* and another 50 tagged with *guilt and shame*. The evaluation was done by a psychology expert, who had no prior exposure to the data, but was explained about the process and informed that the tags were assigned by a language modeling tool. For the first set on *frustration*, the accuracy of LLM tagging was found to be 90%, for which the expert agreed that the post exhibited frustration. For the remaining posts, the expert marked the emotions as *confusion, obsession, etc.* and not frustration. For the posts marked with *guilt*, the expert agreed fully with the LLM tagging. On inspection of the posts, it was found that all these posts had explicit mentions of *guilty, guilt, shame*. Evaluations at a larger scale are being planned. However, the preliminary results do establish the effectiveness of using LLMs in large-scale data analysis for mental health from social networking sites. This also establishes the possibility of deploying LLMs to set up semi-supervised and distant-supervised learning frameworks, by providing a quick approach to generate training data, which is reasonably clean, and not expensive to initiate.

Figure 8 presents an analysis of answers generated in response to Prompt 3. It extracts the relationship of the authors of a post to its subject who is mentioned in it as the patient suffering from ED. These results are from the 2023 collection. As expected, around 70% of the authors are the patients themselves. However, there are a substantial number of posts that are written by friends and acquaintances, parents, partners, and siblings. Friends and acquaintances include colleagues, roommates, family friends, etc. Siblings are mentioned either as such or as brothers or sisters. The partner tag was assigned to authors who were identified by the LLM as "one in a romantic relationship with the person suffering from ED" or a spouse, girlfriend, boyfriend, or "someone in a close relationship with the patient".

Responses to Prompt 4 provide deeper insights into the psychological impact of ED on the patient when the author is "Self", as well as on other people when the author of the post is a friend, parent, partner, colleague, or sibling. These results are presented below.

5.1 LLM inferred psychological impact from posts written by others

- Speaker feels *anxious* (or *concerned, worried, frustrated, stressed*) by the state of the person suffering from ED: 67%
- Speaker is *unsure* (or *confused*) about how to help sufferer and is seeking help from the community as author: 37%
- Speaker feels *overwhelmed* by situation: 10%
- Speaker is *hopeful* of providing support to a person suffering from ED and seeks advice on how to do so: 15%
- Speaker is *worried* that their concern may hurt or induce feelings of embarrassment or shame or guilt in the person suffering from ED: 8%
- Speaker feels *triggered, spiraling, and struggling* with their mental health (indicating the

effect of proximity of ED patients on each other): 5%.

- Speaker *fears relapse* of ED in them due to the other person's diet-related disorders: 1%

Posts related to the above-mentioned situations highlight the difficulties faced by people who stay in proximity to people suffering from ED and hence are indirectly affected by it. It is evident from the representative posts that we have analyzed, that the conditions can pose serious health risks to many of them, as ED impacts their relationships. By talking about relapse, there is an indication that ED patients are affected by mutual proximity.

5.2 LLM inferred psychological impact of authors who are subjects of Eating Disorder

Overwhelmed: It is the most common inference drawn by LLMs to describe speakers' mental states. Summarily, speakers are overwhelmed by their mental state, managing weight-related issues and social pressures around it, relationship with food, and physical well-being - 15%. On analyzing the corresponding posts, these are found to be predominantly about user **struggles** during *recovery*, where they mention *stressing about weight issues, body image, self-perception*. These are directly mentioned in at least 26% of the posts, which in terms of absolute count is around 1800 posts.

Frustrated: Frustration surfaces whenever the user expresses an inability to handle their health, well-being, desires, cravings, or relationships. This shows up explicitly in 10% of the posts. Pain, functional dyspepsia, abnormal hunger, hypermetabolism, abnormal menstrual cycle, digestive disorder, and laxative abuse are some of the symptoms mentioned. It often indicates that the speaker feels misunderstood and unsupported, leading to increased frustration and likely exacerbating their struggle with the eating disorder.

Guilty: The speaker feels pressure and anxiety related to their eating and exercise habits, indicating a potential negative impact on their psychological state - 10%. Around 7.5% or 510 posts expressed explicit feelings of guilt due to the way the subjects feel about their bodies and hence became a subject of eating disorders. This is a complex feeling, where a feeling leads to an action, which in turn has inflicted remorse in the minds of the subject.

Family pressures and relationships: Around 7% of the posts contain discussions centered around the role played by the family. A portion of these reports that *body shaming by family members* was either the cause of disorder or interfered with the recovery process. Another significant portion of these are about *how eating disorders of other family members are affecting them.* This indicates that proximity to a person with an eating disorder or obsession with body image induces an eating disorder. This points out the possibility of having *hubs of eating disorder* within spaces like hostels, schools, campuses, offices, or any other closed social neighborhoods where people eat together.

Help, Support, and Empathy: Speakers appeal for help, and seek support and empathy from other members to aid their recovery - 10%.

Binge eating: Speaker is experiencing anxiety and a sense of helplessness in their struggle with binge eating disorder - 2%. They have mentioned abnormal hunger, cravings for food, and inability to control their negative relationship with food.

Suicidal thoughts: Around 100 posts mentioned suicidal thoughts. This is also a known effect of ED. A low precedence of it in the platform, along with high volumes of appeal for help, reiterates the importance of social network platforms which act as support groups for patients, without feeling judged or misunderstood.

Academic Pressure: Around 40 posts mention academic struggles as their stress inducers.

Ethnicity: Though extremely few, the mention of *Asian* and *African* in posts indicated family-related struggles due to different cultural contexts at home including food, body shapes, and eating habits.

These insights can act as a springboard for designing more focused surveys for targeted groups with better representation.

6 Conclusion

In this paper, we have presented a large-scale study on Reddit posts related to Eating Disorder. We have shown how large language models like GPT can be used effectively to gain insights about facts and figures using their power to summarize and draw inferences against targeted prompts. The most significant insight gained through this study is about people who live in proximity to the subject of Eating disorder, and use the platform to convey their distress. The psychological stress undergone by this group which includes parents, siblings, friends, and partners is not much reported. Though the known effects of ED are found in the data, the study reveals that the platforms are primarily used for advice, support, and seeking empathy from co-users. The results are highly encouraging. Our plan includes devising a way to methodically evaluate the LLM-generated answers. The ultimate intent is to build a framework for analysis of mental health-related posts, that can expedite the whole process of insight generation as well as strategically plan interventions and support mechanisms.

7 Limitations

The limitation of the present work lies in the fact that only a small number of evaluations could be carried out. This is due to a lack of funding and expert resources.

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