Posts, Pills, and Pounds: Understanding User Experiences with Weight Reduction Drugs

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Abstract

With the rising prevalence of obesity and related health concerns, weight reduction drugs have gained widespread use and sparked extensive discussion in online communities. This paper leverages large language models (LLMs) to analyze Reddit posts related to prominent weight loss medications, aiming to extract nuanced insights into user sentiment, reported side effects, dosage adjustments, drug-switching behavior, and demographic influences. Our findings reveal key patterns in user perceptions, highlight commonly reported adverse effects, and identify personal preferences surrounding dosage changes and medication switches. The primary aim of this research is towards a deeper understanding of the real-world impact of weight reduction drugs, offering implications for patient education, healthcare delivery, and drug development.

Introduction

Weight reduction drugs are frequently prescribed as part of the effort to manage obesity and related health issues, which have become increasingly prevalent in many parts of the world, has sparked significant interest in online communities, particularly on platforms like Reddit, where users actively share their personal experiences, opinions, and concerns. While these drugs offer potential benefits, their real-world effects, side effects, and user satisfaction often remain unclear. Traditional clinical trials provide valuable information but are often limited in scope and fail to capture the complexity of user experiences in everyday settings. These online discussions offer an untapped source of real-world data on the efficacy, safety, and user satisfaction of various weight loss medications. It also provides a unique opportunity to understand how users engage with these medications, revealing both positive and negative experiences, side effects, and reasons for drug switching which may not always align with the clinical trial data or marketing claims. However, due to the large and often fragmented nature of these discussions, it can be difficult to systematically assess and understand the diverse sentiments, concerns, and behaviors associated with different weight reduction drugs. This paper seeks to address this challenge by applying large language models (LLMs), to systematically analyze the following:

a) We utilize LLMs to conduct a detailed sentiment analysis of Reddit posts, identifying positive, neutral and negative sentiments related to the four selected weight reduction drugs. This analysis helps to uncover how users feel about the efficacy, safety, and overall experience with these drugs.

b) By employing LLMs to categorize and analyze the side effects mentioned in the posts, we provide a comprehensive overview of the adverse reactions users report. This allows us to identify the most common and severe side effects, which might not be fully captured in clinical trials or official reports.

c) Our study investigates whether users are switching drugs and the reasons behind these decisions. By analyzing drug switching patterns, we can understand what drives users to move from one medication to another, be it due to side effects, efficacy, or other personal preferences.

d) We explore mentions of specific dosages in Reddit posts and examine whether users report adjusting their doses. By analyzing these data points, we can gain insight into how users interpret dosing instructions and why they might change dosages based on personal experiences or perceived drug effectiveness.

e) We explore how demographic factors, such as gender,, influence user experiences and sentiment towards these drugs. This analysis can uncover variations in how different groups respond to weight-reduction medications.

f) We identified cases where users reported taking multiple drugs together, noting specific combinations and related side effects, both physical and psychological, to capture real-world results of polypharmacy.

By leveraging the power of LLMs to analyze large volumes of unstructured Reddit data, we can gain insights that are often overlooked in clinical settings. These insights can help inform better drug development, healthcare practices, and patient education by providing a clearer picture of real world experiences.

Related Work

Social media platforms have become valuable sources for detecting ADRs due to the real-time sharing of personal experiences by users (Saha et al. 2020). For instance, (Dasgupta, Naskar, and Dey 2018; Zhang, Cui, and Gao 2020) utilized deep linguistic features to identify ADRs from social media posts, highlighting the potential of these platforms in pharmacovigilance efforts. (Zhang et al. 2021; Li, Jimeno-Yepes, and Xiao 2020) focused on the identification and extraction of ADR entities from social media, emphasizing the importance of these data sources in supplementing traditional reporting systems. (Dejgaard et al. 2016) investigates the risk–benefit profile of liraglutide as a weight loss intervention. A recent study (Grandl et al. 2024; Liu et al. 2025) provided an update on various diets and drugs for weight loss, discussing their impacts on obesity and related health conditions. Several antiobesity medications approved by the United States Food and Drug Administration (FDA) exist (Beshir et al. 2023); however, the use of these drugs remains controversial, as they are associated with a number of adverse side effects and weight regain when the medication is stopped (Kang and Park 2012; Rivas García et al. 2024). (Shalabi 2023; Wang et al. 2025) examines how social media influences patient decisions regarding weight loss medications, shedding light on the reasons behind medication switches and the role of online information in these choices.

Dataset Description

The dataset for this study comprises text data from user-generated posts on the Reddit platform, specifically within the subreddits `r/ozempic`, `r/wegovy`, `r/semaglutide`, and `r/zepbound`. These subreddits focus on discussions related to specific medications and treatments, providing valuable insights into user experiences and perspectives. The dataset spans a two-year period, from January 1, 2022, to December 31, 2023, and includes the text content of posts along with their associated creation dates and timestamps. This dataset serves as a comprehensive foundation for our analysis. The dataset analyzed in this study comprised $6,902$ posts. Discussions in these subreddits were not limited to their respective drugs; users frequently mentioned multiple medications in their posts.

Table 1: Entries per subreddit and % of Drug mentions.

SubReddit	No. of Entries	% of Drug Mentions
Ozempic	2016	36.24
Wegovy	2037	33.44
Semaglutide	1528	15.98
Zepbound	1321	14.34

Many discussions in these subreddits included mentions of multiple medications. Among these $6,902$ entries, $3,573$ explicitly mentioned at least one of the four drugs (Ozempic, Wegovy, Semaglutide, or Zepbound). The remaining $3,329$ entries either discussed other medications or contained general discussions not directly linked to these four drugs. The number of entries sourced from each subreddit and the distribution of posts where each drug was explicitly mentioned, regardless of the subreddit in which it appeared, is presented in Table 1.

Entity Extractions

Using the Llama-3.1-8B-instruct model (Grattafiori et al. 2024), we treated each entry in the dataset as a distinct entity to extract meaningful information. Initially, irrelevant content, such as deleted or removed posts and image links, was excluded to create a refined dataset. Subsequently, this filtered dataset was processed using carefully designed prompts to extract key insights from the text posted by users. The primary features identified through this approach include:

- **Drug Name:** The specific drug mentioned by the user.
- **Sentiment Analysis:** The overall sentiment expressed in the content.
- **Dosage Information:** This includes mentions of initial dosage, modifications, and the reasons for such adjustments.
- **Side Effects, Symptoms and Adverse Reactions:** includes potential severe or life-threatening adverse reactions, Severity levels (mild, moderate, severe) and frequency of occurrence of the side effects.
- **User Demographics:** Information such as age, gender, past medical history or any other relevant information mentioned.
- **Reported Benefits and Outcomes** associated with the medication.
- **Effectiveness:** Insights on weight loss progress, along with contributing factors and lifestyle changes influencing the results.
- **Comparative Analysis:** Comparison with other medications, including the preferred medication and the rationale behind the user's preference.
- **Social and psychological impacts:** including effects on body image and self-esteem, experiences related to social interactions and stigma associated with weight loss medications, and psychological impacts of using the medication and the weight loss journey.
- **Health Impact:** Description of any health-related consequences mentioned.

Following the extraction of these characteristics, targeted clustering techniques were applied to organize both side-effects and reasons for drug switching into broader, interpretable categories. For side-effects, each extracted entries were processed using specifically designed prompts fed into the Llama 3.1–8B model. The model was prompted to assign a broader, general category to each side effect. After obtaining these higher-level groupings, further refinement was performed manually to merge overlapping or synonymous categories, ensuring cohesive clustering.

For reasons behind drug switching, a multi-step pipeline was employed to define and map the reasons into broader categories. Each user reported reason string was first converted into 384-dimensional embedding using 'thenlper/gte-small' model (Li et al. 2023), followed by dimensionality reduction using UMAP (384 to 5) (McInnes, Healy, and Melville 2018). The reasons were subsequently clustered using HDBSCAN (McInnes et al. 2017). We then employed BERTopic (Grootendorst 2022) for obtaining topic representations for each cluster which were subsequently refined using the KeyBERTInspired (Grootendorst 2020) technique

I have been using ozempic since nov 2021. I had success off the bat, with losing 15 in the first couple months. I have been on 1.0mg since december. unfortunately, I have plateaued for 3 months .not even another lb lost. has anyone gone off of it for a period of time and then gotten back on my a1cwent from 6.2 to 5.1 . I am still on metformin. I have noticed that I am craving so much sugar and my appetite is crazy, like I want to eat all day. normally, I eat small snack sized meals had a gastric sleeve in 2010 . I haven t gained weight, but the fact I haven t even lost one pound for 3 months is disheartening. I know I need to contact my doctor, but has anyone went off o and then went back on a few weeks to a month later looking to kickstart some weight loss again

- Drug Name: Ozempic; Overall Sentiment: Negative;
- Dosage Information: Initial dosage: NA; adjustments: [newdosage: 1.0mg, reason: NA]
- Side Effects, Symptoms and Adverse Reactions: Increased sugar cravings; frequency: constant; Adverse Reactions: NA
- User Demographics: Age: NA; Gender: NA; Medical History: Gastric sleeve in 2010
- Reported Benefits and Outcomes: benefit: Weight loss ; reported_outcome: Lost 15 pounds in the first couple months, A1C went from 6.2 to 5.1
- Effectiveness: Weight loss plateaued for 3 months;
- Comparative Analysis: compared_to: Metformin ; user_preference: Ozempic ; reason: NA

Figure 1: Sample Reddit post and extractions

to obtain the top keywords per cluster. These keywords informed the creation of high-level reason classes. The original reason statements were then classified into these broader categories using Llama-3.1-8B model with prompt-based mapping. This dual approach enabled systematic generalization and pattern discovery, enhancing interpretability of user-reported data and supporting deeper analysis of drug safety and treatment behavior. Figure 1 shows a sample Reddit post and corresponding extractions.

Observations

Sentiment Analysis: Sentiment analysis was performed on the $3,573$ entries that explicitly mentioned at least one of the four drugs. Posts were categorized into positive, neutral, and negative sentiments, and the distribution is summarized in Figure 2. Overall, neutral sentiment is the most dominant across all four drugs, suggesting that many discussions focus on sharing experiences, asking questions, or providing factual information rather than expressing strong opinions.

User Demographics: Figure 3 presents the gender distribution amongst the posts for each drug. It can be observed that while *Male* dominate the discussions around Wegovy, Semaglutide and Zepbound, *Females* are very active in discussions about Ozempic. In the collected dataset, the number of posts by Female users discussing Ozempic was greater than all other drugs combined indicating an orientation towards discussions involving the recent drug.

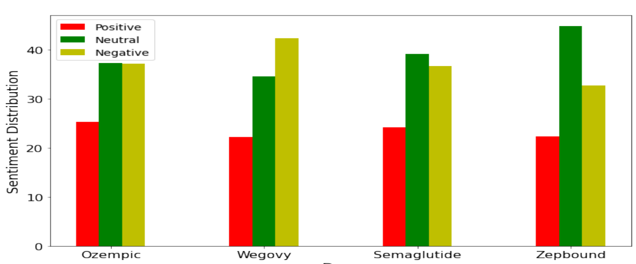

Figure 2: Sentiment distribution of Posts explicitly mentioning each Drug

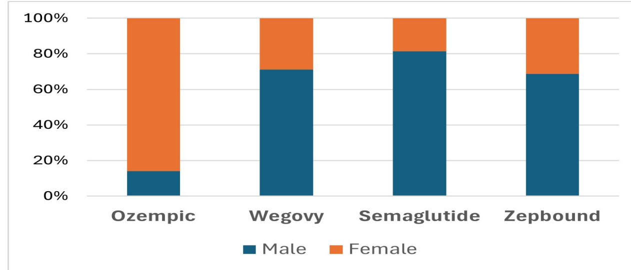

Figure 3: Gender distribution of Users for each Drug

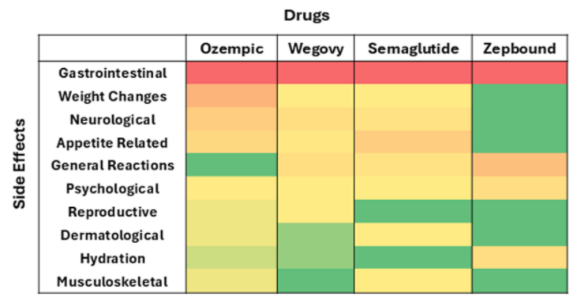

Figure 4: Distribution of side-effects for each Drug

Side Effects: The study of side effects across the four drugs presented in Figure 4 reveals that gastrointestinal issues are the most dominant side effect for all. The color scale uses Red for highest value, Orange/Yellow for mid-range, and Green for the lowest values.

Weight changes are notably frequent with Ozempic, while the other drugs show minimal or no impact in this area. Neurological effects and appetite-related changes are also prominent. Wegovy, however, has a broader distribution of general reactions and milder occurrences of various other side effects including psychological and reproduction related symptoms. Semaglutide shows a more moderate side-effect spectrum but still presents gastrointestinal, neurological, and appetite-related concerns. Zepbound, with the fewest reported side effects, shows a lower incidence across all categories, with minor occurrences in gastrointestinal, general reactions, psychological, and rare hydration effects. Table 2 shows a few examples of side-effects and their cluster representative classes.

Table 2: Clustered side-effects examples

Side Effects	Clustered Class
nausea, vomiting, chills, cold sweats	Gastrointestinal
appetite increase, food noise	Appetite Related
dizziness, blurred vision, blackout, tingling in hands	Neurological

Drug-Drug Interactions: Figure 5 illustrates the most frequently reported side effects across most occurring drug combinations involving weight-loss medications. The intensity of Red color indicates frequency, with dark Red for high and lighter shades fading to White for low frequencies.

Gastrointestinal issues such as nausea, vomiting, and diarrhea are particularly prominent in combinations like Ozem-

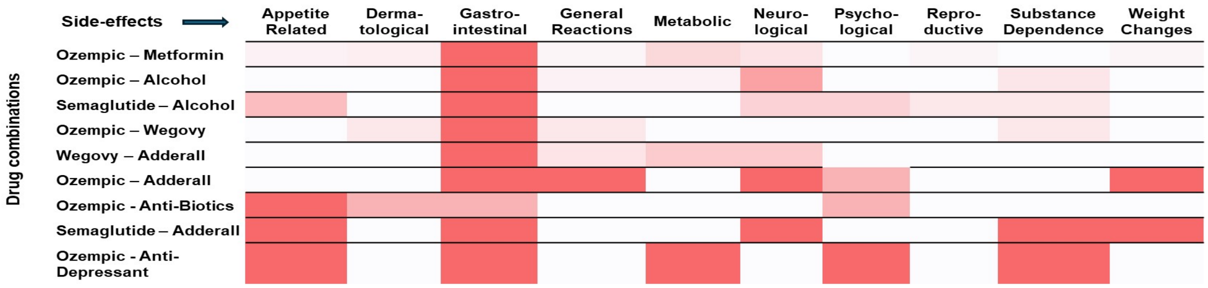

Figure 5: Analysis of drug-drug interactions with side-effects

pic + Metformin, Ozempic + Alcohol, and Wegovy + Adderall. Neurological symptoms (e.g., dizziness, confusion), metabolic disturbances, appetite-related effects, and psychological symptoms are also recurrent, particularly when Ozempic interacts with substances like Alcohol, Adderall, or Anti-depressants.

Combinations involving semaglutide and alcohol or Adderall also reported multiple side effects, including neurological, appetite, and psychological issues. Less frequently reported but noteworthy are issues related to substance dependence, reproductive health, and dermatology in some combinations, especially with Ozempic. These findings suggest that polypharmacy with weight-loss drugs warrants careful monitoring due to a diverse and at times severe spectrum of side effects, underscoring the need for personalized risk assessment and clinician oversight.

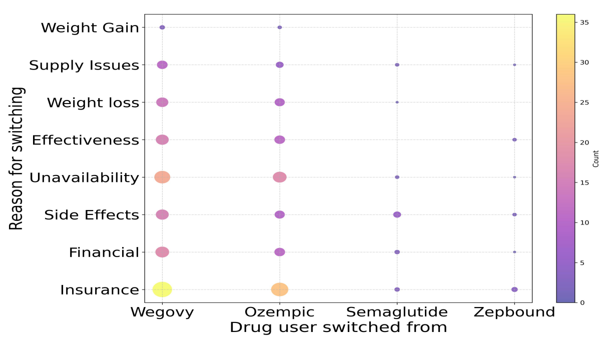

Figure 6: Reasons for switching the Drugs

Drug Switching: We also observed a number of cases where people switched drugs. Figure 6 reveals that Wegovy and Ozempic are the most frequently mentioned drugs in patient shift conversations, indicating their widespread use or interest. The top reasons for switching across all drugs are issues related to insurance coverage, financial constraints, adverse side effects, unavailability, and diminished effectiveness or weight loss plateau. Users have reported high dissatisfaction due to supply issues, ineffectiveness over time, and side effects, while many users primarily cite insurance and financial concerns, suggesting that although the drugs are better tolerated, they have high cost that limits access. Also some concerns—such as appetite, dosage adjustments, and doctor prescriptions—appear infrequently but may reflect individual patient sensitivities or emerging issues. Overall, the analysis highlights that economic and supply factors are as influential as clinical outcomes in shaping patient behavior, underscoring the need for more affordable, accessible, and consistently available treatment options in the weight loss drug market. Table 3 shows a few examples of reasons for drug switching along with their representative classes.

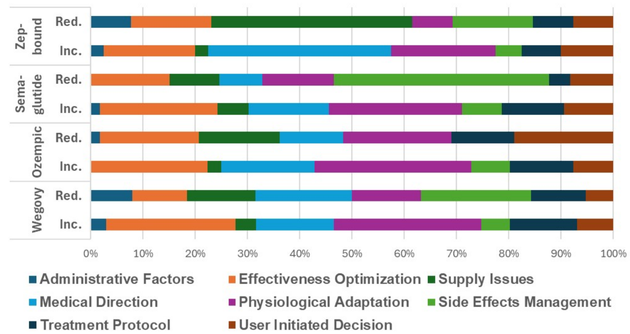

Figure 7: Reasons for Dosage changes

Table 3: Clustered drug switching reasons examples

Reason for Switching	Clustered Reason
cost and availability	Financial; Unavailability
wegovy backorder and insurance coverage	Supply Issues; Insurance
tolerance of side effects and weight loss	Side Effects; Weight Loss

Dosage Changes: Figure 7 depicts the highest overall dosage changes are due to *Effectiveness Optimization* and *Physiological Adaptation*. This suggest users frequently adjust doses to enhance results or adapt to the drug. We also observe high number of dosage reduction for *Side Effects Management* indicating users are actively lowering doses to mitigate adverse reactions.

Conclusion

In this paper we leveraged LLMs to analyze Reddit posts related to prominent weight loss medications. We extract insights into user sentiment, adverse effects, dosage adjustments, drug-switching behavior, and demographic influences. Our findings reveal key patterns in user perceptions, highlight commonly reported adverse effects, and identify personal preferences surrounding dosage changes and medication switches.

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