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Sentiment Analysis and Emotional Language as Predictors of Drug Satisfaction in User Reviews

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ABSTRACT

This study investigates how emotional expressions in user-generated drug reviews predict satisfaction ratings using sentiment analysis and emotion detection. By analyzing over 370,000 reviews from the UCI Machine Learning Repository, the study aims to bridge gaps in understanding the emotional drivers behind user satisfaction across different drug categories. For sentiment analysis, VADER, a *Python*-based lexicon tool, was used to categorize sentiment polarity, while the NRC Word-Emotion Lexicon provided a nuanced mapping of emotions like *joy*, *sadness*, and *anger*. Results reveal that emotions such as *joy* and *trust* are positively correlated with higher ratings, while *anger* and *disgust* are linked to lower satisfaction. However, the R-squared value (~0.043) indicates that emotions alone do not fully predict ratings, highlighting the need to consider additional factors like drug efficacy and side effects. This low R-squared value suggests that while emotions significantly influence satisfaction, other elements play a substantial role. The study's findings have critical implications for pharmaceutical companies and healthcare providers, suggesting the need for emotion-driven marketing strategies and improved patient support systems. Future research could explore more advanced machine learning models, such as BERT or GPT-based approaches, and investigate specific user demographics or drug side effects to enhance predictive accuracy.

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1. Introduction

The rapid rise of user-generated content (UGC) has significantly impacted various industries, with healthcare being among those most profoundly influenced. UGC refers to information voluntarily shared by individuals on digital platforms, often based on personal experiences with products or services (Shyni, 2022). In healthcare, UGC has emerged as a valuable resource for both patients and healthcare providers. For instance, platforms such as Drugs.com and WebMD allow users to review medications, providing insights into drug efficacy, side effects, and overall satisfaction (Yu et al., 2024). These reviews help patients make more informed treatment decisions and serve as critical data for healthcare professionals and pharmaceutical companies, aiding in public health strategies and combating misinformation (Herrera-Peco et al., 2021).

As healthcare providers increasingly rely on UGC, digital platforms like TikTok have become popular for sharing health-related content. Despite concerns over the reliability of non-expert

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information (Hill et al., 2023), these platforms offer healthcare professionals new avenues to engage with patients and foster health literacy. AI assistants, such as Alexa and Google Assistant, also enhance access to healthcare information, amplifying patient voices and incorporating their experiences into healthcare research agendas (Blake et al., 2020; Evans et al., 2021). Analyzing UGC through sentiment analysis enables healthcare providers to gain critical insights into user satisfaction and improve healthcare services.

Sentiment analysis—the process of extracting subjective information from text and classifying it as *positive*, *negative*, or *neutral*—has become a powerful tool for interpreting patient experiences (Mittal & Agrawal, 2022). In healthcare, sentiment analysis is increasingly used to predict patient satisfaction and identify areas for improvement. Studies such as those by Budak et al. (2023) and Kumaresan & Thangaraju (2023) demonstrated how analyzing user feedback can guide personalized healthcare services. In broader contexts like mobile medical applications, researchers such as Fang et al. (2023) and Zhai et al. (2022) have shown how sentiment analysis helps detect trends in user satisfaction and tailor services accordingly. By analyzing patient reviews, healthcare providers can better understand user expectations and respond to concerns more effectively.

However, sentiment analysis goes beyond classifying feedback as merely *positive*, *neutral*, or *negative*. Emotion detection models offer deeper insights by analyzing the specific emotions conveyed in user reviews. For example, Lee et al. (2022) demonstrated how emotion detection could predict patient satisfaction by identifying emotional cues in reviews, while studies by Mawadati et al. (2024) and Li et al. (2024) highlighted the value of emotion detection in enhancing personalized care. These models show that analyzing emotions within reviews can lead to actionable insights, improving patient engagement and satisfaction.

Tools such as VADER (Valence Aware Dictionary and Sentiment Reasoner) and the NRC Emotion Lexicon are widely used in conjunction to analyze the emotional content of reviews. VADER is particularly well-suited for analyzing informal texts such as social media posts, effectively categorizing sentiments as *positive*, *neutral*, or *negative* using a lexicon-based approach (Arifka et al., 2022). However, VADER focuses on sentiment polarity rather than detecting a wide range of emotions. The NRC Lexicon expands on this by mapping words to eight core emotions—*joy*, *sadness*, *anger*, *fear*, *surprise*, *trust*, *disgust*, and *anticipation*—providing a more detailed understanding of emotional expressions (Mohammad, 2009; Mohammad et al., 2018). Combining tools like VADER and the NRC Lexicon offers a more comprehensive analysis of user feedback, as Czarnek and Stillwell (2022) advocated. This is evident, for instance, in the study by Serrano-Guerrero et al. (2022), where the challenges of detecting emotions in non-English languages are emphasized, advocating for the development of robust multilingual lexicons to improve the accuracy of emotion detection across diverse linguistic contexts.

While these tools have gained traction, there remains a significant gap in the literature concerning the correlation between emotional expressions in drug reviews and user satisfaction ratings. Previous studies have largely focused on sentiment analysis in areas such as mental health services (Shao et al., 2023), tourism (George & Ramos, 2024), and product reviews (Salim et al., 2021), but few have examined sentiment and emotion detection specifically within drug reviews. For instance, Feng et al. (2022) explored emotional expressions in drug treatment reviews, particularly the role of emotional arousal in perceived helpfulness. Their findings suggest that emotionally charged reviews are often considered more helpful by other users. Similarly, Gräßer et al. (2018) examined the predictive power of emotional sentiments concerning user satisfaction, side effects, and drug effectiveness. However, these studies did not investigate which specific emotions are the strongest predictors of high or low ratings, nor did they explore how different drug categories elicit distinct emotional responses.

This study seeks to fill these gaps by analyzing how specific emotions correlate with drug satisfaction ratings across various drug categories. Understanding how emotions influence drug ratings is critical for healthcare providers and pharmaceutical companies aiming to improve patient outcomes. Studies such as Admojo et al. (2024) and Zhai et al. (2022) have shown that emotions like *joy* and *trust* are strongly linked to higher satisfaction, while emotions such as *anger* and *fear* correlate with dissatisfaction. Similarly, Golondrino et al. (2023) demonstrated how emotional language in healthcare reviews provides insights into patient preferences and concerns, influencing their satisfaction with treatments.

This study utilizes a drug review dataset from the University of California Irvine (UCI) Machine Learning repository (Gräßer et al., 2018), which includes a wide range of reviews across various drug categories. Although not the most recent dataset, it offers a comprehensive foundation for analyzing the relationship between emotional expressions and user satisfaction. Tools such as VADER and the NRC Lexicon are employed to detect and classify emotions, allowing for the identification of patterns in emotional responses across different drug categories. By combining sentiment analysis and emotion detection, this research aims to provide new insights into the emotional dynamics of drug reviews and their impact on user satisfaction.

In addressing gaps in prior research, this study contributes to a deeper understanding of how emotional language in drug reviews influences patient satisfaction. The findings will offer practical implications for healthcare providers, pharmaceutical companies, and digital health platforms, helping to improve patient engagement, refine drug development processes, and tailor communication strategies to better meet patients' emotional and informational needs.

2. Method

This study analyzed user-generated drug reviews from the *drugsComTest_raw.csv* and *drugsComTrain_raw.csv* datasets, which were sourced from the University of California Irvine (UCI) Machine Learning repository (Gräßer et al., 2018). These datasets underwent preprocessing to ensure data quality before applying sentiment analysis and emotion detection models. The methods used, including tokenization, lemmatization, sentiment analysis, and emotion detection, were chosen based on their suitability for processing healthcare-related texts.

2.1. Datasets Preprocessing

The datasets, *drugsComTest_raw.csv* and *drugsComTrain_raw.csv*, contain user reviews of various drugs, including fields such as:

- uniqueID: Unique identifier for each review.
- drugName: The name of the drug being reviewed.
- condition: The medical condition for which the drug was used.
- review: The full-text review written by the user.
- rating: User rating of the drug on a scale of 1-10.
- date: Date the review was submitted.
- usefulCount: The number of times other users found the review useful.

The preprocessing phase cleaned and prepared the data for sentiment and emotion analysis. First, *drugsComTest_raw.csv* and *drugsComTrain_raw.csv* were combined into a unified dataset for comprehensive analysis (Gräßer et al., 2018). Then, HTML characters and punctuation were removed, and the text was standardized to lowercase (Gräßer et al., 2018). Tokenization split the text into individual words for detailed analysis (Arifka et al., 2022; Maysyaroh & Rusydiana, 2023), while lemmatization reduced words to their base form, simplifying the data (Kimani et al., 2024).

The preprocessing steps, including tokenization and lemmatization, were selected due to their effectiveness in healthcare text processing. Unlike other approaches, these methods ensure that context-specific words related to drug reviews (e.g., conditions, side effects) are analyzed accurately. These standard NLP techniques helped eliminate noise and improved the reliability of the sentiment and emotion analysis.

2.2. Sentiment Analysis

For sentiment analysis, the study employed a *Python* library known as VADER, a lexicon-based tool that categorizes sentiment polarity as positive, neutral, or negative (Kimani et al., 2024). VADER was chosen for its demonstrated effectiveness in processing social media and informal texts (Arifka et al., 2022). Its focus on sentiment polarity, especially in healthcare reviews, made it an appropriate choice for this study (Chalkias et al., 2023; Rao et al., 2020).

a. **Sentiment Scoring**: Each review was assigned a sentiment score ranging from -1 (very negative) to +1 (very positive). Neutral scores fell closer to 0. This approach enabled a clear numerical representation of the sentiment across reviews.

b. **Visualization**: Sentiment distribution plots were created to illustrate the overall emotional tone of the reviews. Additionally, boxplots were used to correlate sentiment scores with user ratings, helping to identify patterns in how users rated drugs based on their expressed sentiments.

2.3. Emotion Detection

Emotion detection was conducted using the NRC Word-Emotion Lexicon, which maps words to eight core emotions—*joy*, *sadness*, *anger*, *fear*, *surprise*, *trust*, *disgust*, and *anticipation*—providing a nuanced understanding of user emotions (Mohammad, 2009). This model was chosen to offer greater emotional depth than standard sentiment analysis tools (Mohammad et al., 2018). Words in each review were classified according to these emotions, allowing for the quantification of emotional expressions and a detailed analysis of the emotional landscape in user feedback.

To further explore emotional patterns, the frequency of each emotion was calculated across the entire dataset, revealing which emotions were most commonly expressed. Additionally, a bar plot was created to visualize the top 10 most frequent emotions, providing a clearer picture of the emotional tendencies within user reviews. Emotion analysis was also conducted by drug condition (e.g., "Depression"), allowing for the examination of how different medical conditions might be associated with specific emotional responses.

2.4. Correlation Analysis

The correlation analysis aimed to explore the relationship between the emotions expressed in user reviews and the corresponding ratings. This involved calculating the correlations between specific emotions, such as *happiness* or *anger*, and the review ratings to identify whether certain emotions are associated with higher or lower ratings. By mapping these correlations through visual tools such as heatmap, the analysis sought to reveal patterns indicating whether particular emotions align with extreme ratings (1-2 or 9-10) or more moderate ratings (5-6).

Additionally, the intensity of emotions expressed in the reviews was measured and correlated with the ratings to assess how strongly emotional expression impacts user satisfaction. This step provided insights into whether reviews with higher emotional intensity, regardless of the type of emotion, tend to correlate with more extreme user ratings, thereby offering a deeper understanding of how emotional content influences drug satisfaction.

2.5. Drug Category Analysis

The drug category analysis involved grouping the reviews into broader categories such as antidepressants, contraceptives, painkillers, and other drug types. This step aimed to investigate whether certain drug categories were more likely to elicit specific emotional responses from users. By calculating the prevalence of emotions within each category, the analysis provided insights into how emotions like *joy*, *sadness*, and *anger* are distributed across different drug types.

To ensure the results accurately reflected the emotional trends within each category, the prevalence of emotions was normalized by the total number of reviews in each category. This normalization allowed for a clearer comparison of emotional expression across drug types, regardless of the category size. Stacked bar plots were generated to visualize the distribution of emotions, helping to identify patterns in emotional language that may be associated with specific drug types and their corresponding user ratings.

2.6. Statistical Testing

The statistical testing phase of this study involved examining the relationships between emotional expressions in user reviews and the corresponding ratings using two key approaches: hypothesis testing and regression analysis. Hypothesis testing employed chi-square tests to determine if the presence of specific emotions (such as *joy*, *anger*, or *sadness*) was significantly associated with the rating levels provided by users. Each emotion was tested individually, with results including the chi-square statistic, p-value, degrees of freedom, and expected frequencies, offering insights into whether the observed emotional trends were statistically significant across varying rating levels.

To further explore the predictive power of emotions, a linear regression model was used to predict review ratings based on the emotional content of the reviews. The presence of specific emotions served as the independent variables, while the user rating acted as the dependent variable. Regression coefficients for each emotion were calculated, indicating the extent to which each emotion influenced the predicted ratings. The performance of the model was evaluated using R-squared and Mean Squared Error (MSE) metrics, which provided an understanding of the proportion of variance in the ratings explained by emotions and the accuracy of the model's predictions. This comprehensive statistical analysis helped uncover the significance and predictive capabilities of emotional expressions within user-generated drug reviews.

2.7. Dataset Limitations

It is important to acknowledge the limitations of the dataset. As the user reviews are sourced from an online platform, there is potential for demographic biases. For example, reviews may be disproportionately written by certain user groups, such as younger individuals or users from specific geographic regions. This may impact the generalizability of the findings to a broader population. While the dataset provides valuable insights, these biases should be considered when interpreting the results.

3. Results and Discussion

3.1. Sentiment Score Distribution

The sentiment score distribution, illustrated in Fig. 1, reveals the polarized nature of user-generated drug reviews, with clusters at the extremes. Specifically, over 14.000 reviews have a sentiment score of -1.00, representing highly negative sentiment, while approximately 12.500 reviews have a sentiment score of 1.00, indicating highly positive sentiment. This finding aligns with the notion of emotionally charged content driving user engagement, as suggested by Feng et al. (2022), who found that emotionally arousing reviews are perceived as more helpful by other users. However, unlike Feng et al. (2022), the present study focuses on which specific emotions are most predictive of user satisfaction, filling a gap in understanding the connection between emotional expression and ratings.

Technically, this bimodal distribution highlights a critical shortcoming in sentiment analysis models: the difficulty in capturing moderate, neutral feedback, a challenge similarly noted by Gräßer et al. (2018). While Gräßer et al. focused more on the overall sentiment, the current study takes a more granular approach by investigating the specific emotional responses that drive these extreme sentiments. The absence of moderate feedback suggests a need to refine sentiment models to capture subtler, mixed reviews that may be underrepresented but critical for nuanced analysis of user experiences.

Operationally, pharmaceutical companies and healthcare providers must pay close attention to these highly polarized reviews. As Feng et al. (2022) suggested, emotionally charged content can drive perceptions of helpfulness, which may amplify the impact of both extremely positive and negative reviews. Companies should, therefore, focus on identifying the recurring issues in negative reviews, such as drug inefficacy or severe side effects, while leveraging the positive sentiment to strengthen adherence to treatment regimens.

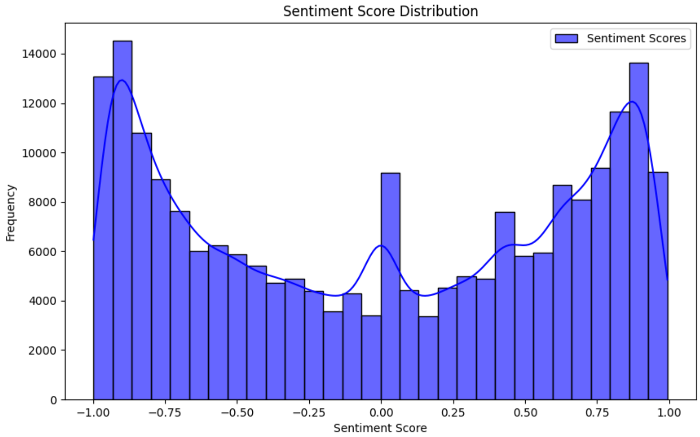

Fig. 1. Sentiment score distribution

From a business and management standpoint, the prominence of extreme sentiment presents both risks and opportunities. While negative reviews may harm a product's reputation, they can also highlight areas for product improvement. Conversely, positive reviews offer marketing opportunities to promote satisfaction and efficacy. The findings from the current study go beyond those of Gräßer et al. (2018) by offering specific actionable insights into which emotional drivers (e.g., joy, trust) should be emphasized in marketing strategies, whereas Gräßer primarily focused on the overall predictive power of emotional sentiments.

Another insight from the sentiment score distribution is that the calculated mean sentiment score across all reviews is slightly negative, at approximately -0.05. This suggests that, on average, user experiences lean slightly towards dissatisfaction, though the magnitude is small. The median sentiment score is also close to 0, indicating that half of the reviews express sentiments that are mildly negative or neutral. These values point to a complex reality where extremes dominate the user review space, but the majority of experiences may be more balanced than the distribution suggests. Pharmaceutical companies, therefore, should not only focus on addressing extreme cases but also pay attention to more moderate user feedback that may not always be vocalized in reviews.

Ultimately, the sentiment score distribution in drug reviews uncovers essential patterns and trends that pharmaceutical companies, healthcare providers, and patient advocates should explore further. By understanding the nuances of user sentiment, these stakeholders can better address patient concerns, optimize drug efficacy, and ensure that marketing and communication strategies align with patient experiences.

3.2. Sentiment Score Distribution by Rating

The relationship between sentiment scores and user ratings offers a comprehensive view of how sentiment expressed in drug reviews aligns with the numerical ratings provided by users. Fig. 2 reveals this relationship through a series of boxplots that showcase the distribution of sentiment scores across different rating levels, from 1 to 10. By examining this distribution, critical insights can be drawn about user experiences, sentiment intensity, and the consistency between qualitative feedback and quantitative ratings.

The boxplot illustrates that lower ratings (1-4) are generally associated with negative sentiment scores, with medians consistently below 0. For instance, the median sentiment score for reviews rated 1 is approximately -0.50, indicating a strong negative sentiment among the lowest-rated reviews. This finding is aligned with the broad variability in user feedback highlighted by Gräßer et al. (2018), who observed that low ratings are often linked to complaints about drug side effects or poor efficacy. Similarly, Feng et al. (2022) reported that emotionally charged reviews, particularly those driven by negative emotions, often attract more attention in terms of perceived helpfulness but did not specifically explore how these sentiments correlate with numerical ratings.

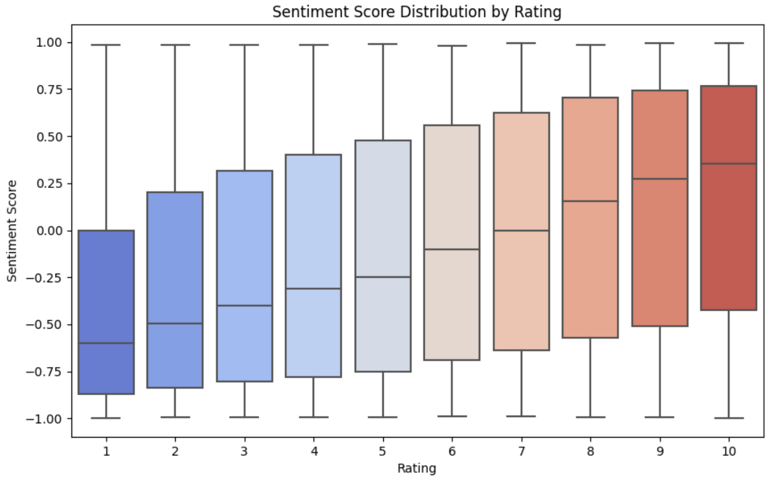

Fig. 2. Sentiment score distribution by rating

For mid-range ratings (5-6), the sentiment scores tend to cluster around 0, with a more balanced distribution of positive and negative sentiments. The median sentiment score for these ratings hovers close to neutral, reflecting a mix of positive and negative experiences. This reinforces the idea that mid-range ratings often represent a balance between user expectations and drug efficacy, a finding that Feng et al. (2022) also touched upon in their analysis of mixed sentiments in reviews. Unlike Feng et al., however, the current study directly correlates sentiment scores with specific rating bands, offering a clearer understanding of how nuanced sentiment expressions influence user satisfaction.

High ratings (7-10) exhibit a clear shift toward positive sentiment scores, with medians steadily rising as the rating increases. The median sentiment score for a rating of 10 is around 0.75, with the upper quartile extending close to the maximum score of 1.00. This strong correlation between high ratings and positive sentiment scores is consistent with findings from Gräßer et al. (2018), which identified a positive relationship between high ratings and favorable sentiment. However, the present study goes further by detailing the specific sentiments, such as *joy* and *trust*, that are most commonly associated with high ratings, offering more actionable insights for healthcare providers and pharmaceutical companies.

Technically, this spread in sentiment scores across ratings highlights a critical gap in current sentiment analysis models, particularly regarding the diversity of opinions within low-rated reviews, which often reflect a mix of negative and positive experiences. Feng et al. (2022) similarly noted that user reviews frequently contain mixed sentiments, even when the overall rating is positive or negative. This finding suggests that sentiment models should not only assess sentiment polarity but also capture the complexity and variability within reviews. Both Feng et al. (2022) and Gräßer et al. (2018) emphasized the predictive power of emotional content but did not explore how specific emotions vary by rating. The current study addresses this gap by showing that while positive emotions such as *joy* are correlated with high ratings, negative emotions such as *anger* and *disgust* significantly drive lower ratings. This deeper analysis is crucial for refining sentiment models to better capture the multifaceted nature of user feedback.

Operationally, the broad range of sentiments associated with low ratings indicates areas where healthcare providers and pharmaceutical companies can intervene. For instance, the variability in negative reviews could be tied to specific drug side effects or mismatched patient expectations. Understanding these patterns can lead to better patient education and support strategies that address the root causes of dissatisfaction. Similarly, high ratings paired with consistently positive sentiments highlight opportunities to improve drug adherence by focusing on the factors that contribute to positive patient experiences.

For pharmaceutical companies, understanding the distribution of sentiment across ratings informs product development and marketing strategies. Companies can analyze which drugs are associated with wider IQRs and thus may require targeted communication or product modifications. Conversely, drugs that are consistently associated with high ratings and positive sentiment could be promoted more aggressively to capitalize on their successful attributes.

3.3. Emotion Detection Analysis

The analysis of emotional content in user-generated drug reviews reveals significant patterns in how emotions are distributed across the dataset. Emotions detected through the NRC Emotion Lexicon offer insights into the underlying sentiments of users based on their experiences with various drugs. By examining the frequency of specific emotions, as depicted in Fig. 3, it is possible to discern which emotions are most prevalent and how they might influence user satisfaction and drug ratings.

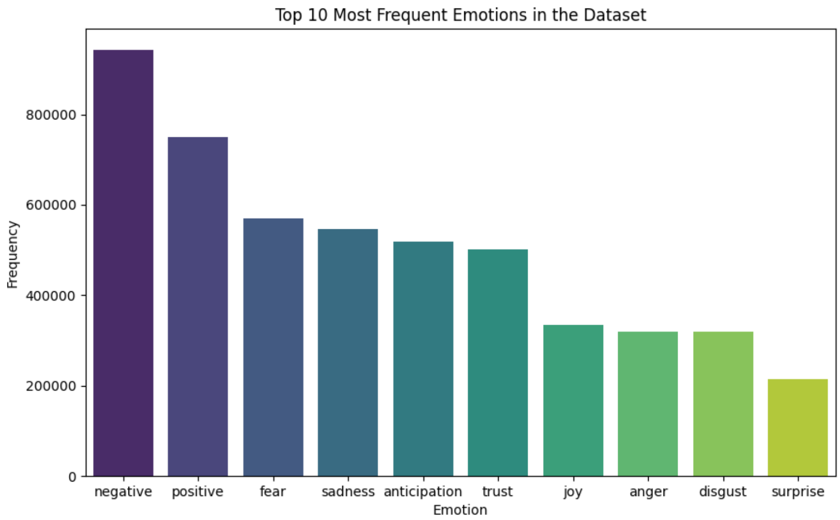

Fig. 3. Most frequent detected emotions

The current study shows that negative emotions technically dominate user reviews, with 942.524 occurrences, followed by positive emotions with 749.878 occurrences. This aligns with the findings of Gräßer et al. (2018), who also reported a high frequency of negative emotions in drug reviews, particularly those related to side effects and drug inefficacy. However, Gräßer et al. did not delve into the specific breakdown of emotions, such as fear or sadness, as this study does. By identifying the most frequently occurring emotions, the current study provides more granular insights into user experiences, allowing for a more targeted analysis of how specific emotions impact overall satisfaction.

Fear and *sadness* are also notably prevalent, with 570.479 and 545.311 occurrences, respectively. These emotions typically reflect user concerns about potential side effects, treatment ineffectiveness, or worsening conditions, all of which are critical factors in healthcare decision-making. The prominence of these emotions underscores the importance of addressing patient anxieties and expectations through better communication and support.

Anticipation and *trust* also appear frequently, with 517.747 and 500.699 occurrences, respectively. The presence of anticipation may indicate hope or expectation regarding treatment outcomes, while trust likely reflects confidence in the medication or healthcare provider. These emotions are vital for maintaining patient engagement and adherence to prescribed treatments. High levels of trust are particularly important for healthcare providers and pharmaceutical companies, as they directly correlate with patient loyalty and continued use of specific drugs.

Joy, *anger*, *disgust*, and *surprise* occur less frequently, with 333.687, 319.416, 319.047, and 215.045 mentions, respectively. *Joy* reflects positive treatment outcomes and satisfaction, while *anger* and *disgust* likely represent frustration with adverse effects or poor efficacy. The presence of surprise might indicate unexpected outcomes, whether positive or negative. Although these emotions are less frequent, they are still significant, as they provide additional context for understanding patient experiences and tailoring healthcare services to better meet patient needs.

Operationally, this emotion detection analysis provides actionable insights for healthcare providers. Negative emotions, particularly *fear* and *sadness*, should prompt further investigation into patient concerns, whether they stem from side effects, ineffective treatment, or anxiety about long-term outcomes. Addressing these emotions through better communication and support services could enhance overall patient satisfaction. On the positive side, emotions such as *trust* and *anticipation* suggest that patients hold optimistic expectations about their treatments, which could be reinforced through educational initiatives that manage expectations and foster confidence in prescribed medications.

From a business perspective, the emotion detection analysis offers valuable insights for developing marketing strategies and improving product support services. For example, *trust* and *anticipation* are linked to positive emotions that pharmaceutical companies can leverage in their messaging to reinforce confidence in their products. Meanwhile, identifying drugs that elicit strong negative emotions, such as *fear* or *disgust*, allows companies to focus on mitigating those issues through product improvements or targeted patient education programs.

3.4. Correlation between Emotions and Ratings

The correlation analysis between emotions and ratings provides valuable insights into how different emotional expressions influence user satisfaction as reflected in the ratings they assign to drug reviews. Fig. 4 illustrates the relationships between emotions such as *joy*, *trust*, *fear*, and *sadness*, and the numerical ratings that users provide. The heatmap enables the identification of strong and weak correlations through color gradations, with stronger relationships represented by deeper shades.

The analysis shows that *joy* has the strongest positive correlation with ratings, at 0.1, indicating that as expressions of *joy* in reviews increase, the ratings tend to be higher. This reflects the natural association between positive experiences and higher satisfaction levels. Similarly, *trust* has a moderate positive correlation with ratings (0.032), suggesting that when users express trust in a drug's efficacy, their satisfaction tends to be reflected in higher ratings.

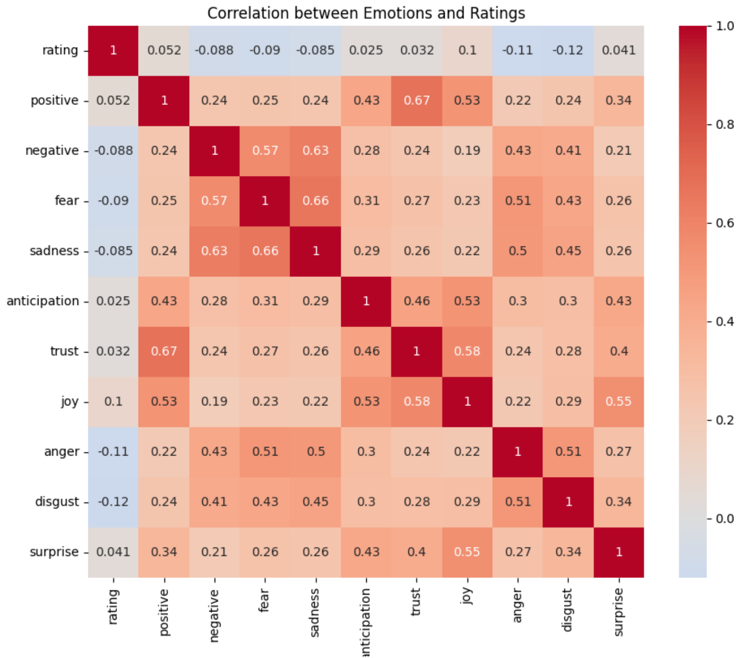

Fig. 4. Correlation between emotions and ratings

On the other hand, negative emotions such as *anger* and *disgust* are negatively correlated with ratings, with correlation coefficients of -0.11 and -0.12, respectively. This indicates that when users express these emotions, the ratings tend to be lower, reflecting dissatisfaction or disappointment with the drug's performance. *Fear* and *sadness* also show negative correlations with ratings (-0.09 and -0.085, respectively), further emphasizing the link between negative emotional expressions and lower user satisfaction.

Technically, the relatively low correlation values between most emotions and ratings suggest that, while emotions do influence ratings, they are not the sole determinant of user satisfaction. Factors such as drug efficacy, side effects, and individual health outcomes likely play a critical role that is not fully captured by emotional expressions alone. For instance, the weak positive correlation for *joy* shows that even positive emotions may not always lead to higher ratings, highlighting the complexity of patient experiences. Similarly, negative emotions like *anger* and *disgust* are linked to lower ratings but do not entirely explain dissatisfaction. This underscores the need for sentiment and emotion detection models to incorporate additional variables like treatment effectiveness and side effect severity. These findings align with those of Feng et al. (2022) and Gräßer et al. (2018), who emphasized the importance of emotional expression in reviews but acknowledged that it is not the only factor driving satisfaction. The current study extends their work by providing a more granular breakdown of emotions, revealing how specific emotional responses contribute to user satisfaction or dissatisfaction, while Feng et al. (2022) focused on emotional arousal, and Gräßer et al. (2018) addressed general sentiment rather than specific emotional patterns related to particular drugs.

Operationally, these findings highlight the need to address both emotional and practical concerns in patient feedback. The correlation between emotions and ratings suggests that pharmaceutical companies should focus not only on enhancing the emotional experience of users but also on addressing practical issues, such as drug side effects and perceived inefficacy. While positive emotions such as *joy* and *trust* are linked to higher satisfaction, improving practical aspects of treatment—such as minimizing side effects or increasing drug effectiveness—could significantly enhance overall patient experiences. Pharmaceutical companies and healthcare providers should develop strategies that integrate both emotional expressions and treatment outcomes to boost user satisfaction. By addressing both emotional and practical factors, companies can more effectively meet patient needs and improve satisfaction.

From a business and management perspective, the findings underscore the potential for emotion-based marketing strategies. Emotions like *joy* and *trust*, which are linked to higher ratings, could be targeted in promotional campaigns to highlight positive user experiences. Conversely, identifying and addressing the sources of negative emotions in user reviews, such as *anger* and *disgust*, could improve overall patient satisfaction and enhance brand loyalty. The ability to quantify and track emotions can also assist in developing more effective communication strategies that resonate with patients on an emotional level, ultimately fostering better relationships between pharmaceutical companies and their consumers.

3.5. Average Emotion Presence by Rating

The breakdown of average emotion presence by rating, shown in Fig. 5, illustrates clear patterns in emotional expression relative to user satisfaction. Positive emotions, such as *joy* and *trust*, are more frequently expressed in higher ratings, particularly in the 8-10 range, where they dominate with an average presence above 0.85. On the other hand, negative emotions such as *anger* and *disgust* are strongly correlated with lower ratings (1-3), where their presence approaches 0.8. This suggests that users who are dissatisfied with their treatment tend to express more intense negative emotions, providing a clear emotional profile of dissatisfaction.

Comparing these findings with Feng et al. (2022), who focused on the emotional arousal in reviews and its role in perceived helpfulness, we observe a broader focus in the current study. While Feng et al. emphasized emotional intensity as a critical factor, the present research quantifies the prevalence of specific emotions, highlighting that it is not merely the intensity of emotion, but the type of emotion (*anger*, *joy*, etc.) that plays a significant role in user satisfaction. Gräßer et al. (2018) similarly examined emotional sentiment but did not break down specific emotions by rating as thoroughly as this study, which fills a gap in understanding how emotion type correlates with rating scores.

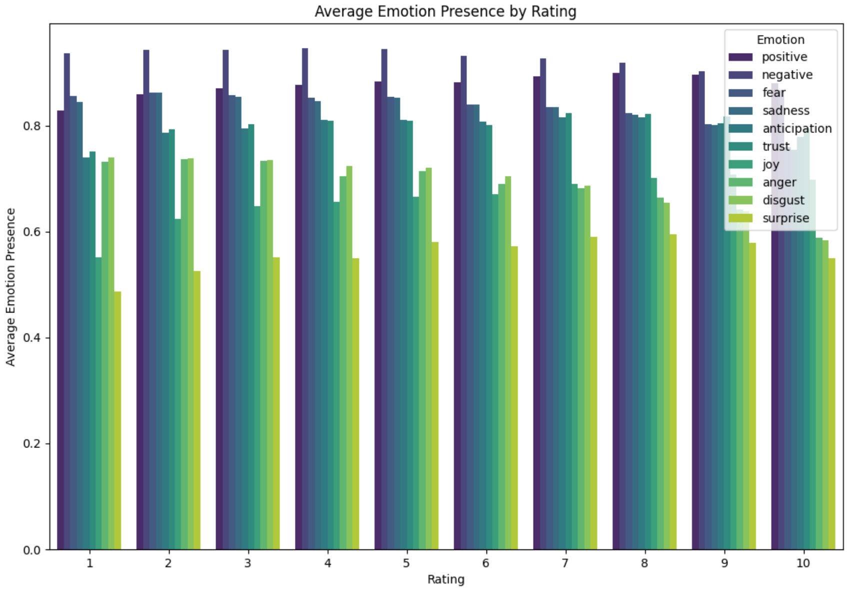

Fig. 5. Average emotion presence by rating

Technically, the findings suggest that targeted sentiment and emotion detection algorithms could help businesses identify areas that require attention, especially when users express emotions such as *anticipation* and *trust* in mid-range ratings (5 to 7). These emotions often signal neutral or mixed sentiments, indicating that while the experience may not have been entirely negative, it did not fully meet user expectations either. The relatively high presence of anticipation across ratings, averaging between 0.55 to 0.7, suggests that users frequently express hope or expectations, regardless of their satisfaction levels. To improve sentiment models, it's important to account for not just the intensity of emotions, but also their specific types. For example, emotions like *joy* and *trust*, which are linked to positive experiences, vary significantly across ratings, signaling that the relationship between emotion and satisfaction is more complex than polarity alone can capture. Developing more sophisticated algorithms, such as BERT (Bidirectional Encoder Representations from Transformers) or GPT-based models, can help detect nuanced emotional expressions by analyzing context, sentiment intensity, and word associations. These advanced models, which leverage deep learning and natural language processing (NLP), can capture the subtleties of emotional variations and provide a more accurate understanding of how specific emotions, even within the same polarity, contribute differently to user satisfaction.

From an operational perspective, analyzing the presence of emotions across ratings reveals valuable insights into user experiences. Negative emotions such as *fear*, *sadness*, *anger*, and *disgust* are notably more prevalent in lower-rated reviews (typically 1 to 3), with *anger* showing a presence of 0.45 to 0.55 and *disgust* peaking within the same range, indicating potential dissatisfaction. This high concentration of negative emotions offers actionable insights for healthcare providers and pharmaceutical companies, as drugs consistently associated with these emotions may require improved patient education or better management of side effects. Conversely, positive emotions in higher-rated reviews highlight areas where companies can enhance patient satisfaction through targeted communication and support services, reinforcing positive experiences and improving user engagement.

From a business and management perspective, companies can leverage emotional data to better tailor their responses and strategies. High ratings accompanied by positive emotions reflect strong customer satisfaction, offering opportunities to reinforce these experiences through marketing and customer engagement efforts. Conversely, identifying lower ratings with heightened levels of negative emotions like *anger* or *disgust* provides actionable insights for addressing dissatisfaction and improving product or service offerings. By understanding the emotional dynamics associated with different ratings, businesses can prioritize improvements that directly enhance customer satisfaction, retention, and overall brand loyalty.

3.6. Emotional Intensity vs Rating

The analysis of emotional intensity in relation to user ratings provides valuable insights into how the depth and variety of emotions expressed by users correlate with their satisfaction levels. Compared to previous studies, Gräßer et al. (2018) analyzed general emotional sentiment but did not break down emotions by specific drug categories. This study extends their findings by categorizing emotions across drug types, revealing the distinct emotional profiles tied to different treatments. Similarly, Feng et al. (2022) focused on emotional arousal without differentiating the emotional types elicited by specific drugs. The present study addresses this gap by showing how different drugs evoke distinct emotional reactions, offering deeper insights into patient experiences.

Fig. 6 visualizes this relationship, using bubble sizes to represent varying levels of emotional intensity across different ratings, ranging from 1 to 10. The calculated correlation between emotional intensity and rating is -0.0494, indicating a very weak negative relationship. This suggests that higher emotional intensity does not necessarily correlate with higher or lower ratings in a linear fashion.

Fig. 6. Emotional intensity vs rating

Moreover, the graph shows that the emotional intensity of reviews does not consistently increase or decrease with ratings. The plot reveals some outliers, particularly one review with a rating of 1 displaying an extraordinarily high emotional intensity of over 400, significantly above the typical range. Additionally, there are other noticeable outliers with intensity values exceeding 300 at ratings 2 and 10. These outliers indicate that certain reviews, regardless of their rating, carry a disproportionately large emotional weight, which may be indicative of extreme experiences (either very positive or very negative) that users feel compelled to express intensely.

From a technical perspective, this analysis highlights the challenge of emotional variability in user-generated content. The relatively low correlation between emotional intensity and rating indicates that emotional intensity alone is not a strong predictor of user satisfaction or dissatisfaction. This suggests that the presence of strong emotions (whether positive or negative) does not always translate into extreme ratings, pointing to the complexity of user experiences and their expression through reviews.

Operationally, the data underscores the importance of monitoring not just the ratings themselves but also the emotional intensity of reviews. For customer service and support teams, high emotional intensity may serve as a signal to prioritize engagement with these users, regardless of whether their ratings are high or low. For instance, the review with the extremely high emotional intensity at a rating of 1 likely represents a particularly negative experience that could merit immediate intervention.

From a business and management perspective, companies should focus on identifying patterns in emotional intensity to better understand user feedback. Emotional intensity, particularly at extreme levels, can indicate deeply impactful experiences (both good and bad). Addressing these high-intensity reviews effectively could be key to improving customer satisfaction and loyalty. The bubble plot suggests that users with high emotional intensity at both ends of the rating spectrum may be the most passionate or emotionally invested in the product, making their feedback particularly valuable for continuous improvement and relationship management efforts.

3.7. Emotional Prevalence by Drug Category

The analysis of emotional prevalence across different drug categories offers a more detailed understanding of how various medications shape user emotions and influence satisfaction or dissatisfaction. While previous studies, such as Gräßer et al. (2018), assessed general emotional sentiment and Feng et al. (2022)

focused on emotional arousal, neither study delved into how specific drugs elicit distinct emotional responses. This study builds on their work by categorizing emotions across different drug types, revealing unique emotional profiles tied to each treatment. By examining the emotional responses to antidepressants, contraceptives, painkillers, and other drugs, deeper insights into patient experiences emerge. Fig. 7 showcases these emotional profiles, showing the prevalence of emotions such as *positivity*, *fear*, *sadness*, *trust*, *joy*, *anger*, and *disgust*. This detailed emotional mapping highlights the complexity of patient reactions to different treatments and offers crucial insights into user experiences.

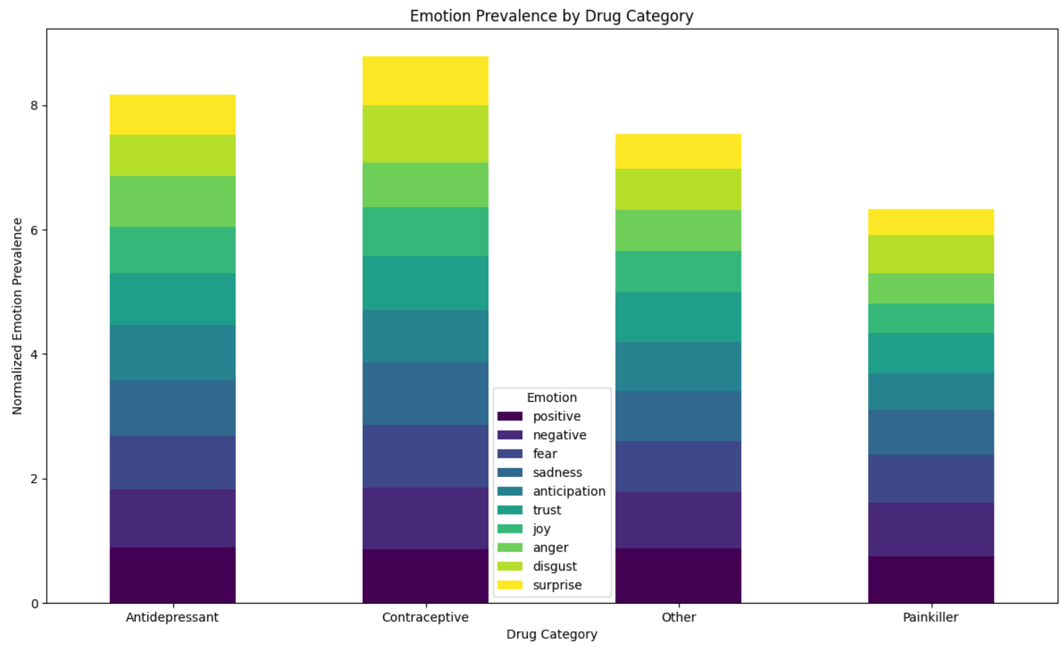

Fig. 7. Emotional prevalence by drug category

The most striking feature of the results is the consistently high prevalence of negative emotions across all drug categories. Antidepressants, for instance, show a 93% prevalence of negative emotions, which is not surprising given the nature of the conditions they treat, where users may often express frustration or *sadness* regarding their struggles with mental health. Similarly, contraceptives have a 100% prevalence of negative emotions, potentially due to side effects or dissatisfaction with the product's impact on users' health and lifestyle. Painkillers, though designed to relieve physical pain, still display a 86% prevalence of negative emotions, which could stem from persistent pain, side effects, or a lack of efficacy.

Conversely, the prevalence of positive emotions is also notably high, particularly for antidepressants, where 89% of reviews express some form of positivity. This duality suggests that while users of antidepressants may face significant challenges, they also experience considerable relief and positive outcomes, perhaps reflecting the mixed and complex experiences typical of those dealing with chronic mental health conditions. This positive prevalence decreases slightly in painkillers (74%) and contraceptives (86%), suggesting that while users report some level of satisfaction, these medications may not always deliver the desired effects consistently.

From a technical perspective, this analysis highlights the utility of emotion detection models in parsing the nuances of user feedback. By breaking down emotions into finer categories such as *joy*, *trust*, and *sadness*, we can better understand the diverse emotional responses elicited by various drugs. The classification model proves effective in capturing the complexity of user experiences, which are not strictly negative or positive but a combination of both, depending on the circumstances.

Operationally, the data suggests that companies manufacturing antidepressants, contraceptives, and painkillers need to pay close attention to the emotional language in user reviews. Understanding the prevalence of negative emotions can help these companies focus on improving specific aspects of their products, whether related to side effects, efficacy, or user experience. On the other hand, the positive emotional responses—particularly the *joy* and *trust* metrics—highlight areas where these products are meeting user expectations and should be emphasized in marketing and customer engagement strategies.

From a business and management perspective, emotional prevalence data provides actionable insights into consumer sentiment, which can drive product development and strategic planning. For instance, the 88% prevalence of *trust* in antidepressant reviews suggests that these medications foster a reliable relationship between the user and the product, even in the face of significant challenges. Companies can leverage this trust to build stronger brand loyalty and foster long-term relationships with users. Similarly, the relatively high levels of *anticipation* and *joy* (e.g., 75% and 78%, respectively, in contraceptives and antidepressants) indicate that despite the difficulties users face, they hold hopeful expectations for their treatments, which is a crucial aspect of maintaining consumer confidence.

In summary, this emotional prevalence analysis serves as a critical tool for understanding the intersection of user emotions and product efficacy, guiding both operational improvements and business strategies in the pharmaceutical sector. Fig. 7 provides a clear visual representation of these dynamics, highlighting the importance of balancing emotional feedback with product development and user engagement efforts.

3.8. Predictive Power of Emotions

The analysis of the predictive power of emotions in determining user satisfaction through drug reviews offers crucial insights into how emotions can influence the ratings given by users. By employing statistical tests and regression analysis, the study aims to quantify the significance and impact of various emotions on user ratings, which can be pivotal for understanding patient experiences and guiding business decisions in the pharmaceutical industry.

Table 1 presents a detailed breakdown of the chi-square statistics, p-values, regression coefficients, and the predictive impact of each emotion on user ratings. The chi-square results indicate that all emotions analyzed have a statistically significant association with user ratings, with p-values approaching zero in almost all cases, suggesting that the presence or absence of these emotions is highly relevant to how users rate their drug experiences.

From a technical standpoint, the regression analysis provides quantitative evidence of how each emotion contributes to the overall prediction of ratings. For instance, the regression coefficient for *joy* is 0.910, indicating that the presence of *joy* in a review significantly increases the predicted rating. Conversely, emotions like *anger* and *disgust* have negative coefficients (-0.440 and -0.790, respectively), highlighting their strong negative impact on ratings. The R-squared value of approximately 0.043 suggests that while emotions do have predictive power, there are other factors influencing user ratings that are not captured by emotions alone.

Table 1. Predictive Power of Emotions

Emotion	Chi-Square Statistic	P-Value	Regression Coefficient	Predictive Impact
Positive	967.60	1.66e-202	0.443	Moderate Positive
Negative	2301.46	0.00	-0.330	Strong Negative
Fear	2200.84	0.00	-0.279	Strong Negative
Sadness	2156.38	0.00	-0.043	Weak Negative
Anticipation	755.54	7.84e-157	0.057	Weak Positive
Trust	644.78	5.08e-133	-0.217	Moderate Negative
Joy	2560.35	0.00	0.910	Strong Positive
Anger	2967.90	0.00	-0.440	Strong Negative
Disgust	3506.79	0.00	-0.790	Strong Negative
Surprise	924.75	2.88e-193	0.234	Moderate Positive

Operationally, these findings can guide pharmaceutical companies in monitoring and responding to user reviews more effectively. By identifying emotions that strongly predict low ratings, such as *anger* and *disgust*, companies can prioritize addressing these concerns in their customer service and product development efforts. For example, if a particular drug frequently elicits negative emotions, it may warrant further investigation to identify and mitigate any underlying issues.

From a business and management perspective, the ability to predict user satisfaction based on emotional content has strategic implications. Understanding which emotions are most strongly associated with high or low ratings allows companies to tailor their marketing and communication strategies accordingly. Positive emotions like *joy* and *anticipation* could be emphasized in promotional materials, while strategies to mitigate negative emotions should be developed to improve overall customer satisfaction and brand perception. The regression analysis suggests that enhancing the emotional experience of users—particularly by fostering positive emotions—can lead to better satisfaction outcomes, ultimately driving customer loyalty and positive word-of-mouth.

The analysis underscores the value of sentiment and emotion detection as tools for enhancing user experience and satisfaction in the pharmaceutical industry. By leveraging these insights, companies can make data-driven decisions that align with customer needs and expectations, thereby improving their competitive edge in the market.

4. Conclusion

This study emphasizes the importance of emotions in predicting user satisfaction in drug reviews, using sentiment analysis and emotion detection to uncover correlations between specific emotions and satisfaction ratings. Joy showed the strongest positive correlation with satisfaction, while disgust had the most negative impact. The research highlights the potential for healthcare professionals to use emotional feedback to refine patient care and for pharmaceutical companies to enhance customer engagement through emotion-based marketing. While emotions significantly influence satisfaction, the low R-squared value suggests additional factors like drug efficacy and patient demographics should be included in future models. Advanced techniques, such as machine learning, could improve predictive accuracy and provide deeper insights into diverse user experiences, offering actionable strategies to improve patient outcomes and satisfaction in the pharmaceutical sector.

Supplementary Materials: The raw datasets, *drugsComTest_raw.csv* and *drugsComTrain_raw.csv*, sourced from the University of California Irvine Machine Learning repository, can be downloaded at: https://www.kaggle.com/datasets/jessicali9530/kuc-hackathon-winter-2018.

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