



# WPI

## **Integrating Generative AI into User Centered Design Approach**

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This report represents the work of one or more WPI undergraduate students submitted to the faculty as evidence of completion of a degree requirement. WPI routinely publishes these reports on the web without editorial or peer review.

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## Abstract

This project investigates digital health tools for Opioid Use Disorder (OUD) and Substance Use Disorder (SUD) individuals with a focus on app retention to enhance long-term outcomes for this vulnerable population. Using data mining techniques and large language models, the project explores app retention factors, evaluates existing retention strategies, and recommends enhanced retention approaches. The goal is to comprehensively grasp user retention dynamics to improve recovery outcomes and reduce relapse rates for individuals with OUD and SUD.

## Executive Summary

The opioid crisis continues to pose a significant public health challenge. Access to effective rehabilitation and recovery support is crucial in addressing this crisis. This project explores the use of digital health tools to aid in the treatment and recovery of individuals with Opioid Use Disorder (OUD) and Substance Use Disorder (SUD). This study examines the role of app retention in improving the long-term outcomes and well-being of this vulnerable population. Mobile health applications have gained popularity as tools to bridge the gap in care, offering personalized and accessible support. Evaluating existing digital health apps and assessing their app retention strategies are essential steps in determining the best features apps offer to provide support for individuals with OUD in their recovery journey. These apps can be essential tools for individuals managing addiction, providing immediate access to resources for their recovery journey.

App retention, a challenging aspect, is influenced by factors like engagement, usability, content quality, and community support within the app's ecosystem. While existing strategies primarily focus on user engagement, personalized content, and social support, there is a need for comprehensive research to uncover additional factors and develop effective retention strategies. The objectives of this project encompass identifying retention-influencing factors, exploring user preferences affecting retention, and developing strategies for improved app retention. By examining the effectiveness of digital health tools in this context, we can gain valuable insights into the specific elements that encourage users to engage with the app over an extended period, contributing to better recovery outcomes for this vulnerable population. This evaluation helps identify the potential benefits of sustained app usage, such as reduced relapse rates and increased access to treatment and community resources, offering a comprehensive understanding of the role mobile health applications play in the rehabilitation process.

The methodology employed in this research is centered around utilizing app reviews to gain a deeper understanding of the factors contributing to better engagement with apps. Traditional data mining methods, coupled with ChatGPT analysis, are employed to extract insights from user reviews of digital health apps designed for individuals with OUD and SUD. This combined approach aims to uncover both quantitative and qualitative aspects, providing a comprehensive understanding of user sentiments, preferences, and recommendations associated

with app usage. The integration of traditional data mining and ChatGPT analysis allows for a more nuanced exploration of the app landscape, offering insights into effective app retention strategies and user engagement dynamics. The research design consists of three phases: identifying factors affecting retention through content analysis, in-depth insight into user reviews, and developing retention strategies.

The research conducted on digital health apps, utilizing both sentiment analysis and ChatGPT prompt response, offers valuable insights into user sentiments and preferences. Positive associations with words like “love”, “support”, and “help” underscore the significance of supportive features in fostering positive user experiences. While both methods highlight common themes such as progress tracking, sentiment analysis provides specific insights from app store reviews, capturing themes within the most frequently used words that demonstrate feedback on issues such as ads, resets, updates, and glitches. In contrast, ChatGPT, though quick in generating responses, lacks the quantitative analysis provided from sentiment analysis. The synthesis of insights across multiple digital health apps reveals consistent positive themes, including community support, progress tracking, educational content, and motivational tools. Users value flexibility, customization, privacy features, and suggest areas for improvement, emphasizing the importance of user-centric design and clear communication. Recommendations for developers of these digital health apps include addressing technical issues, enhancing transparency, and building trust to meet user expectations effectively. This dual-method approach, combining quantitative and qualitative analyses, provides a comprehensive understanding of user experiences, contributing to the continual improvement of digital health applications.

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## 1.0 Introduction

The opioid use disorder (OUD) and substance abuse disorder (SUD) have left a noticeable mark on communities across the United States. In the face of this, individuals grappling with OUD and SUD face particularly formidable challenges as they attempt to reintegrate into society and rebuild their lives. Research consistently underscores that the initial three months of opioid recovery are the most arduous, marked by intense physical and psychological struggles (Sureshkumar, 2021). Given these significant challenges, my project aims to create a new solution through analyzing current digital health tools to determine the most important aspects of these apps for continued use and user retention. The motivation behind this research is rooted in the urgent need to address the devastating consequences of OUD and SUD within our society. Addiction not only harms individuals' lives but also perpetuates a cycle of criminal justice involvement, making reintegration into society a daunting task (DuFour, 2016). Studies have consistently shown that the first three months of opioid recovery are the most crucial and challenging, with a significantly higher risk of relapse and overdose during this period (Kadam et al, 2017). These compelling factors underscore the pressing need for a targeted and innovative approach to support individuals with OUD or SUD during their early recovery.

The development of this research project focuses on leveraging digital health tools to support individuals with OUD during their recovery journey. By incorporating digital health strategies, these apps aim to address critical issues related to harm reduction, including overdose and suicide prevention. They provide users with essential tools and resources aimed at reducing the risks associated with OUD and SUD, such as quick access to emergency services and crisis hotlines. These apps include features such as sobriety clocks, community chat rooms and social aspects, resources for health services, daily motivational messages, goals and milestones, and customization.

This project is rooted in a research-driven approach to identify and implement features that are most effective in supporting individuals with OUD and SUD on their recovery journey. Through extensive research and analysis, I aim to determine which features have the greatest impact on keeping users on track with their goals. Including daily support and monitoring tools, such as reminders, motivational messages, progress tracking, and potential messaging and chat features. The effectiveness of these tools will be researched further in this project. The emphasis

on peer support and community building will be researched for their potential influence of connecting with others who share similar experiences, thereby reducing feelings of isolation and fostering a sense of belonging crucial to recovery.

This research has three main objectives:

1. To identify the factors contributing to high and low app retention rates in mobile health intervention and recovery apps.
2. To explore user preferences and needs that affect app retention and continued recovery.
3. To develop strategies to improve app retention for continued recovery based on collected data.

In the realm of mobile health intervention apps, this project adopts a research-driven approach to identify features that effectively support user needs. Traditionally, user-centered design involves direct interviews and feedback collection from users to understand their needs. However, this project leverages publicly available app reviews as a data source to gain insights into user preferences, likes, dislikes, and needs. By employing data mining techniques suitable for large text datasets, the analysis of app reviews offers a broad and comprehensive understanding of user experiences. This approach provides a unique advantage, tapping into the collective opinions of a diverse user base. The extracted information will contribute to the development of strategies aimed at improving app retention. By utilizing this innovative methodology, the project aims to deliver valuable recommendations to enhance the effectiveness of digital health apps in supporting individuals with OUD and SUD.

## 2.0 Background

This section provides background information on opioid use disorder (OUD) and substance use disorder (SUD) and digital health applications that target individuals with OUD and SUD. This section also delves into the efficacy of communities as interventions, acknowledging the pivotal role of peer support and shared experiences in aiding recovery. Finally, this section provides an exploration of data analytics approaches used in the literature to analyze and derive insights from app reviews, aiming to uncover nuanced patterns and sentiments within user feedback.

### 2.1 Opioid and Substance Use Disorder

Opioid addiction is a formidable adversary, one that has left no corner of our nation untouched. Worcester, Massachusetts, finds itself amidst this crisis, grappling with the repercussions of opioid abuse that span generations and communities. According to the AdCare Treatment Centers, “Massachusetts...faces serious issues related to opioid misuse, addiction, and fatal overdose. From 2016 to 2020, the number of opioid-related overdose deaths per 100,000 people in Massachusetts was approximately double the average in the United States.” (AdCare Treatment Centers, 2023). The absence of comprehensive reintegration programs, coupled with the stigma surrounding addiction, leaves many with few options for recovery. Despite a growing body of evidence supporting the notion that addiction is a treatable brain disorder, the majority of individuals do not access treatment (Sureshkumar et al., 2021). Many individuals end up entangled in the criminal justice system due to their involvement in illegal drug-seeking activities and unlawful behaviors, which are, to some extent, influenced by disrupted conduct resulting from the brain changes induced by repeated drug use (Chandler et al., 2009).

Accessing and continuing treatment for individuals with Opioid Use Disorder (OUD) or Substance Use Disorder (SUD) poses significant challenges influenced by a multitude of factors. Research by O’Brien et al. (2019) highlights that variables contributing to patients' initiation and engagement in treatment encompass individual, provider, health plan, and market and environmental factors. These diverse elements collectively impact the ability of individuals to access and commit to treatment programs. Moreover, stigma, a pervasive issue in the realm of addiction, is identified as a significant barrier. Cheetham et al. (2022) delineate three interacting types of stigma—structural, public, and internalized stigma—which contribute to negative

perceptions and hinder individuals from seeking and continuing treatment. This societal stigma operates at macro, meso, and micro levels, creating pervasive challenges for individuals with OUD or SUD.

Despite these challenges, various treatment options are available to address OUD and SUD. Anti-craving agents, such as Antabuse for alcohol dependence and methadone for opiates, have been recognized for their efficacy (Galily et al., 2017). These pharmacological interventions aim to reduce cravings and support individuals in their recovery journey. Additionally, behavioral therapies, such as Cognitive Behavioral Therapy (CBT), therapeutic communities, and participation in support groups like Narcotics Anonymous, offer comprehensive approaches to address the psychological and social aspects of addiction (Cleveland Clinic Medical, 2022). However, the effectiveness of these treatment options can be influenced by the challenges, necessitating a holistic and integrated approach to overcome barriers and enhance access to quality care for individuals facing OUD or SUD.

## 2.2 Digital Health Interventions

Mobile health interventions represent a groundbreaking approach to tackling the opioid addiction crisis individuals in, both within Worcester as well as globally. These interventions leverage the ubiquity of smartphones and the power of technology to deliver timely, personalized, and accessible support for addiction recovery and reintegration (Bricca et al., 2022). They encompass a range of digital tools and resources, such as mobile apps and telehealth services, designed to empower individuals on their journey to recovery. These interventions can be effective for several reasons. They enhance accessibility by eliminating geographical and logistical barriers, ensuring that individuals can access support and resources in real-time, regardless of their location. This accessibility is especially valuable for those facing transportation challenges or residing in underserved areas. Mobile health interventions can also offer a high degree of personalization, tailoring guidance, treatment options, and resources to suit an individual's unique needs and progress, thereby increasing the likelihood of success in overcoming addiction. These interventions provide privacy and reduce the stigma associated with addiction and mental health issues, as mobile apps and telehealth services enable discreet help-seeking. This heightened privacy can encourage more people to seek the support they need (Fear et al., 2012). Mobile health interventions can offer continuous support, potentially available 24/7, which proves crucial during moments of crisis or vulnerability, particularly in the

initial stages of recovery when the risk of relapse is elevated (Kadam et al., 2017). Lastly, they leverage data-driven insights, enabling the collection and analysis of an individual's progress data, facilitating informed decisions by healthcare providers regarding treatment plans and interventions. These combined advantages make mobile health interventions a valuable tool in addressing addiction and mental health challenges.

Addressing the opioid addiction crisis among individuals in Worcester requires innovative and scalable solutions. Mobile health interventions offer a promising path forward, aligning with our moral imperative to support those in need while safeguarding community well-being and public safety. By harnessing the power of technology and personalized care, these interventions can help break the cycle of addiction, offering a renewed sense of hope for individuals and strengthening the resilience and health of our community. In the following sections, we delve deeper into the potential of a mobile health intervention tailored to Worcester's unique challenges, exploring its capacity to transform lives and build a safer, healthier community. Implementing a productive and effective sober network within the app to promote a sober community is a valuable endeavor for individuals in recovery.

## 2.2 Communities as Interventions

The establishment of a thriving sober community as an intervention comprises several critical elements and considerations. Users are empowered to construct customized profiles, sharing their unique recovery journeys, interests, and objectives, and specifying their preferred form of support. Sinclair et al. (2016) highlight the significance of platforms like Soberistas, a social network site for people with SUD, which offers a form of mutual aid primarily for women who may not have engaged with other treatment or support. The online, flexible platform affords members an accessible and anonymous community to address their difficulties and encourages a positive 'alcohol-free' identity. Within this community, dedicated discussion forums and interest-based groups provide secure spaces for members to engage in conversations, exchange experiences, and extend support. Users can readily exchange valuable sobriety and recovery resources, all while tracking their progress and setting personal goals, which they can share with their sober community. Robust safety measures, reporting procedures, and the presence of trained moderators sustain a secure and nurturing environment, with ongoing enhancements guided by user feedback. Users retain control over their shared information to ensure privacy and

data security. Clearly defined community guidelines maintain a respectful and positive atmosphere, with gamification elements, rewards, and incentives inspiring regular participation within the app and the dynamic sober community.

While incorporating a sober community within an addiction recovery app offers numerous advantages, it also presents certain potential challenges and drawbacks. Privacy concerns may emerge as users disclose personal information and experiences, necessitating robust privacy settings and data security measures to effectively address these concerns (SAMHSA, 2023). Negative interactions, including disputes and potentially triggering content, are conceivable within any community, highlighting the need for effective moderation mechanisms and conflict resolution. Individuals in early recovery may be particularly vulnerable to relapse triggers (Ackermann, 2023) stemming from certain community content, emphasizing the need to establish a secure and trigger-free environment. The operation and management of a sober community can be resource-intensive, calling for staff or volunteers to maintain quality and promptly respond to user reports. Technical issues, such as limited internet access or device compatibility problems, may impede user engagement (Sinclair et al, 2016). Building a cohesive and supportive community can be challenging due to differences in personalities, goals, and experiences among users. There is a potential risk that well-intentioned support within the community might unintentionally enable harmful behavior or codependency (Ackermann, 2023), underscoring the need for users to seek professional help when necessary. Over-reliance on the community may hinder users' development of independent coping skills and access to a diverse range of support sources, and users who actively engage in the community may experience burnout if pressured to continually provide support, emphasizing the importance of promoting self-care and balance within the community.

In the context of addiction recovery, sober communities have proven to be invaluable interventions, offering crucial support for individuals on their path to sobriety. One example of a highly effective sober community is Alcoholics Anonymous (AA), which has demonstrated remarkable success in helping individuals maintain abstinence. AA and similar communities exhibit several core elements and considerations that contribute to their effectiveness. According to Mandy Erickson in Stamford Medicine, “After evaluating 35 studies — involving the work of 145 scientists and the outcomes of 10,080 participants — Keith Humphreys, PhD, professor of

psychiatry and behavioral sciences, and his fellow investigators determined that AA was nearly always found to be more effective than psychotherapy in achieving abstinence” (Erickson, 2020). AA members, like those in digital sober communities, share their unique recovery journeys, interests, and objectives. The shared experience of addiction and recovery fosters a strong sense of community, and individuals specify their preferred type of support, whether it is through sponsorship, attending meetings, or engaging in fellowship activities. AA utilizes a decentralized matching system where individuals choose sponsors who can guide them through the recovery process, akin to digital communities' algorithms matching members based on shared interests or recovery stages.

In both AA and digital sober communities, dedicated discussion forums and interest-based groups provide secure spaces for individuals to share their experiences, struggles, and insights while offering support to one another. Secure messaging and chat functions in digital communities serve a similar purpose, nurturing private and open dialogues, while AA members often form close-knit groups and cultivate one-on-one relationships within the AA framework.

However, while these interventions, including AA and digital sober communities, offer numerous advantages, they also present potential challenges and drawbacks. AA and similar programs have been criticized for issues such as potentially triggering content in meetings and the reliance on volunteers to maintain the community (Criticisms of AA, 2021). Digital communities, on the other hand, may encounter challenges related to privacy concerns and negative interactions, as well as issues with technical accessibility and user engagement. Both AA and digital sober communities are invaluable interventions for individuals in addiction recovery. While they offer essential support, they also face certain challenges that need to be addressed to ensure they remain effective and beneficial resources for those seeking recovery and sobriety. The important takeaway is that a supportive and nurturing community, whether in the digital realm or through traditional interventions like AA, can significantly contribute to successful addiction recovery.

### 2.3 Digital Health Apps for OUD and SUD

The digital health app market has seen a proliferation of applications designed to support sobriety and track overall health progress. These apps cater to a diverse range of users, from

those seeking to maintain sobriety from substance use to individuals aiming to improve their overall well-being. App retention in the context of digital health apps is a critical factor for their effectiveness. Some common factors affecting retention include:

- **Engagement:** Apps that provide consistent engagement opportunities, such as daily check-ins, reminders, or interactive features, tend to retain users better.
- **Personalization:** Apps allowing users to set customized goals, track their progress, and tailor the experience to their needs tend to have higher retention rates.
- **Community Support:** Apps that foster a sense of community and enable users to connect with peers facing similar challenges can improve retention.
- **Quality Content:** Apps with high-quality, regularly updated content, including educational resources, motivational content, and coping strategies, are more likely to retain users.
- **User Experience:** Apps with intuitive interfaces and a positive user experience tend to have better retention rates.

The current market of digital health apps offers a variety of tools and features to support individuals in their recovery journey. Each app has its pros and cons, and app retention can be influenced by factors like engagement, personalization, community support, content quality, and the overall user experience. To maximize the benefits of these apps, users and developers should consider these factors when choosing or creating a sobriety app. The choice of a digital health app should align with an individual's specific goals, whether that is maintaining sobriety, tracking overall health, or addressing specific health issues. Careful consideration of an app's features and limitations is essential for making the right choice.

In summary, recovery apps play a crucial role in treatment. They provide individuals with immediate access to tools and resources, empowering them to manage their addiction and stay on the path to recovery. However, retaining users on these apps can be a challenging task. Several factors influence app retention. These include engagement levels, usability, the quality of content, and the availability of a supportive community within the app's ecosystem (Neale et al., 2022). Existing strategies for improving app retention often focus on user engagement techniques, personalized content, and social support mechanisms. However, these strategies may not address all the underlying factors affecting retention. There are gaps in the literature surrounding app retention in digital health apps. While some strategies have been proposed and



tested, there is a need for more comprehensive research to identify additional factors and develop effective retention strategies.

## 2.4 Methods Used to Conduct App Review Analysis

Mobile and digital health interventions are overwhelmingly recommended to patients by their counselors who specialize in OUD and SUD (Wray, T. B, 2020). As such, it is imperative that data analysis is performed on current digital health applications, to ensure that these apps have what the user is looking for to aid them best on their journey. There have been various data collection methods implored to review analysis of different apps, and specifically, digital health apps.

### 2.4.1. Python Based Approaches

Coding languages, notably Python, have played a pivotal role in the systematic analysis of app store rating and review data. The study conducted by Vasa et al. (2012) exemplifies the effective implementation of coding scripts to gather and process vast amounts of user reviews. In their research, the team developed a script capable of parsing and downloading reviews from the top 400 free and paid apps across 22 categories on the Apple App Store. Python's versatility and robust capabilities enabled the creation of an efficient and automated system to collect this extensive dataset. The script facilitated the extraction of valuable insights, allowing researchers to delve into user sentiments, preferences, and critiques across a diverse range of applications. This approach not only showcases the power of coding languages in handling big data but also highlights the importance of automation in extracting meaningful patterns from the vast sea of app reviews, contributing to a more informed understanding of user experiences and feedback.

Minh Vu et al. (2015) contributes to the advancement of app review analysis with the introduction of MARK (Mining and Analyzing Reviews by Keywords). This innovative framework presents a semi-automated approach to mining user opinions from mobile app reviews. MARK approaches the mining task as an information retrieval problem, employing a keyword-based methodology. Unlike traditional information retrieval systems, MARK allows review analysts to specify their interests in mobile apps through a set of keywords. The framework then utilizes automated, customized techniques to extract, rank, and group keywords from raw reviews. This process involves considering both review ratings and occurrence frequencies, enhancing the precision of identified keywords. Subsequently, MARK searches for

reviews relevant to the specified keywords, visualizes their occurrences over time, and reports any unusual patterns within those occurrences. This sophisticated approach not only streamlines the review analysis process but also provides analysts with a powerful tool to discern and explore user sentiments effectively.

In their collaborative work, Emitza Guzman and Walid Maalej (2014) articulate a comprehensive approach aimed at automatically discerning valuable insights from user reviews to benefit app developers. Their primary objective revolves around the identification of application features, sentiments, and opinions embedded within user feedback, employing the synergies of Natural Language Processing (NLP) and Data Mining techniques. The methodology involves the systematic collection of user reviews for a given app, followed by the extraction of pertinent information, such as titles and textual comments. To enhance the quality of extracted features, the authors employ a meticulous preprocessing step to eliminate noise. Subsequently, a collocation finding algorithm is applied to derive meaningful features from the reviews, providing app developers with a nuanced understanding of user requirements, suggestions for enhancements, sentiments regarding specific features, and detailed descriptions of user experiences. This method, grounded in coding languages and computational techniques, constitutes a valuable resource for developers seeking to refine their applications based on user feedback. Moreover, coding languages, notably Python, have played a pivotal role in the systematic analysis of app store rating and review data. The study conducted by Vasa et al. (2012) exemplifies the effective implementation of coding scripts to gather and process vast amounts of user reviews. In their research, the team developed a script capable of parsing and downloading reviews from the top 400 free and paid apps across 22 categories on the Apple App Store. Python's versatility and robust capabilities enabled the creation of an efficient and automated system to collect this extensive dataset. The script facilitated the extraction of valuable insights, allowing researchers to delve into user sentiments, preferences, and critiques across a diverse range of applications. This approach not only showcases the power of coding languages in handling big data but also highlights the importance of automation in extracting meaningful patterns from the vast sea of app reviews, contributing to a more informed understanding of user experiences and feedback.

### 2.4.2. ChatGPT Based Approaches

While ChatGPT has gained substantial recognition for its versatility in natural language processing tasks, the application of this model to app store review analysis remains underexplored in current research literature. However, Christian Morbidoni (2023) delves into this novel territory in his study titled "Poster: LLMs for online customer reviews analysis: oracles or tools? Experiments with GPT 3.5." Morbidoni's work stands out as it pioneers the use of ChatGPT for generating analysis results through summarizing-like questions. The study focuses on qualitative assessments, evaluating correctness and alignment of answers. In a preliminary experiment conducted on recent (2022-2023) online reviews of two distinct products—a budget smartphone and a kids' bike—Morbidoni carefully annotated 60 reviews for each product. The reviews were coded based on topics and corresponding sentiment polarity, with topics enumerated and aggregated into a topic dictionary. This topic dictionary was then employed as input to GPT prompts. The human annotations served as a ground truth to measure the performance of ChatGPT in each task. Notably, Morbidoni's study opens new avenues for leveraging ChatGPT in app store review analysis, shedding light on its potential in providing insightful and qualitative perspectives on user sentiments and preferences.

It is important to note that the use of ChatGPT in this context introduces a unique dimension to app review analysis, offering a qualitative assessment that complements more traditional quantitative approaches. The method of employing summarizing-like questions highlights the flexibility of ChatGPT in extracting meaningful insights from unstructured data, and the reliance on human annotations as a benchmark ensures a reliable measure of its performance. As more researchers explore and refine the use of ChatGPT in app store review analysis, it holds promise in uncovering nuanced aspects of user experiences and sentiments that may not be readily apparent through other methods.

In addition to academic research, non-research papers and practical applications have recognized the utility of ChatGPT in the realm of app store review analysis. Suleika Vanmaele (2023), in her guide titled "ChatGPT Prompts for App Store Optimization," provides valuable insights into leveraging ChatGPT for in-depth research on app competition, user pain points, and feature inspiration. Vanmaele emphasizes the efficiency of using ChatGPT to summarize extensive information, making it particularly advantageous during the launch of a new app or the refinement of an existing one.

Vanmaele underscores the time-consuming nature of manually reviewing every user comment and highlights ChatGPT's role in streamlining this process. Specifically, ChatGPT can be employed to analyze app user reviews, helping identify common complaints, understand user sentiment, and enhance the overall user experience of an app. By copying and pasting existing reviews into ChatGPT, developers and app managers gain quick insights into recurrent issues or features that users frequently discuss. This approach provides a time-efficient means of comprehending user feedback, allowing developers to focus on areas that resonate most with their user base or even those of competitors. The practical application of ChatGPT, as demonstrated by Vanmaele, displays its adaptability and effectiveness in addressing the challenges of analyzing vast amounts of unstructured textual data inherent in app store reviews.

#### 2.4.3. Manual Analysis

In the pursuit of ensuring the accuracy of app store review analysis, the implementation of manual analysis serves as a crucial validation step. Minh Vu et al. (2015) demonstrated this significance by incorporating a manual analysis component into their study. They randomly selected 400 reviews and undertook the meticulous task of manually labeling them as either English (245 reviews) or non-English (155 reviews). This hands-on approach allowed the researchers to overcome potential limitations in automated language detection algorithms. The findings revealed that, unsurprisingly, most words in non-English reviews did not appear in the English dictionary. However, the manual analysis brought attention to nuanced scenarios where non-English reviews could still contain English words, such as technical terms or instances where words in foreign languages coincidentally shared spellings with English words. This nuanced understanding, derived from the manual analysis, highlights the complexity of language identification in reviews and underscores the necessity of human judgment in refining the accuracy of automated processes.

## 3.0 Methodology

Understanding the challenges and opportunities in designing digital health tools for individuals with OUD and SUD is foundational to this research project. Identifying the factors that contribute to varying app retention rates within mobile health intervention and health apps is a critical starting point. By doing so, we gain a comprehensive understanding of the unique challenges and opportunities facing this population, informing the development of effective solutions that cater to their distinctive needs.

The principles of user-centered design underscore the importance of delving deeply into user preferences, needs, and challenges. In this context, this means exploring the elements that influence app continued use. This thorough investigation is crucial to create tools that extend beyond mere functionality; they must be intuitive, user-friendly, and engaging. To accomplish this, a qualitative data collection approach is employed, which allows for in-depth exploration of these aspects, aligning perfectly with the principles of user-centered design.

User-centered design is an iterative process, demanding continuous improvement (Interaction Design Foundation, 2023). To develop effective strategies for enhancing app retention, it is essential to base these strategies on empirical data. Qualitative data, focusing on user preferences, needs, and challenges, serves as the cornerstone for shaping these strategies. This ensures that the tools created are tailored precisely to the target audience, increasing the likelihood of their success.

Individuals with OUD and SUD face intricate and distinctive challenges that extend beyond what traditional interventions can address. A qualitative data collection approach provides a comprehensive view of the factors impacting app retention and the users journey with digital health tools. This nuanced understanding is often unattainable through quantitative data alone, emphasizing the importance of qualitative insights. Qualitative data also enables the identification of specific pain points, motivators, and user preferences within this population. This granular level of insight is invaluable in the creation of digital health tools that resonate with people with OUD and SUD, addressing their unique needs and challenges.

### 3.1. Identifying Relevant Apps with Reviews

I will perform content analysis by gathering solely publicly available app store reviews and comments on the Apple app store for digital health apps. It is important to clarify that the data collection process does not involve the gathering of personal or private information from app users. This qualitative approach enables me to extract valuable insights from user opinions, complaints, and suggestions regarding app retention. It is essential to note that this information is collected from a large, anonymized user sample, and does not contain any personal or private data. Data analysis of app store reviews has been done in various academic research, and each app chosen for this study has had similar public app store review data collected, which will be further explained in the following sections. By analyzing these behavioral patterns, we aim to identify factors contributing to low app retention rates.

The digital health app market is experiencing a remarkable transformation with a surge in applications specifically designed to support sobriety and track overall health progress. These apps cater to a diverse range of users seeking to enhance their overall well-being. The choice of keywords such as "sober," "sobriety," "addiction recovery," and "opioid recovery" is crucial when searching for apps specific to this research.

#### 3.1.1. Keyword Selection for App Search

The choice of keywords when searching for digital health apps is pivotal in finding the most relevant and effective tools to support one's journey. The selection of keywords reflects the user's intent and the specific needs they hope to address.

1. **Sober and Sobriety:** These keywords are fundamental as they directly address the core goal of some of these individuals - maintaining sobriety from substance use. They resonate with those on a path to sobriety and need dedicated support and tracking tools.
2. **Addiction Recovery:** This keyword encompasses a broader audience, appealing to individuals looking for apps that can help them recover from a range of addictive behaviors, including substance abuse, alcoholism, and even behavioral addictions.
3. **Opioid Recovery:** With the opioid crisis being the specific concern of this research, this keyword is crucial for individuals dealing with opioid addiction. It narrows down the search results to apps tailored to address the unique challenges of opioid recovery.

To find digital health apps to collect data from, I used the above keywords on the iOS app store. The resulting apps below were the top results.

### 3.1.2. Top Apps per Category

For Sobriety and General Addiction Recovery:

- *I Am Sober*: With 127k ratings, this app offers a comprehensive sobriety tracker for individuals on their recovery journey, providing motivational support and progress monitoring.
- *Sober Time - Sobriety Counter*: With 9.6k ratings, this app is an addiction recovery tracker that helps individuals track their sober days, offering motivation and encouragement.
- *Nomo - Sobriety Clocks*: With 12k ratings, Nomo provides an engaging way to track progress in recovery, making sobriety an attainable goal with daily affirmations.
- *Reframe: Drink Less & Thrive*: This app, with 22k ratings, is designed for those seeking to cut back on or quit drinking alcohol, offering positive reminders and motivation.
- *Quitzilla: Bad Habit Tracker*: With 681 ratings, this app empowers users to quit their addiction and stay sober by tracking progress and setting goals.

For Opioid Recovery:

- *Workit Health*: With 682 ratings, Workit Health offers expert guidance in addiction recovery and substance use support.
- *Pelago Health*: This app, with 4.1k ratings, is a valuable resource for individuals seeking substance use support and recovery assistance.
- *Recovery Connect - CMS*: Though it has 63 ratings, this app serves as a companion for opioid treatment and recovery, providing essential resources and support.
- *Boulder Care*: With 636 ratings, Boulder Care focuses on health and fitness during the recovery journey, promoting a holistic approach to wellness.
- *My Opioid Recovery*: Despite having just one rating, this app offers a platform for individuals to explore resources for opioid recovery and treatment.

For General Addiction Recovery and Sobriety:

- *SoberBuddy: Addiction Recovery*: Boasting 1.4k ratings, this app encourages users to quit drinking or using substances while providing essential support.
- *The Phoenix: A Sober Community*: With 4.4k ratings, The Phoenix combines activity, recovery, and sobriety to create a vibrant community of support.
- *Affect: Reward Your Recovery*: Despite having 148 ratings, affect focuses on sobriety and addiction treatment, offering positive reinforcement.
- *Loosid: Sober Recovery Network*: With 6k ratings, Loosid provides a platform for individuals to find sobriety, chat, and receive support from a like-minded community.

The use of these keywords ensures that individuals searching for digital health apps can easily find tools that cater to their specific needs. These apps empower users to track their progress, find support, and achieve their goals, whether it is maintaining sobriety, recovering from addiction, or simply improving their overall well-being. The digital health app market continues to evolve, providing invaluable resources for those on the path to recovery and wellness.

After analyzing these apps, data collection from publicly available app ratings and reviews from I Am Sober, Loosid: Sober Recovery Network, Nomo – Sobriety Clocks, Sober Time – Sobriety Counter, and Reframe: Drink Less & Thrive were chosen. The selection of these apps for further data collection and analysis is well-founded for several reasons. These apps offer diverse perspectives on digital health, and their inclusion in the study can provide valuable insights into how to best increase continued user retention for digital health tools.

### 3.1.3. Relevance in Academic Research

I Am Sober, Nomo, Sober Time, and Loosid have been previously referenced in academic research, indicating their significance and impact within the field of addiction recovery. Their inclusion allows for the consolidation of findings from prior studies and the potential to corroborate or expand upon existing research. "I Am Sober" and "Nomo," for instance, have been acknowledged in the study "Mobile applications for alcohol dependent persons as tools supporting the recovery process," (Klingemann, et al., 2020) which was featured in "Alcoholism and Drug Addiction". This recognition underlines the role of these apps as an asset for individuals on their digital health journey.



"Sober Time" is featured in the study "Smartphone Apps Targeting Alcohol and Illicit Substance Use: Systematic Search in Commercial App Stores and Critical Content Analysis." (Tofighi, Babak, et al, 2019). This recognition reflects its role as an app with a focus on supporting individuals in maintaining sobriety and combating substance abuse. "Loosid" stands out as a tool mentioned in the context of "Substance Abuse: Avenues for Identity Articulation, Coalition Building, and Support During COVID-19." (Shafer, 2021). This recognition highlights Loosid's relevance in providing avenues for identity articulation, coalition building, and support during a critical period.

Including these apps in academic research paves the way for further exploration and the potential to corroborate or expand on prior studies' findings. This validation underscores the importance of these apps in the context of digital health and their substantial impact on individuals seeking support on their journey.

#### 3.1.4. Diversity in Approach

These selected apps represent a diverse range of approaches to digital health. I Am Sober is known for its comprehensive sobriety tracking, while Nomo provides unique sobriety clocks. Sober Time focuses on sobriety counting, and Loosid offers a recovery network for users. Reframe: Drink Less & Thrive specifically targets reducing alcohol consumption. By analyzing these apps, the study can explore different methods and strategies employed to support effective user retention techniques. These apps have notable user bases and substantial ratings, reflecting their popularity and user engagement. This implies a large dataset of user feedback and reviews, which is invaluable for the study's data collection and subsequent analysis.

These apps' user retention rates, reflected in their user ratings and continued use, indicate that they may possess features and mechanisms that effectively retain users. By analyzing these apps, this study aims to identify these features and best practices for user retention. These digital health apps cater to different user needs, from tracking sobriety days to providing social support and motivation. This diversity in target audiences and goals can yield insights into tailoring app features to specific user needs.

The choice of I Am Sober, Loosid: Sober Recovery Network, Nomo – Sobriety Clocks, Sober Time – Sobriety Counter, and Reframe: Drink Less & Thrive for further analysis is rooted

in their prominence, user base, and the recognition they have received in academic research. Table 1 compares each app for features included and app rating data. Analyzing these apps offers the opportunity to aggregate and expand upon existing knowledge, explore diverse approaches to addiction recovery, and identify key factors that contribute to successful user retention in this critical domain of mobile applications.

Table 1: a comparison of the features in selected digital health apps

App Name	IOS or Android	Avg. Rating	Number of Ratings	Paid Subscription	Community based/chat	In-app Motivation Reminders	Resources	Progress Monitoring
I Am Sober	Both	4.9/5	127,000	No	Yes	Yes	Yes	Yes
Loosid: Recovery Network	Both	4.7/5	6,000	No	Yes	No	Yes	Yes
Nomo – Sobriety Clocks	Both	4.7/5	12,000	No	No	Yes	No	Yes
Sober Time – Sobriety Counter	IOS	4.8/5	9,600	No	No	Yes	No	Yes
Reframe: Drink Less & Thrive	IOS	4.8/5	22,000	Yes	Yes	Yes	Yes	Yes

### 3.2. App Review Data Extraction Method

The first step involved data collection, utilizing Python web scraping libraries like BeautifulSoup or Scrapy to access the review pages of the app on the respective app store. This enables the extraction and storage of user feedback and ratings for subsequent analysis. Data

cleaning becomes essential as the collected data may contain superfluous or extraneous information. By applying data cleaning procedures, including text preprocessing, the reviews are refined to ensure that the ensuing analysis is grounded in meaningful and pertinent content. To conduct a comprehensive analysis of user sentiments and usage patterns for the target app, the initial step involves retrieving app store reviews through Python coding. Utilizing the app store API and web scraping techniques, the goal is to gather user reviews from the Apple App Store. By doing so, a rich dataset of user reviews is acquired via an Excel CSV file, which will serve as the basis for further analysis in Python coding. Figure 1 illustrates the code used to scrape app store review data.

```
import pandas as pd
import numpy as np
import json

from app_store_scraper import AppStore
sober_time_ios = AppStore(country='us', app_name='sober-time-sobriety-counter', app_id = '1158895079')

sober_time_ios.review(how_many=1500)

sober_time_iosdf = pd.DataFrame(np.array(sober_time_ios.reviews), columns=['review'])
sober_time_iosdf2 = sober_time_iosdf.join(pd.DataFrame(sober_time_iosdf.pop('review').tolist()))
sober_time_iosdf2.head()

sober_time_iosdf2.to_csv('sober-time-sobriety-counter.csv')
```

Figure 1: Example Python code for extracting publicly available app store reviews for Sober Time – Sobriety Counter

Table 2: Example Excel CSV file output from data scraping via Python for Sober Time – Sobriety Counter

	date	review	rating	isEdited	userName	title
0	4/30/2023 12:15	My days being sober are being spent productivity, I am Healing & so thankful God brought me out of my addiction Alive, healthy & capable to move forward in life! I can not explain the feelings I am having because there are so many emotions I had bottled up that are explosive on a daily! I thank God my children are alive and well, I have some shame	5	FALSE	KTwaters	Sober Days
1	10/3/2021 18:44	helped me organize my clean time and reflect and continue to stay grateful. As well as proud of my clean time. I have been sober and clean for 4 months and 27 days! This is the longest I've been clean in the past 6 yrs. with one day at a time I will continue to work on my progress and am proud to say I am a success story even though at one point Before my recovery journey started I thought I was a lost cause who was destined to peril and succumb to this disease of addiction and die alone in my	5	FALSE	Tahnee (Nenashka)	Sober Time

Following data retrieval, the next phase involved data preprocessing. Table 2 shows the Excel data after the data has been processed. This step included cleaning the data by removing irrelevant characters, symbols, and non-text elements to ensure that the dataset is refined and conducive to analysis. Tokenization is then applied to break down reviews into individual words, facilitating subsequent analysis. To enhance the precision of the analysis, common stopwords, such as "the" and "and," are removed, and lemmatization or stemming is implemented to standardize variations in words.

### 3.3. App Review Sentiment Analysis

Leveraging sentiment analysis tools or libraries like NLTK, TextBlob, or VADER, each review is categorized as positive, negative, or neutral. This categorization aids in understanding the overall sentiment of users towards the app, providing valuable insights into user satisfaction. Feature extraction is a critical component of the analysis, focusing on identifying features related to app usage duration mentioned in the reviews. By examining word and phrase frequency such as "spent hours" or "used it all day," relevant features are extracted, and qualitative data is converted into quantitative values. This step allows Python to show graphs and a word cloud relating to how frequently words in five-, four-, three-, two-, and one-star reviews appear.

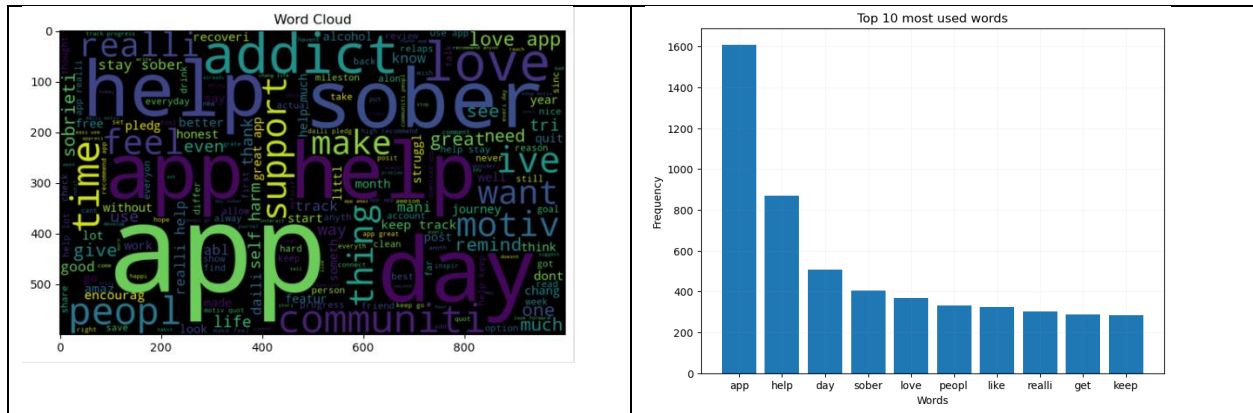


Figure 2: Example of Python word cloud and top 10 frequently used words by rating output for I Am Sober all 5-star reviews.

Figure 2 depicts the word cloud and graph of the top 10 frequently used words data received from this process. The insights gained from the analysis are then integrated into the app improvement process. If users consistently express positive sentiments about extended usage durations, these findings can inform the development team in emphasizing or enhancing the corresponding features.

### 3.4. App Review ChatGPT Analysis

Once the five datasets of the digital health app store reviews were compiled onto a CSV file and the data was sorted within the file into: all reviews, 5-, 4-, 3-, 2-, and 1-star reviews. To gain the data necessary from the GPT analysis, the reviews were compiled using the CONCAT feature

in Excel, allowing a cell to have a complete statement as to which user left the review, the review itself, and the rating it received, as shown in the example data in Table 3.

Table 3: Example row of Excel dataset from Loosid: Sober Recovery Network, with the CONCAT user review and rating statement.

date	developerID	review	rating	isEdited	title	userName	Review
3/25/2019 13:28	{'id': 7900668, 'body': 'Thanks very much for the comment 7 glad you enjoyed the event! Anything we can do to make your experience better please email us at support@loosidapp.com. Thanks again!', 'modified': '2019-03- 25T21:10:35Z'}	Loosid has opened my eyes that there are so many amazing things to do. I went to a Loosid Pilates event a few weeks ago at Hub Seventeen. Awesome!	5	FALSE	Great App!!		User50 said Loosid has opened my eyes that there are so many amazing things to do. I went to a Loosid Pilates event a few weeks ago at Hub Seventeen. Awesome!. User50 gave a 5 rating.

The user review and rating statement for all reviews from each app - 1,500 reviews from Sober Time, I Am Sober, Nomo, and Reframe: Drink Less and Thrive, and 92 from Loosid: Sober Recovery Network – were copied and pasted into ChatGPT. The following questions were plugged in for analysis of each app review:

- The comments above are reviews pulled from app store data. What are the most frequently used words?
- What are the features that users like the most?
- What are the features that users like the least?
- What are recommendations that users have put into the reviews?

These questions were asked with the copy of all app reviews and all reviews in each rating category. The prompt was asked three separate times, shown in the example data in Table 4, and each of the three responses were recorded for further comparison on their accuracy.

Table 4: Example row of Excel data containing the ChatGPT prompt, and three responses generated from the I Am Sober review dataset.

Data Entered	All 5 star reviews
GPT Prompt	The comments above are reviews pulled from app store data. What are the most frequently used words?
First Response	<p>The most frequently used words in the provided reviews are: App, Sobriety, Love, Track, Day, Motivational, Pledge, Support, Features, Community, Journey, Positive, Addiction, Clean, Family, Progress, Quotes, Recommend, Review, Time</p> <p>These words highlight the positive aspects of the app, focusing on features related to tracking sobriety, motivational support, and community engagement. Users frequently mention their love for the app, its ability to track progress, and the positive impact on their sobriety journey.</p>
Second Response	<p>The most frequently used words in the provided reviews are: App, Love, Support, Track, Community, Motivating, Day, Clean, Progress, Sobriety, People, Amazing, Help, Milestone, Thank, Reminder, Daily, Review, Proud, Feature</p> <p>These words emphasize the positive impact of the app on users' lives, focusing on aspects such as support, tracking progress, community engagement, and motivation. Users frequently express love for the app, appreciation for its supportive community, and the positive influence it has on their journey toward sobriety.</p>
Third Response	<p>The most frequently used words in the provided reviews are: App, Love, Support, Track, Motivation, Sobriety, Progress, Community, Day, Clean, Milestone, Review, Recommend, Help, People, Amazing, Encouraging, Download, Network, Interface</p> <p>These words highlight the positive impact of the app on users' lives, focusing on aspects such as support, motivation, progress tracking, community engagement, and encouragement. Users frequently express love for the app, appreciation for its supportive community, and the positive influence it has on their journey toward behavior change and sobriety.</p>

After the collection of this data, manual analysis of randomly selected reviews was conducted on 10% of the reviews to determine the validity of ChatGPT’s responses to the prompts, given the data entered.

### 3.5 App Review Manual analysis

To assess the accuracy of ChatGPT responses in comparison to real user reviews, a systematic approach was employed. Ten percent of the user reviews from each dataset of app store reviews were randomly selected for manual evaluation. These reviews were examined, and the findings were documented in an Excel sheet, categorizing likes, dislikes, suggestions, and any other relevant feedback. This method allowed for a comprehensive understanding of the

alignment between ChatGPT-generated responses and authentic user sentiments, providing valuable insights into the model's performance and accuracy in capturing the nuances of user feedback.

### 3.6 Developing Retention Strategies

To develop effective retention strategies, I reviewed research studies from addiction recovery experts, psychologists, and app developers to generate strategies that align with user needs and address the factors identified in earlier phases. This phase also involved identifying new app features or modifications to existing ones based on what features users of the five chosen digital health applications express positive feedback on, prioritizing improvements that cater to user preferences and needs. This includes excluding, to the best of our ability, aspects of the apps that users express negative sentiment towards, conducting analysis as to how recurrent the complaints are and determining a solution for the problems.

## 4.0 Results

In the analysis of app store reviews, two distinct approaches were employed: a Python code-based word frequency analysis and an examination using ChatGPT. The Python code generated word frequency graphs and word clouds, while ChatGPT was tasked with providing insights into user sentiments, including top ten words, likes, dislikes, and suggestions.

### 4.1 Sentiment Analysis Results

The Python code analysis revealed consistent top 10 words across different star ratings, prominently featuring terms like "App," "Use," "Like," and "Year." The frequency data, presented below for each app, demonstrates a recurring set of words irrespective of the rating.

#### 4.1.1 Nomo – Sobriety Clocks

In the Python output analysis for Nomo – Sobriety Clocks, a discerning examination of the top 10 words per star rating, as depicted in Table 5 and Figure 3, reveals noteworthy patterns. While the term "app" recurrently appears across various ratings, offering minimal insight into users' preferences for their digital health applications, more informative word patterns become known. Specifically, higher-rated reviews exhibit a pronounced usage of terms like "year," "help," and "sobriety," suggesting a positive correlation between these themes and elevated user ratings. On the contrary, lower-rated reviews manifest a prevalence of words such as "delete" and



"update," indicating a potential association between these actions and less favorable user evaluations. This nuanced exploration sheds light on distinct word patterns that extend beyond generic mentions of the app itself, providing developers with valuable cues about user expectations, preferences, and potential pain points associated with different rating levels.

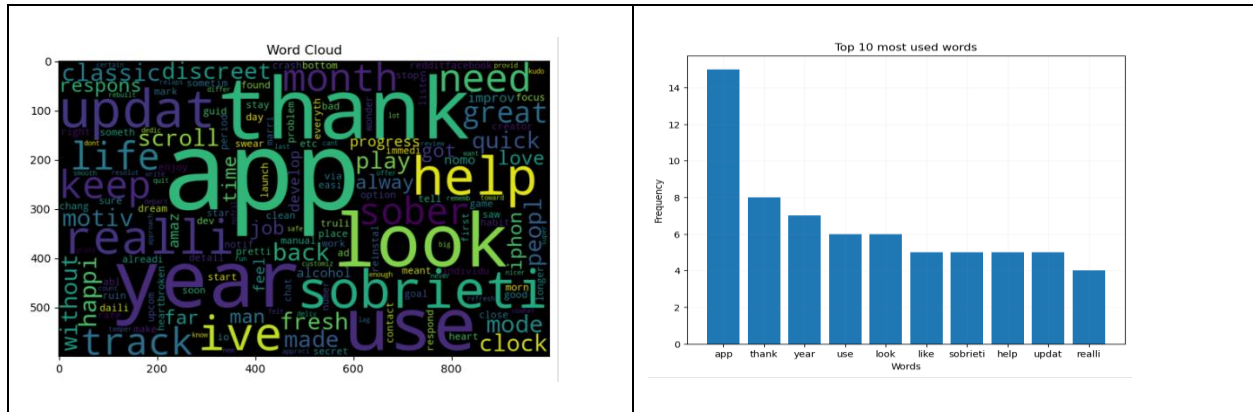


Figure 3: Nomo – Sobriety Clocks word cloud and Top 10 Most Used Words graph results for 5-star reviews.

Table 5: Nomo – Sobriety Clocks word frequency results per star rating from Python.

5 Star	4 Star	3 Star	2 Star	1 Star
App	App	App	App	App
Thank	Use	Day	Clock	Work
Year	Like	Use	User	Update
Use	Feature	Great	Create	Use
Look	Partner	Back	Havent	Day
Like	Great	Account	Found	Delete
Sobriety	Account	Ive	People	Could
Help	One	Part	Remind	Even
Update	Clock	Like	Check	Help
Reality	Function	Partner	Feature	One

#### 4.1.2 Sober Time – Sobriety Counter

In the analysis of Sober Time – Sobriety Counter using Python, the term "app" consistently emerges as the most frequently mentioned word across all star ratings. Delving into specific rating segments, higher-rated reviews prominently feature positive expressions such as "help," "love," and "great," underscoring users' satisfaction with the application's supportive features. Conversely, lower-rated reviews introduce words like "free," "want," and "sobriety," suggesting potential areas of concern or user expectations that might not be fully met. Notably, the ubiquitous term "ad" appears consistently across all ratings, indicating a common observation or experience related to advertisements within the app. These trends are shown in Figure 4

through the use of a word cloud and graph, as well as in Table 6. This nuanced analysis provides valuable insights into user sentiments at different rating levels, offering developers a comprehensive view of both positive aspects and areas for potential improvement.

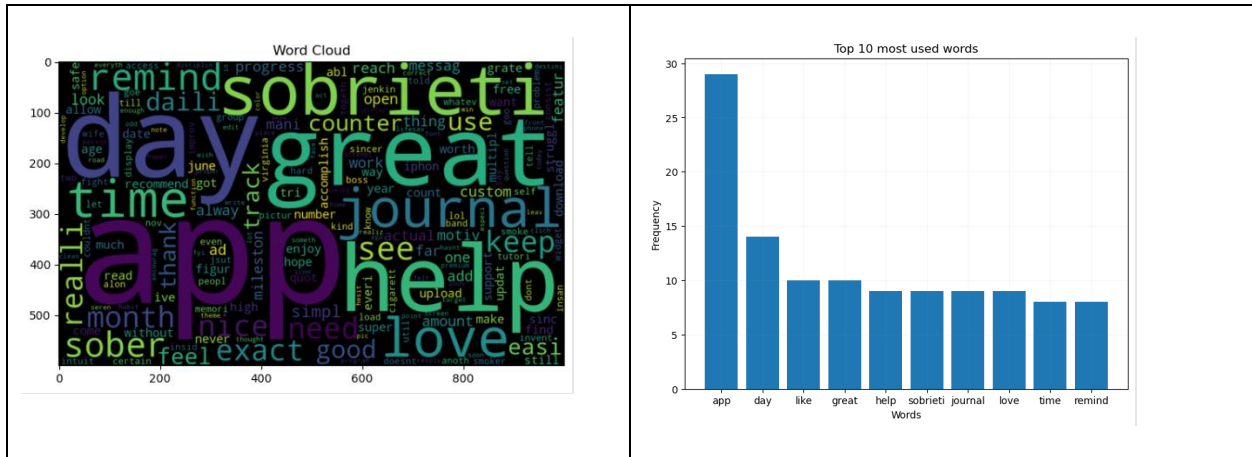


Figure 4: Sober Time – Sobriety Counter word cloud and Top 10 Most Used Words graph results for 5-star reviews.

Table 6: Sober Time – Sobriety Counter word frequency results per star rating from Python.

5 star	4 star	3 star	2 star	1 star
App	App	App	App	App
Day	Dont	Time	Ad	Ad
Like	Use	Many	Use	Time
Great	Like	Use	There	Many
Help	Love	Clean	Time	Sobriety
Sobriety	Ad	Seem	Free	Want
Journal	Year	Just	Like	Every
Love	Premium	That	Make	Make
Time	Good	Tell	Every	Addict
Remind	Even	Noth	Click	Delete

#### 4.1.3 Reframe: Drink Less & Thrive

Examining the Python output for Reframe: Drink Less & Thrive, displayed in the subsequent figures, notable insights emerge. The analysis of the top 10 words by star rating,

Figure 5 and Table 7, unveils consistent appearances of key terms such as "drink" and "alcohol" across various review rating segments. These recurrent themes suggest a significant focus on alcohol-related aspects within user feedback. Additionally, noteworthy patterns surface as the words "charge" and "free" prominently appear in 1-star rating reviews, indicating a potential association between these terms and less favorable user experiences. This detailed exploration of word frequencies provides a nuanced understanding of the app's reception, offering developers valuable cues about prevalent themes and potential areas for improvement across different rating levels.

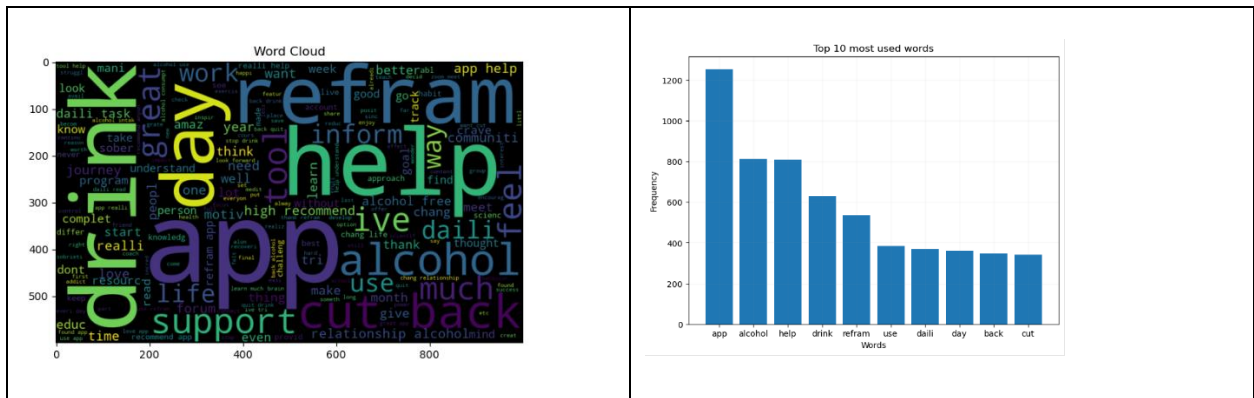


Figure 5: Reframe: Drink Less & Thrive word cloud and Top 10 Most Used Words graph results for 5-star reviews

Table 7: Reframe: Drink Less & Thrive word frequency results per star rating from Python.

5 star	4 star	3 star	2 star	1 star
App	App	App	App	App
Alcohol	Help	Like	Help	Day
Help	Alcohol	Drink	Drink	Free
Drink	Use	User	Day	Help
Reframe	Like	Daily	Read	Charge
Use	Daily	Alcohol	Alcohol	Month
Daily	Day	Get	Month	Get
Day	Drink	Help	Use	People
Back	Back	People	Get	Pay
Cut	Reality	Use	People	Trail

#### 4.1.4 Loosid Sober Recovery Network

Presented below are the Python outputs for Loosid Sober Recovery Network, as depicted in Figure 6 and Table 8. A discerning analysis of the top words by star rating reveals distinct patterns. Notably, positive terms like “community,” “support,” and “great” feature prominently in higher-rated reviews, underscoring the app’s positive impact on users who have bestowed favorable ratings. Conversely, lower-rated reviews exhibit a prevalence of terms such as “local,” “like,” and “love,” suggesting a potential association between these words and less favorable user assessments. This nuanced exploration of word frequencies provides valuable insights into the varying sentiments expressed by users at different rating levels, offering developers key considerations for enhancing user satisfaction and refining specific aspects of the app.

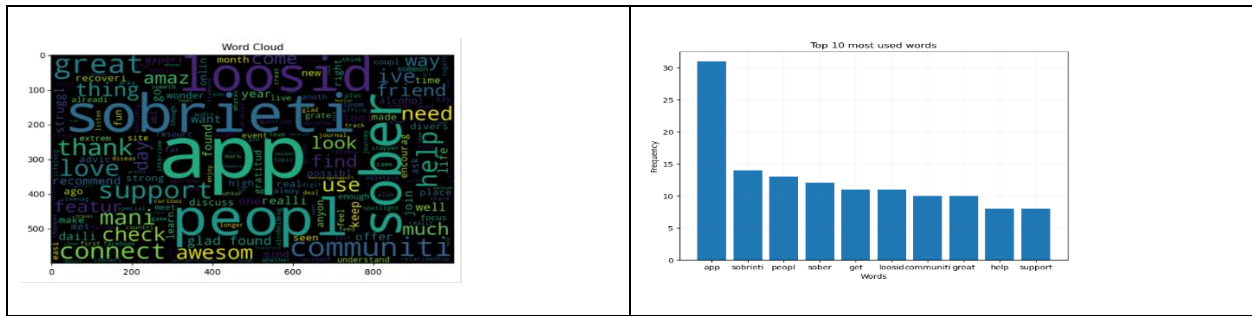


Figure 6: Loosid Sober Recovery Network word cloud and Top 10 Most Used Words graph results for 5-star reviews.

Table 8: Loosid Sober Recovery Network word frequency results per star rating from Python.

5 star	4 star	3 star	2 star	1 star
App	App	Like	Sober	App
Sobriety	Sober	App	Local	Local
People	Need	Get	Connect	Work
Sober	Post	Cant	Even	Profile
Get	Date	Person	Get	Use
Loosid	Recovery	User	App	Get
Community	Great	Also	Seem	Like
Great	Don't	Say	Like	Try
Help	Notify	See	Many	Even
Support	Every	Report	Love	Way



Really	Use	Dont	Get	Pay
Get	Really	Get	Community	Thing
Keep	Thing	Really	Thing	Support

4.1.6 Summary

The analysis of frequently used words in different star rating segments of app store reviews provides valuable insights into user sentiments and preferences for various sobriety apps. In the case of Nomo – Sobriety Clocks, words like "year," "help," and "sobriety" associated with higher ratings suggest that users appreciate features related to long-term support and assistance in maintaining sobriety. Conversely, words such as "delete" and "update" in lower-rated reviews imply dissatisfaction with app functionalities or user experience.

For Sober Time – Sobriety Counter, the persistent mention of "app" across all ratings indicates its ubiquitous presence, while positive terms like "help," "love," and "great" in higher ratings reflect user satisfaction with the app's supportive features. Conversely, words like "free" and "want" in lower ratings suggest potential dissatisfaction with specific app aspects.

Reframe: Drink Less & Thrive exhibits consistent references to "drink" and "alcohol" across various star ratings, indicating users' focus on these aspects in their reviews. The recurrence of "charge" and "free" in 1-star reviews may signal user dissatisfaction with payment-related issues.

Loosid Sober Recovery Network highlights the importance of "community," "support," and "great" in higher-rated reviews, emphasizing the positive impact of these elements on user experience. Conversely, "local," "like," and "love" in lower-rated reviews may indicate areas for improvement or dissatisfaction with certain features.

In the case of I Am Sober, higher-rated reviews feature positive terms like "like," "people," and "day," suggesting user appreciation for social and daily tracking aspects. Lower-rated reviews, on the other hand, include negative terms like "don't," "pay," and "post," indicating concerns related to payment, app functionality, or user interactions.

## 4.2 ChatGPT Analysis Results

Contrary to the Python code results, ChatGPT produced varying top ten words for five-star reviews, suggesting a nuanced interpretation influenced by the extensive information inputted. Notably, "App" emerged as the most recurrent term across all reviews.

### 4.2.1 Nomo – Sobriety Clocks

The recurring themes and frequently used words in the reviews of these sobriety apps offer a comprehensive glimpse into users' experiences, perceptions, and desires. Table 10 shows three responses received from ChatGPT 3.5 after entering all reviews and providing the following prompt: "The comments above are reviews pulled from app store data. What are the most frequently used words?" Across positive reviews, expressions of appreciation and satisfaction emerge through words like "helpful," "motivating," and "encouraging." Users frequently commend features like tracking their progress ("clock," "timers") and the app's ability to support their journey towards sobriety ("recovery," "sobriety," "accountability"). Recommendations and high ratings ("5 stars," "4 stars") indicate overall contentment and willingness to endorse the app to others.

However, amidst the positive sentiments, issues, and concerns surface in negative reviews. Words such as "glitch," "bugs," and "not working" highlight technical problems that impede user experiences. Users express frustration and disappointment when encountering issues like slow performance or malfunctioning features. Improvement suggestions, including calls for updates, fixes, or easier navigation, underline users' desires for smoother, more reliable app functionality.

Moreover, personal stories and addiction-related terms signify the profound impact these apps hold in aiding recovery journeys. Users share experiences of progress, struggles, and achievements, emphasizing the app's role in their rehabilitation process. This signifies a deeper emotional connection users have with the app, beyond its technical aspects, as it becomes an integral part of their sobriety journey.

Overall, these reviews encapsulate a diverse spectrum of user experiences, highlighting the significance of both technical reliability and emotional support in these sobriety apps. Developers can leverage this feedback to prioritize technical improvements while continuing to

foster a supportive and encouraging environment for users navigating their paths towards recovery.

Table 10: Nomo – Sobriety Clocks word frequency results for all reviews from ChatGPT.

First Response	<p>Based on the reviews, some frequently used words include:</p> <ol style="list-style-type: none"> <li>1. App: Referring to the application itself.</li> <li>2. Clock: Mentioned in the context of tracking time and progress.</li> <li>3. Sobriety: Reflecting the primary purpose of the app.</li> <li>4. Features: Describing various functionalities.</li> <li>5. Motivation/Encouragement: Highlighting the positive impact on users.</li> <li>6. Bugs/Glitches: Referring to technical issues.</li> <li>7. Community/Support: Indicating the social aspect of the app.</li> <li>8. Rating/Stars: Mentioning the user ratings given to the app.</li> <li>9. Reset: Often mentioned in relation to resetting progress or clocks.</li> <li>10. Issues/Problems: Pointing out concerns users have encountered.</li> <li>11. Improvement/Update: Suggesting the need for enhancements or fixes.</li> <li>12. Money: Pertaining to the feature that tracks savings.</li> <li>13. Interface/Design: Referring to the user interface and app design.</li> <li>14. Connection/Networking: Describing the ability to connect with others.</li> <li>15. Addiction/Recovery: Expressing the app's relevance to overcoming addiction.</li> <li>16. Notifications: Mentioning alerts or reminders.</li> </ol> <p>It's important to note that these words provide insights into users' experiences and perceptions of the app.</p>
Second response	<p>Based on the reviews, some of the most frequently used positive words include: Helpful, Motivating, Encouraging, Supportive, Useful, Love, Sobriety, Progress, Recovery, Great          For negative reviews, common words include: Glitchy, Bugs, Laggy, Slow, Frustrated, Not working, Abandoned, Useless, Disappointed, Upset</p>
Third Response	<p>Here are some of the most frequently used words in the reviews:</p> <ol style="list-style-type: none"> <li>1. Positive Words: love, helpful, great, amazing, appreciate, favorite, wonderful, encouraging, motivational</li> <li>2. App Features: clock, timers, journal, encouragement, refocus, resources, accountability, recovery, sobriety</li> <li>3. Rating and Recommendation: 5 stars, 4 stars, recommend</li> <li>4. Issues/Concerns: glitch, bugs, slow, lag, difficulty, not working, problems</li> <li>5. Improvement Suggestions: update, fix, features, easier, reset, variety, reset clocks</li> <li>6. Specific Feedback: money saved, customization, community, accountability partners, notifications</li> <li>7. Addiction-related Terms: recovery, sobriety, addiction, relapse</li> <li>8. Personal Stories: rehab, progress, struggles, achievements</li> </ol> <p>These words and themes provide an overview of the users' experiences, highlighting both positive aspects and areas that may need improvement in the app.</p>

#### 4.2.2 Sober Time – Sobriety Counter

The provided information from the app store reviews offers valuable insights into user sentiments regarding the Sober Time app across different rating levels. Table 11 shows three responses received from ChaptGPT 3.5 after entering all reviews and providing the following



prompt: “The comments above are reviews pulled from app store data. What are the most frequently used words?” Positive reviews consistently highlight the app's supportive features, including words such as "help," "love," and "great," indicating user satisfaction with the app's impact on their sobriety journeys. Frequent mentions of terms like "track," "time," and "sobriety" in positive reviews underscore the app's effectiveness in assisting users in monitoring their progress and maintaining a sober lifestyle.

On the other hand, negative reviews reveal areas of concern or dissatisfaction among users. The recurring mention of "ads" in lower-rated reviews suggests a common issue with the frequency or content of advertisements, impacting the overall user experience negatively. Terms like "free" and "buy" associated with lower ratings indicate potential dissatisfaction with the app's free version or concerns related to purchases, respectively.

The term "reset" appears in negative reviews, reflecting user frustration or dissatisfaction with the app's reset feature. The presence of "update" in negative reviews suggests user concerns or dissatisfaction with the app's update process, potentially indicating technical issues or undesired changes.

Table 11: Sober Time – Sobriety Counter word frequency results for all reviews from ChatGPT.

First Response	Here are some of the most frequently used words in the reviews you provided: 1. App, 2. sobriety, 3. time, 4. days, 5. love, 6. great, 7. track, 8. thank, 9. life, 10. Inspirational, 11. Quotes, 12. Progress, 13. Helpful, 14. Encouragement, 15. Journey, 16. Goal, 17. Addiction, 18. Money, 19. Clean, 20. Motivational These words give an overview of the common themes and sentiments expressed by users in their reviews.
Second Response	Based on the provided app store reviews, the most frequently used words can be summarized as follows: Positive Reviews (4-5 Star Ratings): help: mentioned in reviews emphasizing the app's assistance and support. love: users express affection for features, such as daily motivational quotes and customizable options. great: used to highlight positive aspects of the app, such as its functionality and impact on sobriety. like: mentioned in reviews praising certain features or aspects of the app. app: frequently used in reviews, indicating a general reference to the application. day: associated with positive sentiments, likely referring to daily tracking features. sobriety: linked to positive reviews, suggesting users appreciate features related to maintaining sobriety. recommend: used in positive reviews, indicating users suggesting the app to others. people: mentioned positively, likely in the context of a sober community or network. year: associated with higher ratings, possibly indicating long-term success or commitment. Negative Reviews (1-3 Star Ratings): ads: frequently mentioned in lower-rated reviews, indicating dissatisfaction with the frequency or content of advertisements.

	<p>free: associated with lower ratings, suggesting concerns or dissatisfaction with the free version of the app.</p> <p>reset: mentioned negatively, indicating frustration or dissatisfaction with the app's reset feature.</p> <p>update: used negatively, indicating issues or dissatisfaction with app updates.</p> <p>gambling: mentioned negatively, likely associated with dissatisfaction with inappropriate ads.</p> <p>buy: used negatively, indicating concerns about having to purchase features again after updates.</p> <p>history: mentioned negatively, possibly indicating frustration with data loss or lack of a comprehensive history feature.</p> <p>widget: mentioned negatively, suggesting issues or dissatisfaction with the app's widget functionality.</p> <p>milestones: mentioned negatively, possibly indicating dissatisfaction with the tracking or display of milestones.</p> <p>lost: associated with negative sentiments, likely indicating dissatisfaction with data loss or missing features.</p> <p>It's important to note that these word frequencies provide an overview and may not capture every nuance in user feedback. The analysis highlights recurring themes in both positive and negative reviews.</p>
Third response	<p>Certainly, based on the reviews, here are the most frequently used words across different ratings:</p> <p>5-Star Ratings: help, love, great, easy, track, app, time, sobriety, recommend, thank</p> <p>4-Star Ratings: app, good, like, use, help, great, day, ads, motivational, reminder</p> <p>3-Star Ratings: app, use, like, easy, motivated, track, ads, wish, interface, progress</p> <p>2-Star Ratings: ads, app, long, reset, update, lost, panic, angry, refund, buy</p> <p>1-Star Ratings: ads, app, reset, paid, buy, erase, milestones, lost, history, delete</p> <p>These words give an overview of the sentiments and experiences expressed across various rating levels for these sobriety apps.</p>

### 4.2.3 Reframe: Drink Less & Thrive

The analysis of user reviews for the app "Reframe: Drink Less & Thrive" reveals distinct patterns and sentiments expressed by users. Table 12 shows three responses received from ChaptGPT 3.5 after entering all reviews and providing the following prompt: "The comments above are reviews pulled from app store data. What are the most frequently used words?"

Positive reviews emphasize the app's impact on empowering individuals in their journey towards sobriety. Words such as "alcohol," "daily," "tasks," and "community" highlight the app's role in fostering a supportive environment and providing educational resources. The emphasis on "reflection" suggests that users appreciate the app's focus on self-awareness and personal growth.

In neutral/mixed reviews, users mention aspects related to app functionality, subscription costs, and tracking progress. The inclusion of terms like "subscription," "cost," and "progress" indicates that users are evaluating the app based on its practical features and effectiveness in supporting moderation. The term "journaling" suggests that users may find value in the reflective aspect of tracking their journey within the app.

Negative reviews reveal concerns around charges, subscriptions, and potential privacy issues. The use of words such as "charge," "subscription," "refund," and "privacy" indicates that users have encountered challenges related to the app's financial model and question its transparency. The term "advertising" suggests that users may have experienced issues with unwanted promotional content within the app.

Table 12: Reframe: Drink Less & Thrive word frequency results for all reviews from ChatGPT.

First Response	Here are the most frequently used words in the provided reviews: App, Alcohol, Rating, User, Subscription, Charged, Month, Trial, Use, Year, Time, Information, Free, Review, Refund, Help, Day, Experience, Community, Support, Relationship, Daily, Tasks, Reflect, Forum, Features, Health, Money, Cost, People These words reflect common themes in the reviews, such as issues with subscriptions, charges, user experience, support, and the overall impact of the app on users' relationships with alcohol.
Second Response	Here are some of the most frequently used words extracted from the reviews you provided: 1. Positive Reviews: Encouraged, empowered, fact-based, community, reflection, journey, reduction, alcohol-free, forum, understanding, transformative, motivation, sobriety, grateful. 2. Neutral/Mixed Reviews: Tracker, period, payment, advisor, periods, time, tedious, useful, moderate, switch, progress, successful, different, membership, subscription. 3. Negative Reviews: Charged, subscription, misleading, spam, money, auto-enrollment, cancel, app, issues, details, waste, money, customer service, cancel, refund, support, difficulties, glitches, misleading, spam, waste. These words give an overview of the sentiments expressed by users in their reviews. Positive reviews highlight the app's empowering and transformative aspects, while negative reviews often focus on issues related to subscriptions, transparency, and user experience. Neutral/mixed reviews touch on various aspects of app usage, including tracking, progress, and costs.
Third Response	Here are some of the most frequently used words extracted from the reviews: Positive Reviews: alcohol, app, daily, tasks, forum, community, reflection, empowerment, education, sobriety Neutral/Mixed Reviews: app, subscription, cost, time, functionality, moderation, information, usage, progress, journaling Negative Reviews: charge, subscription, app, refund, spam, misleading, cancel, support, privacy, advertising It's important to note that these word frequencies are based on the reviews provided, and the context and sentiment around each word can vary. Positive reviews tend to focus on the app's benefits, empowerment, and community features, while negative reviews often highlight issues with charges, refunds, and privacy concerns.

#### 4.2.4 Loosid Sober Recovery Network

Based on the reviews extracted from app store data, users frequently mention both positive and negative aspects of the Loosid Sober Recovery Network. Table 13 shows three responses received from ChaptGPT 3.5 after entering all reviews and providing the following prompt: "The comments above are reviews pulled from app store data. What are the most frequently used words?" Positive sentiments are expressed through words like "love," "great,"

and "community," indicating users appreciate the supportive environment and sense of connection fostered by the app. The emphasis on terms such as "support" and "great" suggests that the app successfully cultivates a positive community for individuals in their sobriety journey.

However, the presence of words like "glitch," "bug," and "difficult" in the negative or critical category signals that some users have encountered technical issues or challenges while using the app. The terms "fake" and "catfished" imply concerns about authenticity or deceptive profiles, suggesting that users may have faced issues related to the credibility of information or interactions within the app.

The inclusion of words like "dating," "events," and "groups" indicates that users engage with various features offered by the app, emphasizing its role in facilitating connections beyond mere sobriety tracking. The mention of "location" and "local" suggests that the app incorporates geographical elements, for connecting users within specific regions.

The ratings-related words, including "5 stars" and "4 stars," reflect the diversity of user experiences, with some users expressing high satisfaction through top ratings, while others may have had more moderate experiences.

The words related to improvements and development, such as "develop," "improvement," and "update," suggest that users have expectations for ongoing enhancements to the app, in response to identified glitches or to introduce new features.

Table 13: Loosid Sober Recovery Network word frequency results for all reviews from ChatGPT.

<p>First Response</p>	<p>Based on the provided reviews, some of the most frequently used words are:</p> <ol style="list-style-type: none"> <li>1. App: Mentioned frequently as users are providing reviews for the mobile application.</li> <li>2. Love: Used positively in the context of users expressing affection or appreciation for the app.</li> <li>3. Sobriety: Referenced in relation to the app's focus on supporting individuals in their journey to sobriety.</li> <li>4. Rating: Often accompanied by a numerical value (e.g., 5 rating, 4 rating).</li> <li>5. Community: Describing the sense of connection and support found within the app.</li> <li>6. Location: Mentioned in the context of users facing issues with setting or entering their location.</li> <li>7. Support: Indicating the app's role in providing assistance and encouragement.</li> <li>8. Dating: Referenced in the context of the app's dating features and experiences.</li> <li>9. Work: Used in the context of the app not working properly or experiencing technical issues.</li> <li>10. Events: Describing features related to organizing or participating in sober events.</li> </ol> <p>Note: The frequency of words is based on the reviews provided, and common words such as articles and prepositions may not be included in this list.</p>
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<p>Second Response</p>	<p>Based on the reviews provided, here are some of the most frequently used words:          Positive Words: Love, Great, Amazing, Awesome, Grateful, Excited, Happy, Supportive, Quick, Strong          2. Neutral Words: App, Concept, Idea, Community, Sobriety          3. Negative or Critical Words: Glitch, Bug, Fake, Broken, Buggy, Terrible, Difficult, Confusing, Non-responsive, Catfished          4. Technical Issues: Location, Birthday, Unable, Freeze, Load, Error, Glitch, Delete, Support          5. Usage and Experience: Use, Like, View, Profile, Date, Report, Field, Save, Feature, Working          6. Rating-related Words: 5 rating, 4 rating, 3 rating, 2 rating, 1 rating          These words capture the sentiments and concerns expressed by users in their reviews.</p>
<p>Third Response</p>	<p>To analyze the most frequently used words in the reviews, let's compile a list based on the comments provided. Keep in mind that common words such as "the," "and," or "it" are likely to appear frequently but may not provide meaningful insights into the reviews. Here are some of the more significant words and themes from the reviews:          1. Positive Words: love, great, awesome, amazing, thanks, happy, excellent          2. Concept/Idea: concept, idea          3. App Features: dating, events, groups, tools          4. Issues/Challenges: glitch, bug, problem, difficult, broken, error, fake, catfished          5. Sobriety: sobriety, sober, recovery, support          6. Community/Connections: community, connections, friends, networking, meeting          7. Location: location, local          8. Rating: rating, 5 stars, 4 stars, 3 stars, 2 stars, 1 star          9. Improvements/Development: develop, improvement, update, fix          10. Usage Experience: use, using, navigate, experience, user          These words provide a glimpse into the sentiments and experiences of users with the Loosid app, highlighting both positive aspects and challenges faced by users. Keep in mind that the analysis is based on the comments provided and may not capture all nuances of user feedback.</p>

4.2.5 I Am Sober

The frequent use of words like "Love," "Support," and "Motivation" across these reviews reflects a highly positive sentiment toward the app, I Am Sober. Users repeatedly express appreciation for its supportive community, the motivational features, and its role in tracking their progress on the journey toward sobriety. Table 14 shows three responses received from ChaptGPT 3.5 after entering all reviews and providing the following prompt: “The comments above are reviews pulled from app store data. What are the most frequently used words?”

"Track," "Progress," and "Day" emphasize the core functionality of the app, allowing users to monitor their sobriety, track their milestones, and stay focused on their daily commitment to a sober lifestyle. This tracking aspect is crucial for users, providing a tangible measure of their progress and commitment.

"Community" and "Support" suggest that users find value in the social aspect of the app, connecting with others on a similar journey, sharing experiences, and feeling supported. The positive reviews often mention feeling encouraged and motivated by this community aspect, highlighting the importance of social reinforcement in their recovery process.

"Encouraging," "Motivation," and "Encouragement" point to the app's ability to inspire and uplift users through various features, including daily messages, motivational quotes, or encouraging prompts. This positive reinforcement plays a significant role in users' experiences and their commitment to maintaining sobriety.

Overall, the repeated use of positive words like "Love," "Amazing," and "Recommend" underscores users' strong endorsement and satisfaction with the app's impact on their journey toward sobriety. It indicates that I Am Sober effectively addresses their needs by offering robust tracking tools, fostering a supportive community, and providing consistent motivation and encouragement.

Table 14: I Am Sober word frequency results for all reviews from ChatGPT.

<p>First Response</p>	<p>The most frequently used words in the provided reviews are: App, Sobriety, Love, Track, Day, Motivational, Pledge, Support, Features, Community, Journey, Positive, Addiction, Clean, Family, Progress, Quotes, Recommend, Review, Time</p> <p>These words highlight the positive aspects of the app, focusing on features related to tracking sobriety, motivational support, and community engagement. Users frequently mention their love for the app, its ability to track progress, and the positive impact on their sobriety journey.</p>
<p>Second Response</p>	<p>The most frequently used words in the provided reviews are: App, Love, Support, Track, Community, Motivating, Day, Clean, Progress, Sobriety, People, Amazing, Help, Milestone, Thank, Reminder, Daily, Review, Proud, Feature</p> <p>These words emphasize the positive impact of the app on users' lives, focusing on aspects such as support, tracking progress, community engagement, and motivation. Users frequently express love for the app, appreciation for its supportive community, and the positive influence it has on their journey toward sobriety.</p>
<p>Third Response</p>	<p>The most frequently used words in the provided reviews are: App, Love, Support, Track, Motivation, Sobriety, Progress, Community, Day, Clean, Milestone, Review, Recommend, Help, People,</p>

	<p>Amazing, Encouraging, Download, Network, Interface          These words highlight the positive impact of the app on users' lives, focusing on aspects such as support, motivation, progress tracking, community engagement, and encouragement. Users frequently express love for the app, appreciation for its supportive community, and the positive influence it has on their journey toward behavior change and sobriety.</p>
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4.2.6 Summary

The analysis of reviews from various sobriety apps reveals a nuanced and diverse spectrum of user experiences. Positive sentiments are consistently expressed through words like "love," "support," and "motivation," indicating a prominent level of satisfaction with the apps' impact on users' journeys towards sobriety. The apps are lauded for their supportive communities, motivational features, and effective progress tracking.

On the other side, negative reviews shed light on technical issues such as "glitches" and "bugs," indicating challenges that some users face with the apps' functionality. Complaints about ads and concerns regarding subscriptions highlight areas where users experience dissatisfaction, emphasizing the need for developers to address these pain points for improved user experience.

The significance of the emotional and communal aspects of these apps is evident in users sharing personal stories, struggles, and achievements. The apps serve as more than just technical tools, becoming integral companions in users' rehabilitation journeys.

Across all reviews, the desire for continuous improvement is evident, with users expressing expectations for updates, fixes, and easier navigation. This emphasizes the importance of maintaining technical reliability while fostering a supportive and encouraging environment within the apps.

The feedback from these reviews provides developers with valuable insights to enhance both the technical and emotional dimensions of sobriety apps. As users seek reliable functionality, they also crave a sense of community, motivation, and support on their paths to recovery. Integrating these insights can lead to more holistic and effective sobriety apps that cater to the diverse needs of individuals striving for a healthier and sober lifestyle.

### 4.3 Manual Analysis Results

While automated processes can efficiently extract and compile word frequencies, manual analysis offers a human-driven approach that adds an extra layer of validation and context. This method ensures that the words identified align with the actual sentiments, themes, and patterns present in authentic user reviews. Additionally, manual analysis allows for the detection of subtle nuances, contextual relevance, and potential errors that automated algorithms might overlook, thus contributing to a more precise and reliable understanding of the data's accuracy and similarity.

The results of the manual analysis, shown in the example provided in Table 15, underscored the accuracy of ChatGPT in reference to the sampled review data. The responses generated by ChatGPT exhibited a notable alignment with the sentiments expressed in real user reviews. The model effectively captured the recurring themes, preferences, and concerns highlighted in the manually evaluated samples. The likes, dislikes, suggestions, and other feedback identified through manual analysis were consistently reflected in the ChatGPT responses, demonstrating a high level of concordance between the model's outputs and the authentic user sentiments present in the app store reviews. This validation through manual analysis enhances confidence in the reliability and accuracy of ChatGPT's ability to understand and generate responses that closely mirror real user feedback.

Table 15: I Am Sober manual review analysis data example.

Review	Rating	Likes	Dislikes	Suggestions	Other
User1099 said You guys need to add a chat option so people who have friends on the app don't have to keep posting email addresses or tiktok accounts. It would be so helpful. User1099 gave a 4 rating.	4	N/A	No chat option	Add a chat option	N/A

### 4.4 Summary of Findings

The analysis of frequently used words in Python output and ChatGPT prompt responses for various sobriety apps reveals interesting correlations and insights. In both cases, positive sentiments are consistently associated with words like "love," "support," "help," and "great," emphasizing the importance of supportive features and positive user experiences. Terms related



to tracking progress, such as "track," "progress," and "day," also recur across both Python output and ChatGPT responses, highlighting the significance of monitoring milestones.

However, there are nuanced differences between the two methods. Python output, derived directly from app store reviews, provides concrete insights into specific user sentiments, concerns, and preferences associated with different star ratings. It captures real user feedback, including issues with ads, resets, updates, and technical glitches, offering a detailed understanding of the user experience.

On the other hand, ChatGPT responses demonstrate a capability to generate responses that align with the general sentiments expressed in the app store reviews. While it captures overarching themes and frequently used words, it may lack the specificity and contextual accuracy found in the Python output directly derived from user reviews.

Pros of Python Output Analysis:

1. **Authentic User Feedback:** Python output directly reflects the sentiments, likes, dislikes, and suggestions expressed by real users in app store reviews.
2. **Concrete Insights:** The analysis provides specific information on user concerns, technical issues, and preferences associated with different star ratings.
3. **Contextual Understanding:** Python output offers a more nuanced and contextually accurate understanding of user sentiments.

Cons of Python Output Analysis:

1. **Limited to Available Data:** The analysis is limited to the data available in the app store reviews and may not capture sentiments outside the reviewed sample.
2. **Potential Bias:** The sample of reviews selected for manual analysis might introduce bias based on the chosen percentage, potentially overlooking certain sentiments.

Pros of ChatGPT Prompt Responses:

1. **Quick Generation:** ChatGPT rapidly generates responses, providing a convenient way to analyze frequently used words without manual review.

2. **Broad Understanding:** ChatGPT captures general themes and sentiments, offering a broad understanding of frequently used words.

Cons of ChatGPT Prompt Responses:

1. **Lack of Specificity:** ChatGPT responses may lack the specificity and contextual accuracy found in the detailed insights provided by Python output.
2. **Potential Overgeneralization:** ChatGPT might generate responses that overly generalize sentiments, missing specific nuances present in user reviews.

In comparing ChatGPT and coding for app store review analysis, it becomes evident that each method has its own set of advantages and limitations. Coding, executed through Python, proves to be efficient in delivering concise and consistent results through numerical frequency data, which are visually presented in graphs and word clouds. However, this approach requires interpretation, making it challenging to directly discern user sentiment from the generated statistical insights. On the other hand, ChatGPT surpasses this limitation by providing more in-depth and contextual information about user preferences, dislikes, and suggestions. The information is presented in easy-to-understand statements, offering a qualitative layer to of analysis. Despite these strengths, ChatGPT's responses lack conciseness, and the results can vary with each input, introducing an element of unpredictability.

The disparity observed in the top ten words between the Python coding and ChatGPT raises important considerations and implications for the research approach. The statistical insights generated by the Python code contribute valuable quantitative data, while ChatGPT's qualitative insights offer a nuanced understanding. The combination of both methods yields a balanced and thorough analysis, harnessing the strengths of each to paint a more complete picture of user sentiments and preferences in the app store reviews. This dual-method approach holds promise for future research, acknowledging the complementary roles of quantitative and qualitative analyses in providing a holistic evaluation of user experiences.

To ensure the analysis remains relevant over time, a system for continuous monitoring should be established. This involves setting up a process to regularly collect and analyze new the latest reviews, allowing for ongoing assessment of user sentiments and feedback related to app

usage duration. This iterative approach ensures that the app evolves in response to user needs and preferences.

## 5.0 Conclusions and Recommendations

The synthesis of user reviews and insights across Reframe: Drink Less and Thrive, Nomo – Sobriety Clocks, Sober Time, I Am Sober, and Loosid: Sober Recovery Network reveals a rich tapestry of user experiences and expectations within the realm of digital health apps aimed at supporting sobriety. The consistent positive themes, including supportive communities, progress tracking, motivational features, flexibility, and educational content, underscore the profound impact these apps have on users' journeys toward recovery.

### 5.1 Retention Rate

Several factors contribute to high app retention rates in sobriety apps. Users consistently express positive sentiments, including "love," "support," and "motivation," highlighting a strong satisfaction with the app's impact on their sobriety journey. The apps receive praise for fostering supportive communities, incorporating motivational features, and implementing effective progress tracking, all of which play pivotal roles in user retention. The significance of progress tracking is underscored by positive associations with terms like "track," "progress," and "day," emphasizing the importance of monitoring milestones in maintaining user commitment. Features such as sobriety clocks and metrics receive widespread acclaim, contributing to a dynamic and personalized user experience. The emotional and communal aspects of these apps are also crucial, as users emphasize their role as integral companions in rehabilitation journeys, fostering a sense of belonging and support. Additionally, positive reviews expressing the desire for continuous improvement and updates reflect users' active engagement and high expectations, further contributing to app retention rates.

### 5.2 User Preferences

Positive sentiments, expressed through words like "love," "support," and "motivation," highlight users' satisfaction with the apps' impact on their journeys toward sobriety. The prominence of supportive communities, motivational features, and effective progress tracking contributes to positive user experiences.

However, negative reviews shed light on technical challenges, such as "glitches" and "bugs," indicating areas where some users face issues with the apps' functionality. Complaints about ads and concerns regarding subscriptions underscore dissatisfaction points, emphasizing the need for developers to address these aspects for an enhanced user experience.

Emotional and communal aspects play a crucial role, with users sharing personal stories, struggles, and achievements. These apps transcend mere technical tools, becoming integral companions in users' rehabilitation journeys. The desire for continuous improvement is evident across all reviews, with users expressing expectations for updates, fixes, and easier navigation. This underscores the importance of maintaining technical reliability while fostering a supportive and encouraging environment within the apps.

### 5.3 Recommendations

Foremost, the sense of community support emerges as a cornerstone, with users valuing the opportunity to connect with others facing similar challenges. The communal atmosphere created by these apps is instrumental in fostering motivation, sharing experiences, and cultivating a sense of unity among users. This communal support plays a pivotal role in overcoming obstacles and staying committed to the path of recovery.

The inclusion of Progress Tracking features, such as sobriety clocks and metrics, garners widespread praise. Users find these visual representations pivotal in maintaining commitment to their sobriety goals. The dynamic and personalized experience created by tracking tools, coupled with supportive features, aligns seamlessly with users' individual needs and progress, empowering them to celebrate achievements and stay focused.

Apps offering Educational Content on the science behind alcohol consumption receive commendation for providing insights into the cognitive and physical effects of drinking. This educational component empowers users to make informed decisions, contributing to a deeper understanding of the consequences of alcohol consumption and facilitating a healthier lifestyle.

Motivational elements, including daily lessons and positive reinforcement, emerge as crucial in keeping users engaged. The incorporation of motivational quotes and lessons adds a

holistic dimension to the user experience, promoting a positive mindset and sustaining motivation throughout the recovery process.

The theme of Flexibility and Customization resonates strongly with users. The ability to tailor the app to different goals, from moderate reductions to complete abstinence, is appreciated. Customization options, such as tracking multiple habits or addictions, enhance the overall personalization of the app, allowing users to adapt it to their unique needs.

Privacy and Anonymity features, particularly in forums, are underscored as essential. Users value the option to share their experiences anonymously, fostering a non-judgmental and safe space for open communication.

Despite the positive feedback, users identify areas for improvement. Enhanced Usability, Improved Communication and Reminders, Compatibility Across Devices, Additional Literature and Resources, Integration of Meeting Locator, Chip Rewards Variety, Clock Resetting Process, and an Online Meeting Feature are suggested enhancements to create a more comprehensive and user-friendly experience.

The analysis of Reframe and Sober Time apps highlights specific points of dissatisfaction related to subscription pricing, refund policies, customer service, limited tracking options, and perceived lack of customization. Users express a need for enhanced transparency, better communication, improved user interfaces, and more flexible subscription options. This feedback underscores the significance of user-centric design, transparency, and effective communication in the development and maintenance of addiction recovery apps.

In moving forward, developers should prioritize user-centric design, clear communication, and addressing technical issues to enhance the overall user experience. The user feedback serves as valuable insights for refining these apps to better meet the needs and expectations of individuals on their journey to recovery. By aligning development efforts with user expectations, developers can build trust, foster a supportive community, and contribute meaningfully to the process of addiction recovery through digital health applications.

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## Appendix A. Apps Used in the Study

Table A1. Selected Apps Feature Comparison

App Name	IOS or Android	Avg. Rating	Number of Ratings	Paid Subscription	Community based/chat	In-app Motivation Reminders	Resources	Progress Monitoring
I Am Sober	Both	4.9/5	127,000	No	Yes	Yes	Yes	Yes
Loosid: Recovery Network	Both	4.7/5	6,000	No	Yes	No	Yes	Yes
Nomo – Sobriety Clocks	Both	4.7/5	12,000	No	No	Yes	No	Yes
Sober Time – Sobriety Counter	IOS	4.8/5	9,600	No	No	Yes	No	Yes
Reframe: Drink Less & Thrive	IOS	4.8/5	22,000	Yes	Yes	Yes	Yes	Yes

Table A2. Links to Selected Apps with Date Data was Captured

App Name	Link	Data Captured
I Am Sober	<a href="https://apps.apple.com/us/app/i-am-sober/id672904239">https://apps.apple.com/us/app/i-am-sober/id672904239</a>	Nov. 1 <sup>st</sup> , 2023
Loosid: Sober Recovery Network	<a href="https://apps.apple.com/us/app/loosid-sober-recovery-network/id1413514350">https://apps.apple.com/us/app/loosid-sober-recovery-network/id1413514350</a>	Nov. 1 <sup>st</sup> , 2023
Nomo – Sobriety Clocks	<a href="https://apps.apple.com/us/app/nomo-sobriety-clocks/id566975787">https://apps.apple.com/us/app/nomo-sobriety-clocks/id566975787</a>	Nov. 1 <sup>st</sup> , 2023
Sober Time – Sobriety Counter	<a href="https://apps.apple.com/us/app/sober-time-sobriety-counter/id1158895079">https://apps.apple.com/us/app/sober-time-sobriety-counter/id1158895079</a>	Nov. 1 <sup>st</sup> , 2023
Reframe: Drink Less & Thrive	<a href="https://apps.apple.com/us/app/reframe-drink-less-thrive/id1485756576">https://apps.apple.com/us/app/reframe-drink-less-thrive/id1485756576</a>	Nov. 1 <sup>st</sup> , 2023

## Appendix B. Python Code for Data Extraction and Analysis

### Figure B1 Data Scraping Code

Example code of how Python app store scraper was used to extract publicly available app store review data for Sober Time – Sobriety Counter. This code format was copied for all five apps to scrape app store review data. Editing of this code to be used for different apps can be done by replacing the `app_name =` the name of the app, followed by copying that new app's ID into `app_id =`. Change the name of your dataset to match the name of the app chosen.

```
import pandas as pd
import numpy as np
import json

from app_store_scraper import AppStore
sober_time_ios = AppStore(country='us', app_name='sober-time-sobriety-counter', app_id = '1158895079')

sober_time_ios.review(how_many=1500)

sober_time_iosdf = pd.DataFrame(np.array(sober_time_ios.reviews), columns=['review'])
sober_time_iosdf2 = sober_time_iosdf.join(pd.DataFrame(sober_time_iosdf.pop('review').tolist()))
sober_time_iosdf2.head()

sober_time_iosdf2.to_csv('sober-time-sobriety-counter.csv')
```

### Figure B2 Data Extraction Code

Example code of how Python libraries were imported to clean the scraped data, segment the data by ratings, create a graph of the top 10 frequently used words by review rating, and show a word cloud of the frequently used words. This code format was copied for all five apps to segment the reviews by ratings and graph how frequently words appear in each rating category. Editing this code to be used for different apps can be done by replacing the imported CSV file to another CSV file of app store review data.

```
import pandas as pd
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

import nltk
from nltk.corpus import stopwords
from nltk.tokenize import word_tokenize
from nltk.stem import SnowballStemmer

import warnings
warnings.filterwarnings('ignore')

from sklearn.preprocessing import LabelEncoder

import re
import collections
!pip install wordcloud
from wordcloud import WordCloud

df = pd.read_csv('C:/Users/veron/Downloads/Sober Time - Sobriety Counter-app-reviews.csv', sep=',',
encoding='latin-1')
```

```

df.info()

df.isna().sum()

df.dropna(inplace = True)

print(df['rating'])

df['rating'].unique()

encoder = LabelEncoder()

df['rating'] = encoder.fit_transform(df['rating']) + 1

Highest_rating = [rating for rating, i in df.groupby('rating')]
Highest_rating = sorted(Highest_rating, reverse = True)
Highest_rating[:5]

print(Highest_rating)

Data_Highest_1 = df[df['rating'] == Highest_rating[0]]
Data_Highest_2 = df[df['rating'] == Highest_rating[1]]
Data_Highest_3 = df[df['rating'] == Highest_rating[2]]
Data_Highest_4 = df[df['rating'] == Highest_rating[3]]
Data_Highest_5 = df[df['rating'] == Highest_rating[4]]

def clean_text(text):
    text = re.sub(r'http\S+|www\S+|https\S+', '', text)
    text = re.sub(r'^\x00-\x7F+', '', text)
    text = re.sub(r'^a-zA-ZÀ-ú\s', '', text.lower())
    tokens = text.split()
    tokens = [token for token in tokens if not token.isdigit()]
    tokens = [re.sub(r'^\w\s', '', token) for token in tokens]
    tokens = [token.strip() for token in tokens]
    tokens = [token for token in tokens if len(token) > 2]
    cleaned_text = ''.join(tokens)
    return cleaned_text

def preprocess_data(data):
    data['cleaned_text'] = data['review'].apply(clean_text)

    stop_words = set(stopwords.words('english'))
    stemmer = SnowballStemmer('english')

    data['cleaned_text'] = data['cleaned_text'].apply(word_tokenize)
    data['cleaned_text'] = data['cleaned_text'].apply(lambda x: [word for word in x if word not in stop_words])
    data['cleaned_text'] = data['cleaned_text'].apply(lambda x: [stemmer.stem(word) for word in x])
    data['final_text'] = data['cleaned_text'].apply(lambda x: ''.join(x))

def plot_rating_distribution(data):
    ratings = data['rating']
    rating_counts = ratings.value_counts().sort_index()
    plt.figure(figsize=(8, 6))
    sns.barplot(x=rating_counts.index, y=rating_counts.values)
    plt.xlabel('Rating')
    plt.ylabel('Count')

```

```

plt.title('Rating Distribution', fontsize=12)
plt.show()

def plot_top_words_bar(data):
    words = []
    for text in data['final_text']:
        words.extend(text.split())
    word_count = collections.Counter(words)
    top_words = dict(word_count.most_common(10))

    plt.figure(figsize=(8, 6))
    plt.bar(range(len(top_words)), list(top_words.values()), align='center')
    plt.xticks(range(len(top_words)), list(top_words.keys()))
    plt.grid(alpha=0.1)
    plt.title('Top 10 most used words', fontsize=12)
    plt.xlabel('Words')
    plt.ylabel('Frequency')
    plt.show()

def plot_wordcloud(data):
    all_text = ''.join(data['final_text'])

    plt.figure(figsize=(8, 6))

    wordcloud = WordCloud(width=1000, height=600, background_color='black').generate(all_text)

    plt.imshow(wordcloud, interpolation='bilinear')
    plt.title('Word Cloud', fontsize=12)
    plt.show()

preprocess_data(Data_Highest_1)

plot_rating_distribution(Data_Highest_1)

plot_top_words_bar(Data_Highest_1)

plot_wordcloud(Data_Highest_1)

def Rating(data):
    ratings = data['rating']
    rating_counts = ratings.value_counts().sort_index()
    plt.figure(figsize = (8,6))
    sns.barplot(x=rating_counts.index, y=rating_counts.values)
    plt.xlabel('Rating')
    plt.ylabel('Count')
    plt.title('Rating Distribution', fontsize = 12)
    plt.show()

def Graph_Bar(data):
    words = []
    for text in data['final_text']:
        words.extend(text.split())
    word_count = collections.Counter(words)
    top_words = dict(word_count.most_common(10))

    plt.figure(figsize = (8,6))

```

```

plt.bar(range(len(top_words)), list(top_words.values()), align = 'center')
plt.xticks(range(len(top_words)), list(top_words.keys()))
plt.grid(alpha = 0.1)
plt.title('Top 10 most used words', fontsize = 12)
plt.xlabel('Words')
plt.ylabel('Frequency')

def Wordcloud(data):
    all_text = ''.join(data['final_text'])

    plt.figure(figsize = (8,6))

    wordcloud = WordCloud(width = 1000, height = 600, background_color = 'black').generate(all_text)

    plt.imshow(wordcloud, interpolation = 'bilinear')
    plt.title('wordcloud', fontsize = 12)
    plt.show()

preprocess_data(Data_Highest_2)
plot_rating_distribution(Data_Highest_2)
plot_top_words_bar(Data_Highest_2)
plot_wordcloud(Data_Highest_2)
preprocess_data(Data_Highest_3)
plot_rating_distribution(Data_Highest_3)
plot_top_words_bar(Data_Highest_3)
plot_wordcloud(Data_Highest_3)
preprocess_data(Data_Highest_4)
plot_rating_distribution(Data_Highest_4)
plot_top_words_bar(Data_Highest_4)
plot_wordcloud(Data_Highest_4)
preprocess_data(Data_Highest_5)
plot_rating_distribution(Data_Highest_5)
plot_top_words_bar(Data_Highest_5)
plot_wordcloud(Data_Highest_5)

```

# Appendix C. Word Clouds and Graphs Generated by the Python Code

Table C1. Most frequently used words in “I Am Sober” app reviews

5*		<table border="1"> <caption>Top 10 most used words (5*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>1800</td></tr> <tr><td>help</td><td>1000</td></tr> <tr><td>day</td><td>500</td></tr> <tr><td>sober</td><td>450</td></tr> <tr><td>love</td><td>400</td></tr> <tr><td>people</td><td>350</td></tr> <tr><td>like</td><td>300</td></tr> <tr><td>real</td><td>250</td></tr> <tr><td>get</td><td>200</td></tr> <tr><td>keep</td><td>150</td></tr> </tbody> </table>	Word	Frequency	app	1800	help	1000	day	500	sober	450	love	400	people	350	like	300	real	250	get	200	keep	150
Word	Frequency																							
app	1800																							
help	1000																							
day	500																							
sober	450																							
love	400																							
people	350																							
like	300																							
real	250																							
get	200																							
keep	150																							
4*		<table border="1"> <caption>Top 10 most used words (4*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>250</td></tr> <tr><td>help</td><td>110</td></tr> <tr><td>like</td><td>100</td></tr> <tr><td>would</td><td>95</td></tr> <tr><td>people</td><td>85</td></tr> <tr><td>day</td><td>80</td></tr> <tr><td>love</td><td>75</td></tr> <tr><td>side</td><td>70</td></tr> <tr><td>real</td><td>65</td></tr> <tr><td>thing</td><td>60</td></tr> </tbody> </table>	Word	Frequency	app	250	help	110	like	100	would	95	people	85	day	80	love	75	side	70	real	65	thing	60
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people	85																							
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love	75																							
side	70																							
real	65																							
thing	60																							
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real	20																							
2*		<table border="1"> <caption>Top 10 most used words (2*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>55</td></tr> <tr><td>people</td><td>28</td></tr> <tr><td>addict</td><td>22</td></tr> <tr><td>help</td><td>22</td></tr> <tr><td>good</td><td>20</td></tr> <tr><td>ban</td><td>18</td></tr> <tr><td>get</td><td>18</td></tr> <tr><td>communiti</td><td>18</td></tr> <tr><td>thing</td><td>18</td></tr> <tr><td>say</td><td>18</td></tr> </tbody> </table>	Word	Frequency	app	55	people	28	addict	22	help	22	good	20	ban	18	get	18	communiti	18	thing	18	say	18
Word	Frequency																							
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help	22																							
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1*		<table border="1"> <caption>Top 10 most used words (1*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>70</td></tr> <tr><td>people</td><td>35</td></tr> <tr><td>help</td><td>20</td></tr> <tr><td>got</td><td>18</td></tr> <tr><td>good</td><td>18</td></tr> <tr><td>make</td><td>18</td></tr> <tr><td>dare</td><td>18</td></tr> <tr><td>pay</td><td>18</td></tr> <tr><td>thing</td><td>18</td></tr> <tr><td>support</td><td>18</td></tr> </tbody> </table>	Word	Frequency	app	70	people	35	help	20	got	18	good	18	make	18	dare	18	pay	18	thing	18	support	18
Word	Frequency																							
app	70																							
people	35																							
help	20																							
got	18																							
good	18																							
make	18																							
dare	18																							
pay	18																							
thing	18																							
support	18																							



Table C3. Most frequently used words in “Nomo – Sobriety Clocks” app reviews

<p>5*</p>		<table border="1"> <caption>Top 10 most used words (5*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>14</td></tr> <tr><td>thank</td><td>9</td></tr> <tr><td>year</td><td>8</td></tr> <tr><td>use</td><td>7</td></tr> <tr><td>look</td><td>6</td></tr> <tr><td>love</td><td>5</td></tr> <tr><td>sobriety</td><td>5</td></tr> <tr><td>help</td><td>5</td></tr> <tr><td>update</td><td>5</td></tr> <tr><td>real</td><td>4</td></tr> </tbody> </table>	Word	Frequency	app	14	thank	9	year	8	use	7	look	6	love	5	sobriety	5	help	5	update	5	real	4		
Word	Frequency																									
app	14																									
thank	9																									
year	8																									
use	7																									
look	6																									
love	5																									
sobriety	5																									
help	5																									
update	5																									
real	4																									
<p>4*</p>		<table border="1"> <caption>Top 10 most used words (4*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>14</td></tr> <tr><td>use</td><td>12</td></tr> <tr><td>love</td><td>11</td></tr> <tr><td>great</td><td>9</td></tr> <tr><td>help</td><td>8</td></tr> <tr><td>real</td><td>7</td></tr> <tr><td>day</td><td>6</td></tr> <tr><td>work</td><td>5</td></tr> <tr><td>people</td><td>5</td></tr> <tr><td>chip</td><td>4</td></tr> </tbody> </table>	Word	Frequency	app	14	use	12	love	11	great	9	help	8	real	7	day	6	work	5	people	5	chip	4		
Word	Frequency																									
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<p>3*</p>		<table border="1"> <caption>Top 10 most used words (3*)</caption> <thead> <tr> <th>Word</th> <th>Frequency</th> </tr> </thead> <tbody> <tr><td>app</td><td>14</td></tr> <tr><td>day</td><td>6</td></tr> <tr><td>use</td><td>5</td></tr> <tr><td>great</td><td>5</td></tr> <tr><td>back</td><td>4</td></tr> <tr><td>account</td><td>4</td></tr> <tr><td>live</td><td>3</td></tr> <tr><td>part</td><td>3</td></tr> <tr><td>the</td><td>3</td></tr> <tr><td>partner</td><td>3</td></tr> </tbody> </table>	Word	Frequency	app	14	day	6	use	5	great	5	back	4	account	4	live	3	part	3	the	3	partner	3		
Word	Frequency																									
app	14																									
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