Beyond Grindr: Evaluating The Gay Dating App Landscape And Comparing User Satisfaction Across Gay-Focused And General Dating Apps

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Executive summary

Introduction: The paper begins analyzing the global online dating app market and its growth opportunities.
Objective: This study aims to test the hypothesis that users of gay dating apps express lower levels of satisfaction than users of non-gay dating apps and whether gay dating app users perceive these apps as less safe and supportive of long-term relationships than general dating app users.
Methods: We analyzed App Store user reviews of the top 3 dating apps in each product category: gay dating apps (Grindr, Scruff, Hornet) and general dating apps (Tinder, Badoo, Bumble). Data was collected using the Python Library App_store_scraper, and 2,000 reviews from each app were retrieved for analysis. Variables retrieved are listed in Appendix E.

Results: Contrary to our hypothesis, gay dating app users expressed higher satisfaction levels (mean rating score of 3.08) than non-gay specific dating app users (mean rating score of 2.48). A T-statistic of 19.469 and a P-value of 3.82e-83 indicate a statistically significant difference in satisfaction scores between the two groups.
Qualitative analysis: We interviewed 3 gay dating app users. We used the interview to find six common themes: Preferences for Detailed Profiles, Concerns Around Anonymity and Privacy, Communication and Matching, Casual vs. Serious Relationships, Features and Functionality, and Safety’s Impact on User Experience.
Conclusion: The data collected demonstrates a significant difference in satisfaction levels between users of gay dating apps and users of general dating apps, with gay dating app users expressing higher levels of satisfaction. However, concerns about safety and the potential for long-term relationships remain important factors influencing user experience on gay and non-gay dating apps.
Limitations and Future Research: our study has limitations, including the inability to differentiate users' sexual orientation and potential overlap between user groups. Future research should collect more specific demographic data, utilize alternative research methods such as in-depth interviews, focus groups, or user-generated content analysis, and explore more robust statistical tests like mixed-effects models or repeated measures ANOVA to address these limitations.

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Abstract

This study aimed to investigate user satisfaction levels of gay dating apps compared to non-gay dating apps, as well as users' perceptions of safety and support for long-term relationships through a mixed-methods approach. Data was collected from App Store reviews of the top three gay dating apps (Grindr, Scruff, Hornet) and general dating apps (Tinder, Badoo, Bumble). Quantitative analysis revealed that gay dating app users expressed higher satisfaction levels (mean rating score of 3.08) than non-gay dating app users (mean rating score of 2.48), with a T-statistic of 19.469 and a P-value of 3.82e-83 indicating a statistically significant difference. Qualitative analysis identified themes such as preferences for detailed profiles, concerns around anonymity and privacy, communication and matching, casual vs. serious relationships, features and functionality, and safety's impact on user experience. Despite the limitations in our study, such as the inability to differentiate users' sexual orientation, future research should employ alternative methods, demographic data collection, and robust statistical tests to comprehensively understand user satisfaction and sentiment in the dating app landscape. These insights can inform the development of improved dating app services, catering to the unique experiences and needs of minority user groups.

Beyond Grindr: Evaluating The Gay Dating App Landscape And Comparing User Satisfaction Across Gay-Focused And General Dating Apps

A Brief History And Social Context Of Online Dating

The Kinsey Institute for Research in Sex, Gender, and Reproduction has deemed online dating the most significant change in human reproductive history since becoming a non-migratory species (Silic, 2021). However, online dating did not start as we know it today. The precursor to modern online dating was personal ads. Lee (2016) estimates that the first personal ad looking for a partner was published by a British newspaper in 1695. Soon after, in 1700, the first personal ad featuring coded words and female pseudonyms was used by a gay man to find companions. At that time, homosexuality or "sodomite acts" were criminalized in most of the world. As a result, the LGBTQ+ community had to be creative to find safe spaces to explore sex and companionship. Personal ad popularity fluctuated through the subsequent centuries, influenced by social markers, such as women's stride towards sexual liberation and soldiers' loneliness in WW I and II.[1]

In 1965 a team of Harvard undergrads created the first computer dating service, Operation Match, in which users answered questions and received a list of matches. Through the next 40 years, as computers developed, so did dating solutions. In 1994 kiss.com was launched, the first modern dating website. Gaydar.com was created in 1999 to provide a secure online environment for gay men and prevent them from experiencing harassment which was commonly encountered in chat rooms on websites meant for heterosexual individuals (Garrett, 2021). Grindr was released in 2009 following the launch of the iPhone 3G. Grindr was the first dating app to use Apple's newly released geolocation technology (Kuefler, 2018). Kuefler (2018) describes the launch of Grindr as a "sexual revolution in the gay community". Grindr responded

[1] #context

to the gay community's increasing need for a place of its own by utilizing geolocation to solve a common issue faced by non-geolocation dating websites - matching users with partners who were too far away (Rear, 2018).

Kuefler is not the only one that sees Grindr as a landmark for the gay community. Eight months after the launch of Grindr, Vernon (2010) wrote in The Guardian that Grindr was socially significant for two reasons: firstly, Grindr gave gay men an easy way to find who else around them might be a potential partner. Secondly and more importantly, she believed that Grindr was the beginning of the post-gay era, where the divide between the gay and straight world was increasingly diminishing. Joel Simkhai, Grindr's founder, also mentioned how Grindr went beyond giving people access to fast sex but fulfilled the innate human desire not to feel alone (Vernon, 2010).

In a 2017 press release Landen Zumwalt, the Director of Corporate Communications at Grindr, the app introduced new features that enabled users to discuss gender expression in more detail. Additionally, the app also added sexual health fields (Garrett, 2021). [2]

The Gay Dating App Market

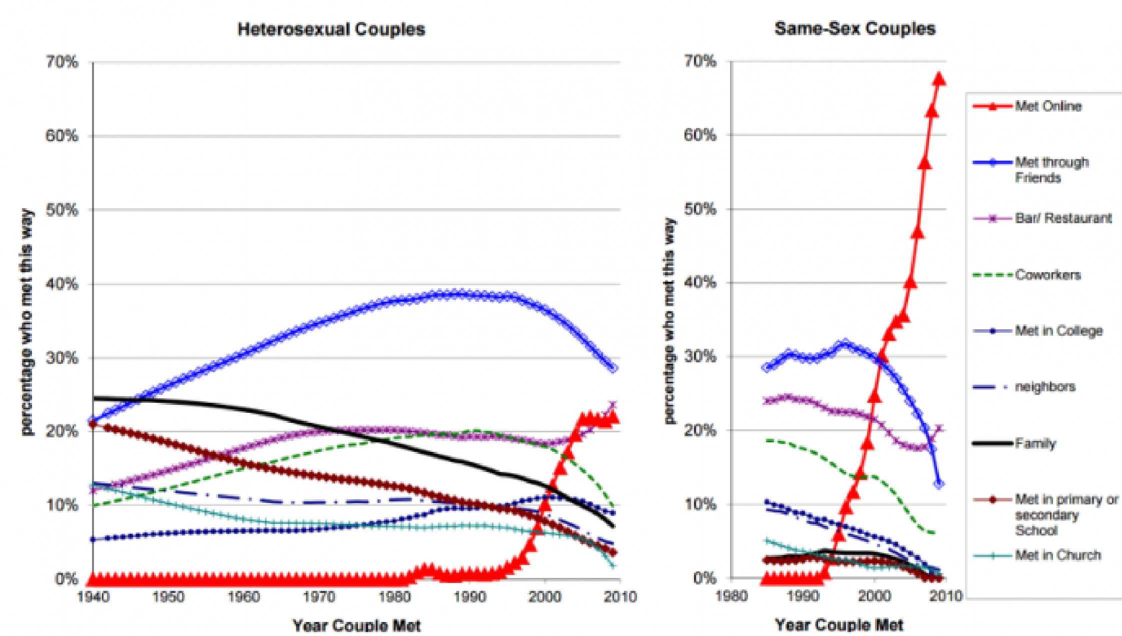
The dating app industry is not a modern invention but rather an evolution of centuries-long efforts by humans to find partners. This industry, which has been evolving for around 300 years, is unlikely to disappear anytime soon. Additionally, online dating has significantly impacted the gay community since its inception. The emergence of the online dating market enabled gay men to move away from using coded language in newspapers. Specialized websites like Gaydar.com and the Grindr revolution have provided the gay community with new ways to connect and form relationships.

[2] #b112-socioCulturalStrat

As illustrated in Figure 1, online dating has not only revolutionized the gay community but has also reshaped society's approach to dating in general. In 2017, 39% of heterosexual couples met online (Shashkevich, 2019). This percentage is even higher for same-sex couples, with almost 70% meeting online, as the 2017 MIT Technology Review reported.

Figure 1

Most common ways of meeting a partner by sexuality. Source: MIT Technology Review (2017).



This paper's central research question is: **Are users of gay dating apps less satisfied with gay dating apps than general dating app users?** We will draw from available market data to answer our question. Whenever gay dating app insights are unavailable, we will use data from general dating apps to support our analysis.

The Dating App Industry

Growth

The global online dating application market is still in expansion. The market has a predicted compound annual growth rate (CAGR) of 6.0% from 2022 to 2030 (Polaris Market Research, 2022). The continuous growth is explained by increased smartphone usage and internet accessibility worldwide. For example, the percentage of adults using the internet in emerging economies went from 40% to 60% in 5 years (Rosenberg, 2019). Another factor supporting the growth of dating app usage is the increase in singleness (Grand View Research, 2022). In 2020, almost 25% of adults ages 25 to 54 in the US were never married nor living with a partner, a 30% increase since 1990 (Bruinius, 2021).

Moreover, the stigma around dating apps has been reduced with the consolidation of mainstream apps and the increase in niche solutions targeting various groups, including more conservative sectors of society. With dating apps now catering to specific religious groups, sexual orientations, and political views, how people perceive using these services has shifted, resulting in greater acceptance of these apps as an integral part of dating culture (ReportLinker, 2022).

Other more transient social factors have also influenced dating app activity. The COVID-19 pandemic led people to social distance, decreasing chances of meeting partners in offline social activities such as bars. In this context, in May 2020, the online dating service OkCupid reported a 700% increase in dating app usage (Konrath, 2020).

Similarly, in March 2020, a survey found that Tinder's user base swiped collectively 3 billion times daily (Polaris Market Research, 2022). Figure 3 shows the number of dating users globally. The numbers continue to increase steadily, from 200 million users in 2015 to over 300 million in 2022 (Stockal, 2022). The increase is even steeper when the industry's global revenue went from a little over 1 billion dollars in 2015 to over 5 billion in 2021 (Stockal, 2022).

Transient social factors, including the COVID-19 pandemic, have influenced dating app activity. With people practicing social distancing, offline social activities like visiting bars have decreased, leading to a surge in online dating. For instance, in May 2020, OkCupid reported a 700% increase in dating app usage, while Tinder's user base swiped 3 billion times daily in March 2020 (Konrath, 2020; Polaris Market Research, 2022). The global number of dating app users has steadily risen from 200 million in 2015 to over 300 million in 2022, as indicated in Figure 3. The industry's revenue has also grown substantially from a little over 1 billion dollars in 2015 to over 5 billion in 2021, as shown in Figure 4. (Stockal, 2022).

Figure 3

Dating App Industry Global Users. Source: Appfigures, Blackstone Group, IAC, Spark Networks, Toptal (as cited in Stockal, 2022).

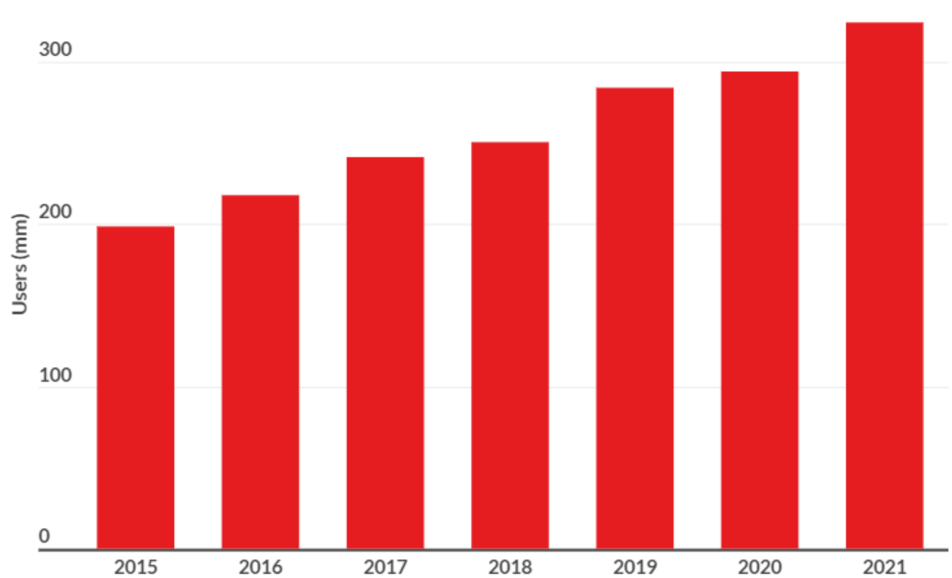
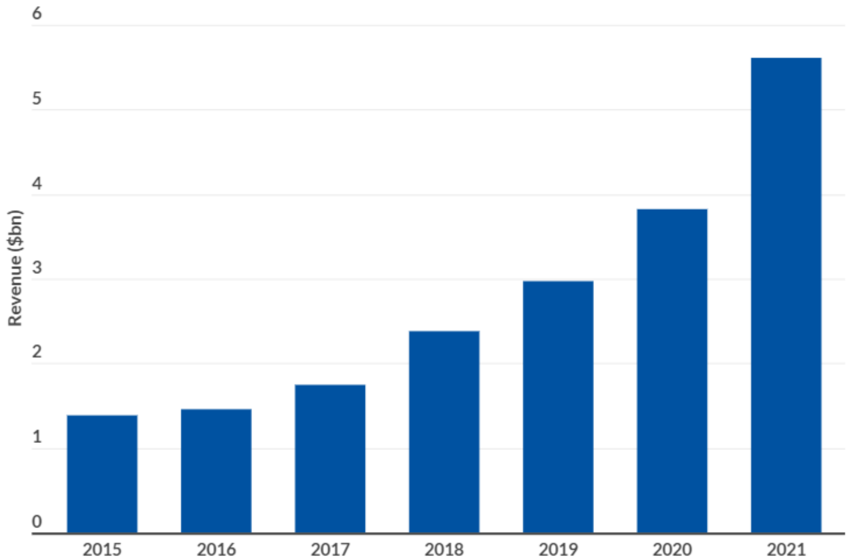


Figure 4

Dating App Industry Global Revenue. Source: Appfigures, Blackstone Group, IAC, Spark Networks, Toptal (as cited in Stockal, 2022).



Size and Revenue

In 2021, the dating app industry was worth USD 7.5 billion (Polaris Market Research, 2022). Most dating apps use a freemium model to generate revenue and attract a large user base. While ads are in free plans, over 60% of revenue comes from subscriptions (Grand View Research, 2022). For instance, only 3% of Bumble's revenue comes from ads (Goldfine, 2021). Of the 300 million people using dating apps in 2021, around 20 million, or 6.67%, paid for premium features (Curry, 2020). This may seem small compared to Spotify's 39% paid users in Q3 2022 (Gotting, 2022a; Gotting, 2022b), but subscription commerce is still growing. Andrew Dailey at MGI Research notes that an average subscription service grows by at least 30% annually (Dailey, 2019), consistent with Spotify's Compound Annual Growth Rate of 39.16% between Q1 2015 and Q1 2022 (see appendix A for calculations). The numbers from subscription models in the audio industry are a good benchmark for potential growth in the dating app industry.[3]

The dating app market presents an opportunity due to its growth prospects, increasing user base, and expanding subscription industries. In the following sessions, we will introduce our hypotheses and analyze relevant data to gain further insights.

Gay Men And Dating App Usage

The LGBTQIA+ community has been at the forefront of online dating. Grindr, launched in 2009, is the only early dating app still standing, while others, like Tinder, were launched later in 2012 (Garratt, 2021; Dating Sites Reviews, n.d.). According to Grand View Research (2022), LGBTQIA+ individuals are among the fastest-growing users of dating apps. Pew Research Center reports that 55% of gay, lesbian, and bisexual adults use dating apps, nearly double that of straight adult users at 28% (Brown, 2020). The main driver of this growth is a social stigma around gender and sexual diversity in many countries, which inhibits or punishes finding partners offline (Grand View Research, 2022).

Grindr is the largest gay dating app, with 74% of gay single men using it. Other popular apps include Scruff (31%), Hornet (27%), Tinder (27%), Jack'd (24%), and Planet Romeo (23%). Grindr has 11 million monthly active users, 765,000 of whom pay for a subscription tier (Bursztynsky, 2022). Perry Street Software, parent company of SCRUFF and Jack'd, has 20 million global users (Assunção, 2020). Tinder, not exclusive to queer individuals, reports that 20% of its matches are between queer users (Scott, 2020).

[3]#b110-marketanalytics

Safety And Satisfaction

Although the above statistics indicate that a significant number of queer individuals use dating apps, it is crucial to recognize that high usage does not necessarily equate to high satisfaction. Inferring that LGBTQIA+ individuals are content with dating apps because they use them is a logical fallacy that arises from the following flawed reasoning:

> Many gay folks use dating apps;
>
> Dating app usage among gay folks is increasing;
>
> Therefore, gay folks are satisfied with dating apps.

The reasoning above illustrates the logical fallacy of Post hoc ergo propter hoc (after this, therefore because of this), which assumes that if event B follows event A, then event B must have caused event A. However, using formal representation, we can see that the mere fact that B follows A does not necessarily imply a causal relationship between them. This type of reasoning is also associated with the single-cause fallacy, where a complex event is reduced to a single cause. For example, some users may continue using dating apps despite their dissatisfaction because they have no other way of looking for partners due to safety or geopolitical factors or because they perceive dating apps as the current social norm within the LGBTQIA+ community (Grand View Research, 2022; Figure 1). To avoid making fallacious arguments, it is essential to investigate user satisfaction rates for current gay dating app solutions.[4]

A survey conducted on 200,000 iPhone users by tech consulting Time Well Spent found that 77% of Grindr users feel miserable after spending time in the app (Corner, 2018). Results from other recent surveys can explain the reasons for the alarming number of dissatisfied users. A study by the Australian Institute of Criminology found that 72% of dating app users have been

[4] #fallacies

subjected to online sexual violence, and 1 in 3 users have been subjected to in-person sexual violence caused by someone they met online (Jurss-Lewis, 2022). Pew Research Center (Brown, 2020) also found that gay, lesbian, and bisexual individuals are more likely to experience some form of sexual harassment coming from online applications — 69% of LGB individuals versus 52% of straight folks (Brown, 2020). Adding to that, 56% of respondents to a survey by the gay outlet Gay Star News reported encountering fake profiles on gay dating apps (Woodley, 2016).

Lastly, dating apps amplify certain issues faced by minorities. A recent Australian study with 1039 men who have sex with men found that men of color experience "significantly more race-based sexual discrimination" than their white counterparts (Thai, 2020). The author also found that race-based discrimination leads to lower self-esteem among respondents (Burkholder, 2019). A 2014 study by Match.com also found that white users get significantly more messages, and a 2015 study found that 15 percent of Grindr users openly express racism in their profile (Rudder, 2014 as cited in Burkholder, 2019; Callander et al., 2015 as cited in Burkholder, 2019). Grindr functions, such as filtering by body types, reinforce the social view that there are certainly desirable and undesirable body types (Conner, 2018). Intra-community social pressure harms the LGBTQIA+ community, especially because folks are already four times as likely to attempt suicide as their straight peers (Johns et al., 2019; Johns et al., 2020, as cited in The Trevor Project, 2021). The United Kingdom's Mental Health Foundation (n.d.) found that 53% of LGB folks feel anxious about their body image compared to 33% of heterosexual adults.

The statistics above beg the question, why would users still engage in dating apps such as Grindr, given that self-reporting surveys and scientific literature point to their negative consequences for users? A 2019 survey done by UK-based company Compare the Market, trying to uncover the reasons for gay dating app use, found that 56% of respondents believe they can find "the love of their life" on Grindr, and 84% have fallen in love with another user (Reddish, 2019; Damshenas, 2019). Capitalizing on the user's need and hope for more than a hookup, in November 2022, Grindr launched the film campaign Come Home with Us, with the tagline #MetOnGrindr. The series features five docu-films showcasing the stories of couples who met on the platform. Analyzing the campaign, Shot News (2022) said that the creative director of Grindr, Evan Sterrett, "draws from ads for traditional matchmaking sites that emphasize emotional intimacy and commitment to highlighting how Grindr, too, can generate stories of happily ever after."

Hypothesis Development

We have discussed several reasons why users of Grindr and other gay apps may experience high levels of dissatisfaction with these platforms. These reasons include harassment, the reinforcement of systemic prejudices, and challenges forming relationships. Based on the findings above, we argue that **users of gay dating apps will express lower satisfaction levels than non-gay dating apps**. Based on this thesis, we predict that

1. Gay dating app users will express lower levels of satisfaction than non-gay dating app users,
2. Gay dating app users will perceive these apps as less safe and supportive of long-term relationships than general dating app users.

The hypotheses are testable in principle because testing them will not infer ethical violations of user privacy; it is also testable in practice because we have the necessary technological tools to gather data and test our predictions. In the sections below, we will use web scraping techniques to collect the data required to test the proposed hypotheses in two ways.

First, we will evaluate overall satisfaction through app store reviews. Second, we will analyze the factors contributing to satisfaction through qualitative interviews.[5,6,7]

The Competitive Landscape

Before looking into user reviews of dating apps, it is essential to establish (1) what the competitive landscape looks like and (2) which competitors can yield the most relevant information to answer the research question: **Are users of gay dating apps less satisfied with gay dating apps than general dating app users?**

Tidio, an AI consultant, reports that over 1500 dating apps are available (Szaniawska-Schiavo, 2022). Despite this seemingly saturated market, there is still potential for new entrants. One way to gauge market saturation is by examining the *user penetration rate* (Kenton, 2022). *User penetration rate* measures the percentage of potential customers who use a product. User penetration in the dating app market is growing. However, it remains low at 4.8% globally in 2022, with a forecasted increase to 5.5% by 2027 (Statista, 2022a), leaving room for current and new players to expand their reach. The Music Streaming App Market has a much higher user penetration rate of 37.2%, indicating a more mature market (Statista, 2022b).

Porter's Five Forces: What Is The Competitive Landscape?

To better understand user satisfaction across different dating apps, we will use Porter's Five Forces framework to analyze the market as a whole and identify common themes. This approach allows us to examine the broader market trends instead of focusing on the specific factors related to one company's position, consistent with the framework's original purpose.

[5] #thesis
[6]#hypothesisdevelopment
[7]#testability

One of the main criticisms of Porter's Five Forces framework is that it assumes a static industry structure and a zero-sum game, which may not always be applicable in dynamic industries where new entrants can disrupt the market and create new opportunities. Furthermore, the framework may not consider the full complexity of an industry or market, such as changing consumer preferences, technological innovation, or government regulations that can affect a company's competitiveness (The Open University of Hong Kong, 2015). It is also important to note that the framework may not adequately account for the fact that big players may not currently be in the industry but could enter and disrupt it, as Facebook did in 2019 with the launch of Facebook dating (Sharp, 2019).

Nonetheless, the framework is still valuable for a panoramic view of an industry. The variety of data in this report so far, such as user penetration, Compound annual growth rate analysis, revenue, and growth drivers, provide us with a larger picture of the market, accounting for some of the limitations of Porter's five forces.[8]

Threat of new entrants

The online dating industry is continuously evolving, and the market for gay dating apps is no exception. The entry barrier is relatively low, mainly requiring technological expertise and marketing to develop and launch a new app. However, established players like Grindr, Scruff, and Hornet have a significant advantage in terms of user base and brand recognition (Crowdbotics, n.d.; USM Systems, 2022; Dogtiev, 2022). If new entrants can offer unique features, better user experiences, or target specific niches, they may be able to attract dissatisfied users from existing apps.

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[8] #critique

Power of suppliers

In the dating app industry, suppliers' power is considered low for a few reasons. First, the primary inputs for dating apps are technology and marketing, which are widely available from many suppliers meaning that dating app companies have many options for sourcing these inputs. Thus, companies can work with suppliers who offer the best price and quality.

Furthermore, many dating app companies have invested heavily in in-house technology development, reducing their dependence on external suppliers even further, as they can produce the necessary technology themselves. By producing their technology, dating app companies can also ensure that it is tailored to their specific needs and preferences, giving them a competitive advantage by better satisfying user needs.

Overall, the low power of suppliers in the dating app industry means that companies have more control over the inputs they need to produce and market their products. This can benefit companies, as it allows them to negotiate better prices and ensure the quality of their inputs.

Power of buyers

The power of buyers in the dating app industry is moderate. First, while individual consumers may not have significant bargaining power, the large and growing number of people using dating apps means that the aggregate buying power of consumers is substantial. This means that dating app companies must pay attention to the needs and preferences of their users if they want to remain competitive in the market.

Due to the intense competition in the dating app industry, buyers have more options, giving them more bargaining power to demand features and pricing that meet their expectations (Szaniawska-Schiavo, 2022). Users may be more likely to switch to a competitor if they feel that a dating app needs to provide more value for its price, which can pressure dating app companies to improve their offerings and provide better value to their users.

Another factor contributing to the moderate power of buyers in the dating app industry is the ease of switching between different apps. Users dissatisfied with one app can quickly and easily switch to another, forcing dating app companies to improve their offerings continually.

Threat of substitutes

In the context of gay dating apps, substitute products primarily come from general dating apps that cater to a broader audience, including LGBTQ+ users. These substitutes pose a potential threat to the gay dating app market as they offer alternatives for users dissatisfied with their current app experience. A few aspects of this threat include:

1. Inclusivity and diversity:

General dating apps like Tinder, Bumble, and Hinge have tried to be more inclusive and diverse, allowing users to identify their sexual orientation and preferences within the app. This inclusivity appeals to LGBTQ+ users who may feel more comfortable using an app that caters to a broader audience than a specialized gay dating app.

2. User experience and features

General dating apps often invest in user experience, interface design, and innovative features to stand out in the competitive dating app market. These efforts may lead to a more enjoyable experience for LGBTQ+ users, prompting them to switch from gay dating apps. For example, Tinder's swiping mechanism and Bumble's women-first messaging have become popular features among users.

3. Safety and security

One of the concerns for LGBTQ+ users is safety and security while using dating apps. General dating apps might invest more resources in implementing safety measures, such as profile verification, photo moderation, and in-app reporting tools. A perception of better safety and security on general dating apps could attract LGBTQ+ users who are dissatisfied with the safety measures on specialized gay dating apps.

4. Network effects

As general dating apps have larger user bases, they can benefit from network effects, where the value of the app increases as more people join. This can make the app more attractive to potential users, including LGBTQ+ users, as they may have a larger pool of potential matches.

5. Brand recognition

Well-established general dating apps have a significant advantage in brand recognition and trust. As a result, LGBTQ+ users who are new to the dating app scene might gravitate towards these recognized brands rather than specialized gay dating apps.

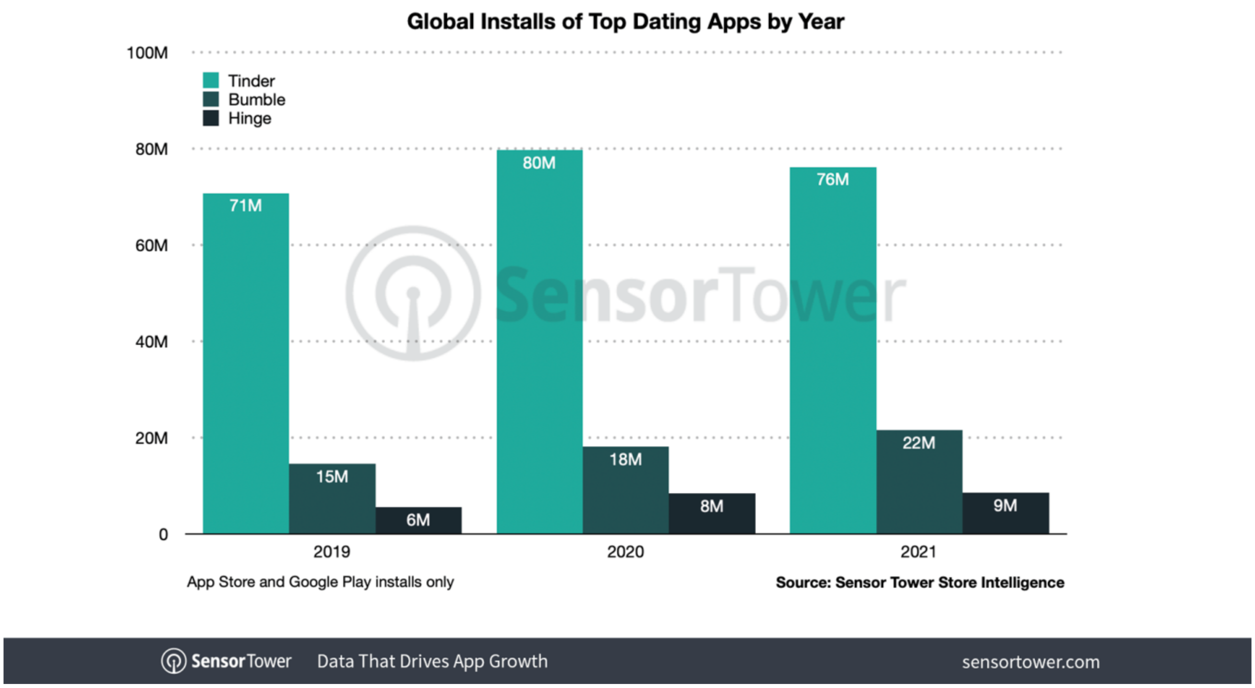
People can also meet potential partners through friends, at social events, or through other online platforms such as social networking sites. While these alternatives provide viable options for people looking to form romantic connections, dating apps are more efficient and convenient.

Data also supports a low chance of people migrating to offline substitutes. As we see in Figure 1, online dating has been the most popular form of meeting a partner in the LGBTQIA+ community since the early 1990s, with a steep curve with the popularization of the internet. Moreover, as seen in Figure 5, dating app installs stayed reasonably consistent over the last three years.[9]

Figure 5

The Most Popular Dating Apps in the U.S. (2022). Source: Buchholz (2022).

[9] #breakitdown



Competitive rivalry

The dating app industry competitive rivalry is high due to the crowded market, with many apps vying for the same pool of users. The dating app industry is also highly dynamic, constantly introducing new technologies and features. As a result, dating apps must constantly innovate and differentiate themselves to satisfy users and stay competitive (Szaniawska-Schiavo, 2022).

Competitive rivalry in the gay dating app industry, focusing on user satisfaction, has led to the rise of new entrants catering to specific user needs and preferences. Bumble, for example, emerged as a strong competitor in the dating app market by addressing the unique requirements of female users (O'Connor, 2017). Despite Tinder's dominance, with nearly 80 million users worldwide (Curry, 2020), other apps have successfully carved out their market share, as seen in Figure 6, by offering a unique selling proposition (USP).

One such entrant is Hinge, which has experienced remarkable growth by multiplying its user base tenfold in just seven years. A comparison of the top dating apps' monthly usage growth between January 2019 and January 2022 reveals that while Tinder maintained steady growth, Bumble and Hinge saw exponential increases of 96% and 344%, respectively, as shown in Figure 7 (Freer, 2022).

This competitive rivalry, driven by user satisfaction, has led to innovations and improvements in the industry. Apps like Bumble and Hinge have attracted users by addressing their specific needs and providing a tailored user experience. In the context of the gay dating app market, this could imply that developers should focus on understanding and catering to their target audience's unique preferences and requirements.

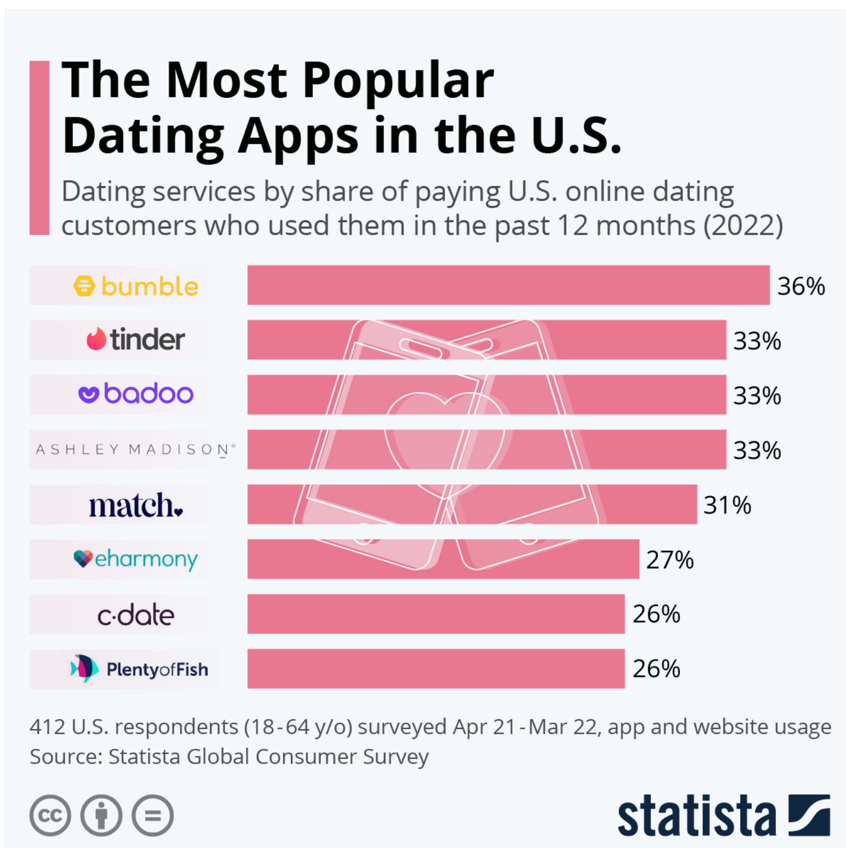
To enhance user satisfaction, developers of gay dating apps must pay attention to factors such as user experience, safety, inclusivity, and community-building. By learning from the success of apps like Bumble and Hinge, which have differentiated themselves through their USPs and user-centric approaches, developers can ensure that the competitive rivalry in the gay dating app industry leads to higher levels of user satisfaction and sustained user satisfaction growth.

In conclusion, the competitive landscape of the gay dating app industry is marked by intense rivalry, low entry barriers, and moderate buyer power. Porter's Five Forces framework has provided valuable insights into the factors shaping the industry, allowing for a comprehensive analysis of user satisfaction across various dating apps. The increasing number of new entrants and their ability to differentiate themselves by addressing users' specific needs indicates that user satisfaction is crucial in driving market competition and innovation.

In this dynamic environment, dating app developers must prioritize user experience, safety, inclusivity, and community-building to enhance user satisfaction and secure their market share. As demonstrated by the success of apps like Bumble and Hinge, a user-centric approach is essential for catering to the unique preferences and requirements of the target audience. By continually adapting to users' changing needs and preferences, developers can ensure that the competitive rivalry in the gay dating app industry ultimately results in better products, higher levels of user satisfaction, and sustained growth for the industry.[10]

Figure 6

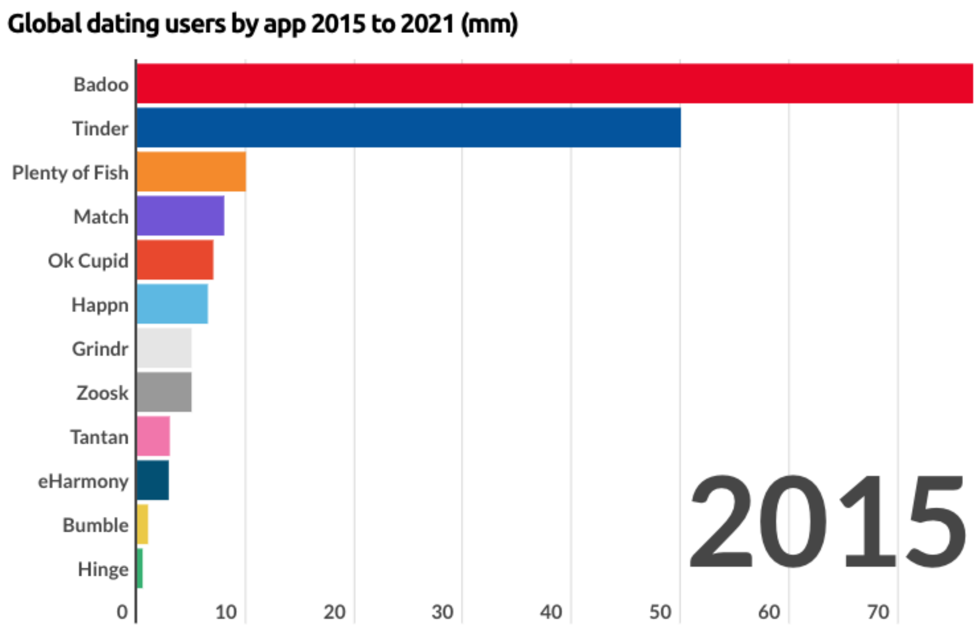
The Most Popular Dating Apps in the U.S. (2022). Source: Buchholz (2022)

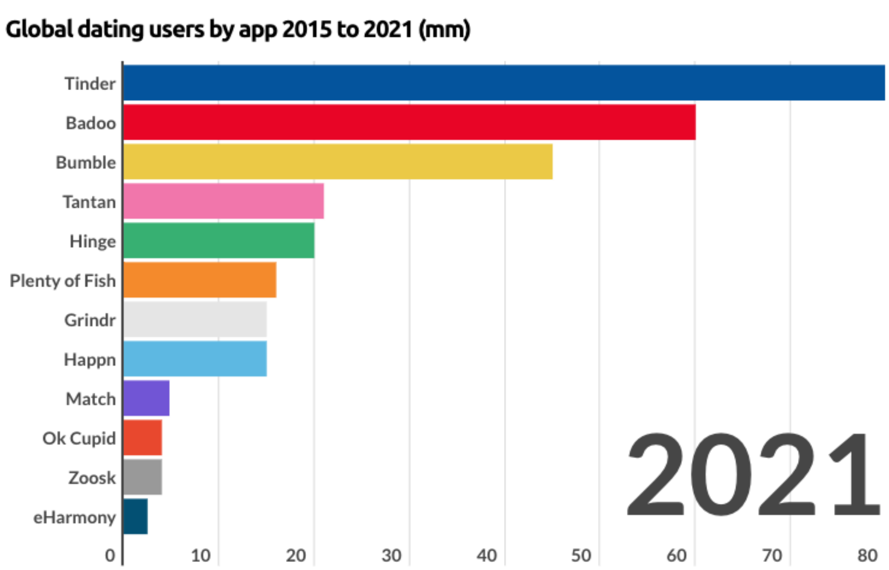


[10] #strategize

Figure 7

Global dating app users by app. Top: 2015, Bottom: 2021. Source: Curry (2022).





Finding Competitors That Can Yield Relevant Information

The Biggest Players In The Market

Although over 1500 dating apps are available, not all are globally relevant (Szaniawska-Schiavo, 2022). Many cater to niche communities and are unsuitable for understanding the gay dating market. For example, Christian Mingle is for single Christians, and EliteSingles targets successful single professionals (Spark Networks, n.d.). To gather testable data for our thesis that **gay dating app users express lower satisfaction than non-gay users**, we will examine the biggest global apps. Next, we will identify constraints in using data from these market leaders and consider if other apps could add nuance to our analysis.

Tinder is by far the most popular dating app on a global scale. According to Data.ai (2022), Tinder is the top-grossing dating app in the world, with more than 75 million monthly active users in over 190 countries (Iqbal, 2022). In Q1 2022, Tinder had over 10.7 million subscribers and 1.6 billion daily swipes (Barnett, 2021). In 2021, its revenue exceeded USD 1.6 billion (Iqbal, 2022).

The second-largest dating app globally is Badoo, with an estimated 60 million users in over 190 countries (Curry, 2022; Badoo, 2016). While it does not generate revenue on the same level as Tinder, Badoo has many features that make it attractive to users, such as its "encounters" game, which allows users to browse and connect with other users quickly. It shows users a grid of photos of people nearby, and users can click on the photos to view more information about that person. If two users mutually like each other, they can initiate a conversation (Dating Expert, n.d.).

Bumble is the third-largest dating app globally, with an estimated 45 million users and growing (Curry, 2022). Unlike Tinder, Bumble requires women to make the first move, which has been a significant selling point for the app. Additionally, Bumble has partnerships with several celebrities, such as Serena Williams and Priyanka Chopra, which has helped to increase its popularity further (Heisler, 2019).

Finally, Hinge is the fourth-largest dating app globally, with an estimated 20 million users (Curry, 2022). Unlike the other apps, Hinge is focused more on relationships than casual hookups and has many features that cater to this goal, such as its "We Met" feature, which allows users to share stories about their first dates (Hinge, n.d.).

The drawbacks of using data from the top market players

Undeniably, all the top apps mentioned above have queer and gay users. Bumble acknowledges its inclusivity for all sexual orientations. Hinge created an LGBTQIA+ guide after finding that 80% of these users had difficulty navigating its dating questions due to their "experiences being so unique" (Bumble, n.d; Connellan, 2022). On Tinder, 1 in 5 matches is queer (Scott, 2020). However, these are the only statistics available about the gay community for any of the top apps mentioned above.

Further, some of the top dating apps have historically overlooked the needs of the queer community. This includes lacking LGBTQ-specific questions and resources and failing to invest in marketing efforts to attract new queer users. Hinger, for example, only released LGBTQIA+ prompts in January 2022, 10 years after the app's launch (Hinge, 2022). First-person complaints of LGBTQIA+ folk using non-queer-specific dating apps are also easily found online (Coates, 2014; acidbb_, 2021; Fiettkau, 2021).

Another difficulty is obtaining valuable data that can help us understand the satisfaction, pain points, and opportunities for gay and bi men on dating apps, as even finding the number of queer users in mainstream apps is challenging. To answer our research questions, we would need to access user demographics, which are not publicly available and are biased by the factors the company decides to investigate. Unfortunately, sexuality is usually not one of those factors.

One exception to this is OkCupid, where Kim and Escobedo-Land (2015) and Kirkegaard & Bjerrekær (2016) web scraped user profile information from 59,946 and 68,371 users, respectively. However, while both datasets contain information about sex and sexuality, they do not provide insights into user experience. The variables in the dataset are mostly qualitative, such as "Which characteristic is most attractive on a date?" and "Do you like kissing in public?". While these variables could help answer questions about user preferences regarding behavior on dates and their correlation to sexuality, we are not interested in making generalizations about user dating preferences.

Research Variables

Independent Variables

1. In the review data analysis:

   Product Category (binary variable): refers to the classification of dating apps as either gay dating apps (specifically designed for the gay community) or non-gay dating apps (designed for heterosexual individuals or the general population).

2. In the qualitative interviews:

   a. Perceived Safety (continuous variable): refers to an individual's perception of the safety provided by dating apps for the LGBTQIA+ community.

b. Social Support (continuous variable): refers to an individual's perception of the supportiveness of dating apps for the LGBTQIA+ community.

Dependent Variable

Satisfaction with Dating Apps (continuous variable): refers to the level of satisfaction an individual experiences while using a dating app.

Relationships between variables

In the review data analysis, the dependent variable, satisfaction with dating apps, is influenced by the independent variable, product category. The hypothesis predicts that users of gay dating apps will express lower satisfaction levels than non-gay dating apps.

In the qualitative interviews, satisfaction with dating apps is influenced by the independent variables, perceived safety, and social support. Specifically, we hypothesized that gay dating app users will perceive these apps as being less safe and supportive of long-term relationships than general dating app users.

We aim to investigate these relationships by collecting and analyzing user reviews for the data analysis and conducting interviews with users for the qualitative study to gain a better understanding of their experiences and opinions.[11]

Data Collection And Constraints

A limitation in obtaining data for this study is the scarcity of available datasets. The existing datasets primarily consist of handpicked reviews from dating apps that meet strict criteria based on their authors' objectives (Kriplani, 2021). We can overcome this obstacle by using Python to directly scrape data from the App Store, as this information is publicly available. However, App Store reviews do not provide any information about the gender or sexuality of the

[11]#variables

reviewers, which makes it impossible to differentiate between LGBTQIA+ or heterosexual individuals.

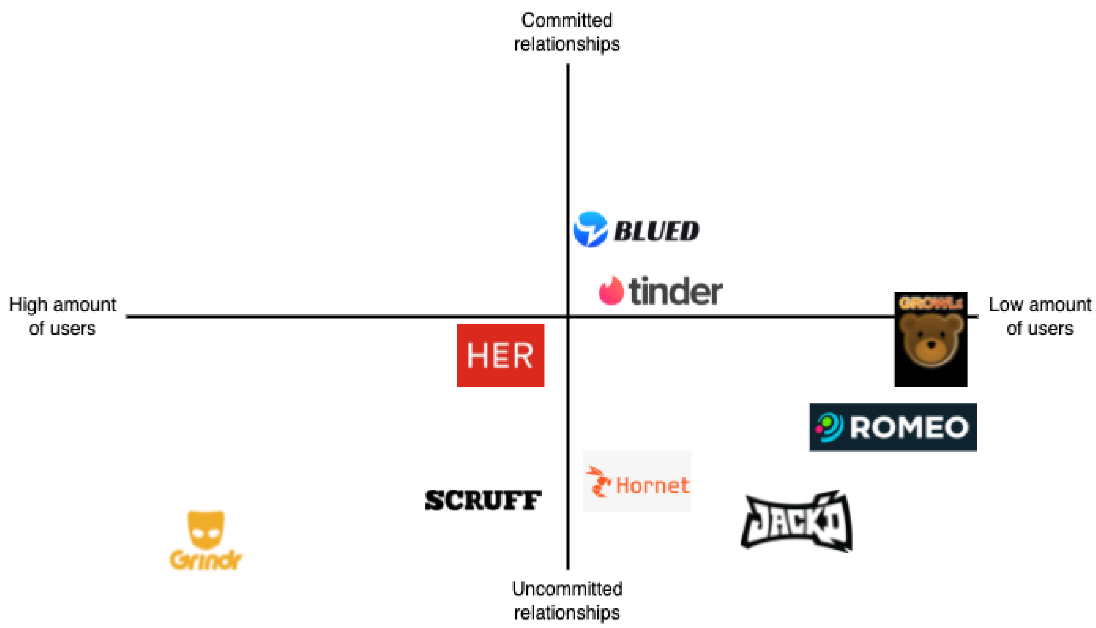
We will collect data from both non-gay specific dating apps and gay dating apps in order to compare user satisfaction levels between both product categories. We understand that some gay and bisexual men might use both platforms, causing some overlap. Some overlap may occur as some gay and bisexual men might use both platforms. This overlap may not significantly bias general dating app reviews, considering that gay and bi are a small percentage of those using general dating apps. According to Tinder, only 1 in 5 matches is queer (Scott, 2020). Thus, the percentage of gay and bi men on Tinder must be smaller than 20%, since the above official statistics includes other individuals who identify as queer and are not gay or bi men.

A limitation in analyzing data from gay dating apps is that these apps, as depicted in Figure 8, predominantly cater to non-committed relationships. This focus may not accurately represent the full spectrum of user satisfaction among gay and bisexual men, as individuals who are not interested in non-committed relationships might not use gay-specific apps. Consequently, we cannot generalize our findings to represent the user satisfaction of all gay and bisexual men using dating apps. Instead, we are assessing the satisfaction of those using one of the gay dating apps selected for this analysis.[12]

Figure 8

Perceptual map of dating apps used by the queer community. Data from Woodley (2016) and Queer in the World, (2020).

[12] #constraints



Top Gay Dating Apps

The three most popular gay dating apps, according to total users, are Grindr, Hornet, and SCRUFF. Grindr was launched in 2009 and is the most popular gay dating app, with over 12 million users, 723 thousand paying users, and present in over 190 countries (Grindr Investor Relations, n.d.). It has an estimated yearly revenue of $46.6 million (Williams-Alvarez, 2022). Hornet was launched in 2011 and is the second most popular gay dating app. Although it is not public and thus data is more scarce, the app claims to have over 30 million users, has raised $8.5 million in investments, and has a $2.5 million of estimated revenue (Hornet, n.d.; Crunchbase, n.d.; LATKA, n.d.). SCRUFF, launched in 2010, is the third most popular gay dating app, with over 20 million users. Scruff is owned by Perry Street Software, which also owns gay dating app Jack'd. Perry street Software has an estimated yearly revenue of $7.2 million (SCRUFF, n.d.; Growjo, n.d.).

The top three gay dating apps, ranked by revenue, are Grindr, SCRUFF, and Hornet. Grindr, established in 2009, has over 11 million users and 723,000 paying users across more than 190 countries, making it the leading app with an estimated yearly revenue of $46.6 million (Grindr Investor Relations, n.d.; Williams-Alvarez, 2022). SCRUFF, launched in 2010, is owned by Perry Street Software, which also owns the gay dating app Jack'd. With over 20 million users, Perry Street Software has an estimated annual revenue of $7.2 million (SCRUFF, n.d.; Growjo, n.d.). Hornet, introduced in 2011, ranks third in revenue with more than 30 million users, $8.5 million in investments, and an estimated $2.5 million in annual revenue (Hornet, n.d.; Crunchbase, n.d.; LATKA, n.d.). While Hornet and Scruff have a higher number of users, Grindr is the most well known gay dating app. Grindr is also the only publicly traded app among the three, thus it has the most reliable publicly available data (Tognini, n.d.).

Distinctive features

Grindr allows users to see who is online and nearby in a grid view and chat with them. It also has a feature called "Tribes," which enables users to identify themselves with a particular group and filter their searches to help find their type of guy (Grindr, n.d.). Hornet is also geosocial networking; uniquely, it has a "stories" feature, which allows users to share their experiences with other users. It also has "Hornet Places," a feature that allows users to search for places to meet people based on their interests (Hornet, n.d.). Scruff's unique features include a "Travel" section that allows users to search for destinations and events in nearby cities (SCRUFF, n.d.).

Data Analysis

We want to test our hypothesis that **users of gay dating apps will express lower levels of satisfaction than users of non-gay dating apps**. More specifically, we will use the data to test the following predictions:

1. Gay dating app users will express lower levels of satisfaction than non-gay dating app users,
2. Gay dating app users will perceive these apps as being less safe and supportive of long-term relationships than general dating app users.

Word Associations

To investigate the second prediction, gay dating app users perceive these apps as being less safe and supportive of long-term relationships compared to general dating app users, we examined the word associations for the top 3 dating apps in each product category using GPT-3.

GPT-3 (Generative Pre-trained Transformer 3) is an artificial intelligence (AI) language model developed by OpenAI. It is the biggest autoregressive language model with 175 billion parameters (OpenAi, 2021). Using GPT-3's natural language processing, we extracted insights from large amounts of text data fed into the algorithm to identify associations consumers make with brands and the topics and trends associated with those brands. GPT-3 provides a quick way to identify common associations being made on internet pages, compared to more traditional research methods for brand perception.

Table 1 shows GPT-3 association with Grindr, Scruff, and Hornet. Table 2 shows GPT-3 associations with Tinder, Badoo, and Bumble.

For Grindr and SCRUFF, the top associated words include "gay," "dating," "hookup," "chat," and "social," which suggest that users might see these apps more as a means for casual encounters and socializing rather than fostering long-term relationships. Hornet, on the other hand, has associations with "private messaging," "chatting," "secure," and "encryption," which indicates a focus on secure communication rather than relationship building.

In contrast, general dating apps like Tinder, Badoo, and Bumble have word associations that include "swipe," "match," "profile," "chat," "dating," "relationships," and "connecting." These terms highlight the matchmaking and relationship-building aspects of these apps, potentially making them seem more conducive to long-term relationships.

Based on the word associations provided by GPT-3, we can interpret that gay dating apps Grindr, SCRUFF, and Hornet might be perceived as less safe and supportive for long-term relationships compared to general dating apps like Tinder, Badoo, and Bumble. These findings are in line with Figure 8 and data from Woodley (2016) and Queer in the World (2020) that suggest that gay dating apps are frequently associated with casual sex and hookups, which may impact user satisfaction and perceptions of safety and supportiveness for long-term relationships.

It's important to note that these interpretations are based on the provided word associations and may not necessarily reflect the actual experiences or perceptions of all users.

Appendix B shows the algorithm used to obtain these results.[13]

Table 1

Top 10 words associated with each of the top 3 gay dating apps using GPT-3

Grindr	Scruff	Hornet
1. Gay	1. Gay	1. Private messaging
2. Dating	2. Dating	2. Chatting
3. Hookup	3. Social	3. Secure
4. Chat	4. Chat	4. Encryption

[13] #algorithms

5. Social	5. Connect	5. Group conversations
6. Men	6. Profile	6. Video calls
7. Grind	7. Friends	7. Voice messages
8. Network	8. Men	8. Share files
9. Location	9. Hookup	9. Notifications
10. Profile	10. Messaging	10. Messages

Table 2

Top 10 words associated with each of the top 3 dating apps using GPT-3

Tinder	Badoo	Bumble
1. Swipe	1. Chat	1. Swiping
2. Match	2. Date	2. Matching
3. Profile	3. Meet	3. Messaging
4. Chat	4. Profile	4. Dating
5. Right swipe	5. Match	5. Relationships
6. Left swipe	6. Find	6. Profile
7. Super Like	7. Message	7. Connecting
8. Boost	8. Friends	8. Networking
9. Discovery	9. Flirt	9. Flirting
10. Location	10. Swipe	10. Chatting

Grindr User Satisfaction: A Complex System Decomposition

To better understand the user satisfaction levels with gay dating apps, especially those associated with hookups like Grindr, we can examine Grindr as a complex system (Reddish, 2019; Damshenas, 2019). This analysis will help us understand the various internal and external factors contributing to the perception of Grindr and how these factors might also influence the user experience on other gay dating apps mentioned previously.

Users

Grindr's users include individuals seeking connections with other queer people for various reasons, from serious relationships to casual sexual encounters. Grindr's design features, such as its focus on physical proximity and the ability to filter profiles based on sexual preferences, cater to individuals seeking casual connections, which might impact satisfaction levels of users looking for non-casual types of connections.

Algorithm

Grindr's matching algorithm aims to optimize user engagement by showing profiles of nearby and active users. This feature allows users to find potential partners more easily, which might increase their satisfaction levels.

Social norms

Grindr operates within a culture of social norms around queer sexuality and relationships, which may include greater sexual openness. These norms can influence users' behavior and satisfaction on the app. If users seek hookups due to perceived norms, they may experience higher satisfaction.

Design

Grindr has focused on design elements that facilitate quick connections, such as an efficient chat interface and profile customization tools emphasizing users' sexual preferences. While this may satisfy users seeking casual encounters, it can reduce feelings of safety by not requiring pre-approval for communication, unlike apps that need a match before messaging. Additionally, the lack of a matching algorithm may hinder users seeking long-term relationships, as it does not prioritize connecting users with similar interests.

Marketing

Grindr's marketing has evolved over time. While it initially focused on casual hookups, campaigns like #MetOnGrindr have shifted the emphasis towards long-term relationships that started on the app. However, Grindr's branding and advertising still often feature sexually suggestive imagery and messaging, such as their 'A Kink for a Kink' campaign, which may influence user satisfaction depending on individual expectations and desires (Shot News, 2022; Little Black Book, n.d.).

Overall Analysis

Personal preferences play a significant role in user satisfaction, as individuals have unique desires and expectations when using dating apps. Users seeking casual connections might appreciate Grindr's design features, such as its emphasis on physical proximity and profile filtering options based on sexual preferences. These features facilitate quick and easy connections, resulting in higher satisfaction levels for users with casual intentions. On the other hand, users looking for long-term relationships might find Grindr less satisfying, as its design and focus may not be as conducive to fostering deeper connections and meaningful conversations.

Social norms around queer sexuality and relationships also impact user satisfaction. Users who align with prevailing social norms, which may include a greater degree of sexual openness and exploration, might feel more at ease and satisfied using Grindr. These users may view the platform as a safe and welcoming space to express their desires and connect with like-minded individuals. Conversely, users who do not align with these norms or who prefer more traditional relationship structures may find Grindr less satisfying, as the app's features and user base may not be as supportive of their preferences.

Finally, the app's design and marketing contribute to user satisfaction by shaping perceptions and expectations. Grindr's user interface and features cater to quick, casual connections, which may attract users seeking such interactions. However, this design may also discourage users seeking more meaningful connections, leading to lower satisfaction levels. Additionally, Grindr's marketing, which has historically focused on casual hookups but has recently begun to showcase long-term relationship success stories, can create mixed expectations among users. While the marketing shift may encourage some users to explore Grindr for long-term relationships, the app's lingering association with casual encounters may continue to impact user satisfaction for those with different relationship goals.

In summary, user satisfaction with Grindr and other gay dating apps is a multifaceted issue influenced by personal preferences, social norms, and the app's design and marketing. Recognizing these factors and their interconnections can help inform future app development and research to better cater to the diverse needs and preferences of the LGBTQ+ community.[14]

User App Ratings

As mentioned previously we decided to focus our analysis on App Store user reviews of the top 3 dating apps in each product category, gay dating apps and general dating apps. Focusing on the top three dating apps enables us to obtain a representative sample of the broader user population and gain a comprehensive understanding of user satisfaction. These well-established and recognized platforms offer users familiarity and extensive experience, which in turn leads to more in-depth feedback on satisfaction levels. By concentrating on a smaller number of apps, we can efficiently identify common trends and patterns, as well as pinpoint similarities and differences in user experiences more effectively.

[14] #systemmapping

Data Collection

There were no publicly available datasets containing recent dating app reviews. Thus, we used the Python Library App_store_scraper to collect data from Apple's App Store for the top 3 dating apps in the market for each product category, gay and general dating apps. The full code for the web scraping is shown in Appendix C.[15]

On Feb 25, 2023, at 7 pm Taipei Time, we retrieved the last 2000 reviews from each App: Grindr, Scruff, Hornet and Tinder, Badoo, Bumble. No data cleaning was done. A Github repository containing a data set of reviews for each app is linked in Appendix D. This repository also contains all code used in this paper. Variables retrieved are listed in Appendix E.

Results

We plotted a histogram of the reviews for each app using Python libraries Pandas and Matplotlib. The code is in Appendix F. Figure 9 shows the distribution of user reviews for each app.

Figure 9

User ratings for top 3 gay (top) and general dating apps (bottom) from the App Store (n=2000).

[15] #cs110-CodeReadability

16

Table 3 compares the descriptive statistics of product ratings for each app. Gay dating app users express higher levels of satisfaction with dating apps than non-gay specific dating app users, as the mean rating score for gay dating apps (Grindr, Scruff, and Hornet) is 3.08, which is higher than the mean rating scores for general dating apps (Tinder, Badoo, and Bumble) which is around 2.48. A higher rating score indicates higher levels of satisfaction, contradicting hypothesis 1.

Table 3

Descriptive Statistics Of Product Rating For Each App.

Product	Mean	Mode	Median	SDV	Variance
Grindr	2.44	1	2.0	1.60	2.57

[16]#dataviz

Scruff	3.29	5	4.0	1.70	2.91
Hornet	3.51	5	4.0	1.57	2.67
Tinder	1.54	1	1.0	1.09	1.20
Badoo	3.56	5	4.0	1.66	2.77
Bumble	2.34	1	2.0	1.47	2.15

Statistical Significance

We will use an independent samples t-test to determine if the difference in satisfaction scores between gay and general dating app users is significant. We assume sample independence and will carefully interpret results as we can't assess user overlap in both apps. The max overlap is estimated at 20% based on Tinder's estimations (Scott, 2020). This is a high upper bound as gay and bisexual men are only two of many gender and sexual identities using the apps. Other tests may be more appropriate for a more robust statistical analysis and are discussed in the limitations and future research section.

Before conducting the t-test, we state the null and alternative hypotheses:

Null hypothesis (H0): There is no significant difference in satisfaction scores between gay dating app users and non-gay dating app users.

Alternative hypothesis (H1): There is a significant difference in satisfaction scores between gay dating app users and non-gay dating app users.

To make the calculation more accurate, we calculated the descriptive statistics for the app categories rather than for each app. Table 4 shows the results. Using this data, we used the code in Appendix H to calculate a two-tailed t-test with $\alpha = 0.05$. The test shows a T-statistic of 19.469 and a P-value of 3.82e-83. Thus, the results indicate that there is a statistically significant difference in satisfaction scores between gay dating app users and non-gay dating app users. Since the p-value is much smaller than the significance level (alpha = 0.05), we can reject the null hypothesis that there is no significant difference in satisfaction score between the two groups. This means that there is a significant difference in the satisfaction levels between users of gay dating apps and users of general dating apps, based on the data collected. Further, a t-statistic of 19.469 is quite large, which indicates a substantial difference between the ratings of the two groups.[17]

Nonetheless, we acknowledge that while our analysis showed a statistically significant difference in satisfaction levels between users of gay dating apps and users of general dating apps, it is essential to consider the practical implications of this finding. For instance, even though there is a significant difference in the means of the two groups, it may not necessarily translate to a meaningful difference in real-world situations, depending on the context and the effect size.

Further, to measure the magnitude of the difference between the two groups, we used the code in Appendix J to calculate Cohen's d effect size. A calculated effect size of 0.355, the difference between the two groups (gay dating apps and general dating apps) can be considered small to medium. In this context, the effect size suggests that there is a small to medium difference in user satisfaction between gay dating apps and general dating apps.[18]

[17] #significance
[18]#cs110-pythonProgramming

Table 4

Descriptive Statistics Of User Rating For Each Product Category.

Product Category	Mean	Mode	Median	SDV	Variance
Gay Dating Apps	3.08	5	3.0	1.71	2.93
General Dating Apps	2.48	1	2	1.65	2.73

Safety And Support For Long-Term Relationships On Dating Apps

To find out if gay dating app users will perceive these apps as being less safe and supportive of long-term relationships than general dating app users, we will do a textual analysis of app store ratings since descriptive statistics do not provide data to answer this hypothesis.

We used the code in Appendix F, to process the App Store reviews and generate word clouds based on word frequency. Figure 10 shows the resulting word clouds. We expected to see more negative words associated with gay dating apps. However, besides Grindr, both Scruff and Hornet had its top 5 words being positive. A similar pattern was seen in the mainstream dating apps, with Tinder having negative words being the most frequent in its reviews, and Badoo and Bumble only having positive words in the top 5 most frequent words. Thus, we cannot suggest that the word cloud indicates any significant difference between gay dating apps and general dating apps negative reviews.

We processed App Store reviews using the code in Appendix F to generate word clouds based on word frequency (Figure 10). We expected more negative words for gay dating apps, but besides Grindr, Scruff and Hornet had mostly positive top 5 words. Similarly, Tinder had frequent negative words while Badoo and Bumble had only positive top 5 words. Thus, the word cloud shows similar patterns for both categories of apps and does not indicate differences in negative reviews between them.

Figure 10

Word cloud for most frequent words in App Store reviews of top 3 gay dating apps and top 3 mainstream dating apps.

Sentiment Analysis

To further understand the written reviews, we used the deep learning model BERT (Bidirectional Encoder Representations from Transformers), a state-of-the-art deep learning model that has been shown to be highly effective at natural language processing tasks, including sentiment analysis, to analyze the textual content of the reviews. BERT is trained on a large corpus of text data and has the ability to understand the context of a given word or phrase in a sentence, allowing it to better capture the meaning of text and accurately identify the sentiment expressed. BERT can understand the context of each word in a sentence, rather than just looking at individual words in isolation, making it particularly effective at sentiment analysis.

After analyzing the input text, Bert outputs a score that indicates the sentiment of the text. This score can be positive, negative, or neutral, and the magnitude of the score can indicate the strength of the sentiment. We used a scale ranging from 1 (most negative sentiment) to 5 (most positive sentiment), with 3 representing neutral sentiment. Appendix G shows the Python code used for this analysis.

Table 5 shows the descriptive statistics for the sentiment score for each app.

Table 5

Descriptive Statistics Of Sentiment Score For Each App.

Product	Mean	Mode	Median	SDV	Variance
Hornet	3.42	5	4.0	1.57	2.47
Grindr	1.95	1	1.0	1.32	1.75
Scruff	3.03	5	3.0	1.59	2.51
Badoo	3.04	1	3.0	1.57	2.45
Tinder	1.60	1	1.0	1.06	1.13
Bumble	2.19	1	2.0	1.28	1.65

The mean user sentiment for gay dating apps (2.80) is higher than for non-gay dating apps (2.28), indicating slightly more positive sentiment from gay dating apps users. Modes are 1 or 5, showing users tend to have extreme sentiments towards dating apps, either very positive or very negative. The median sentiment for gay dating apps (3.0) is higher than for non-gay dating apps (1.5). Standard deviation and variance for gay dating apps (1.22 and 1.49) are lower than for non-gay dating apps (0.98 and 0.96), indicating tighter clustering around the mean. Descriptive statistics suggest that users of gay dating apps may have a more positive sentiment towards these apps than the sentiment that general dating app users have towards their apps. To determine if these results are statistically significant and to either reject or accept the null hypothesis, we will perform statistical significance tests.[19]

Statistical Significance

Similarly to what we did above for App Store rating by users, we will calculate the statistical significance of the sentiment analysis results. We will also use an independent samples t-test for significance and Cohen's d for effect size. Before conducting the t-test, we state the null and alternative hypotheses:

Null hypothesis (H0): There is no significant difference in user sentiment between gay dating app users and non-gay dating app users.

Alternative hypothesis (H1): There is a significant difference in user sentiment between gay dating app users and non-gay dating app users.

Table 6 shows descriptive stats for user sentiment in reviews, calculated for app category (gay dating apps, general dating apps). We used code in Appendix H to calculate a two-tailed t-test ($\alpha = 0.05$), T-statistic of 18.60 and a P-value of 3.55e-76.

Results show a statistically significant difference between user sentiment of gay dating app users and non-gay dating app users. The p-value is much smaller than the significance level (alpha = 0.05), so we reject the null hypothesis. A t-statistic of 18.60 indicates a substantial difference. We calculated Cohen's d effect size (0.34) using code in Appendix J, suggesting a small to medium difference in user sentiment between gay and general dating apps.

Table 6

Descriptive Statistics Of User Sentiment for Each Product Category.

[19]#descriptivestats

Product Category	Mean	Mode	Median	SDV	Variance
Gay Dating Apps	2.8	1	3.0	1.62	2.63
General Dating Apps	2.28	1	2.0	1.45	2.09

User interviews

We conducted interviews with three users of gay dating apps to gain a broader understanding of user satisfaction. We chose to focus specifically on gay dating app users and did not interview folks who only use general dating apps. After analyzing the interviews, we identified six overarching themes and 18 subthemes. Table 7 outlines these themes and subthemes. Table 8 shows the themes and supporting quotes from the interview.

The transcriptions of the interviews and the questionnaire used are available in the full document linked in Appendix I. The interviewees were found through a social media post and were recommended by friends of the interviewer, but were not personally known to the interviewer. While this may introduce self-selection bias, our goal is not to make generalizations based on this small sample size. Instead, we aim to supplement our quantitative analysis with insights from the interviewees' perceptions and experiences.

Table 7

Themes and Subthemes From Interviews With Gay Dating App Users

Themes	Subthemes
Preferences For Detailed Profiles	Preference for physical characteristics and sexual role information in profiles Importance of bios and photos Encouraging users to add photos
Concerns Around Anonymity and	Large number of anonymous profiles on Grindr

Privacy	The balance between respecting user privacy and requiring photo uploads Blocking and reporting tools for user safety
Communication and Matching	Matching as a mutual interest starter on Tinder and Bumble Grindr's tap feature as a match simulator The impact of swiping vs. seeing all profiles in a radius
Casual vs. Serious Relationships	Grindr's association with casual encounters Importance of profile content for determining relationship intent Changing preferences and concerns about safety in casual encounters
Features and Functionality	Facebook Dating's free feature of seeing who has already liked you Bumble’s filter becoming paid Neighborhood search on Scruff Interest hashtags on Grindr
Safety’s Impact on User Experience	Ghosting in dating apps The importance of blocking and reporting tools Concerns about scams, blackmail, and other dangers in dating apps

Table 8

Themes And Supporting Quotes From Gay Dating App Users

Theme	**Interviewee**	**Quote**
Preferences For Detailed Profiles	3	"I hate it when people don't fill in their details on Grindr. I like to know their height because I have a preference for people almost the same height or shorter than me. Grindr also has the role of the person. I wish Tinder had a place to fill in this information, like Inner Circle has height. But in Inner Circle there is no role."
	1	"I don't like the profiles without photos, but I don't know if they should be forced. Rather, they should be encouraged

		to add one."
	1	"Knowing if someone is into casual stuff or not depends a lot on what they put into their profiles."
Concerns Around Anonymity and Privacy	1	"The number of people who expose their own face there, who put a description on their profile, is lower than the number of people who have generic photos on Grindr, thus something more anonymous. This might be linked to people using it mostly for casual stuff."
	2	"Being able to block people is very important. Also a reporting tool for your own safety."
	3	"Be able to block people on Grindr is great."
Communication and Matching	1	"The reason why I love swiping and matching, versus apps like Grindr, is because with a match you already start with both liking each other. With other apps, it feels like there's always someone pursuing the other alone."
	3	"On Grindr, there's that tap thing, if you don't feel like saying hi to the person, you tap them and wait for them to tap back. I think it makes contact easier. Sometimes the person isn't comfortable to start by speaking, then he just shows interest and whoever is less shy can say hello."
	3	"Swiping isn't something I like. It gamifies the experience a lot. Also, seeing all the profiles in a radius facilitates communication and profile visualization."
Casual vs. Serious Relationships	3	"I don't use apps to find fast-fuck. I've had that phase, but I don't feel like it anymore. Also it's very unsafe. I've heard stories of people being raptured, blackmailed, robbed. Scammer won't have the patience to keep talking to someone for a long time or meet over coffee."
	3	"One thing that I find annoying is that you're talking to the person, he shows interest, and then suddenly disappears. It seems like someone a little better appeared and he already forgets about you."

Features and Functionality	1	"I love Facebook dating because they have a free feature of seeing who has already liked you. That accelerates the process."
	2	"In scruff there is a very cool function where you can search for people by neighborhood."
	2	"On Grindr you put your interests as hashtags, like on twitter. For example, here on my profile, there's a hashtag theater. If I click on this hashtag, I'll see all the people close to me that have this hashtag."
	2	"I used to love Bumble for the ability to apply filters to people. Now that's a paid function, so it's much harder to find people who are compatible with me and who will match me."
Safety's Impact on User Experience	3	"One thing that I find annoying is that you're talking to the person, he shows interest, and then suddenly disappears. It seems like someone a little better appeared and he already forgets about you."
	3	"Being able to block people is very important. Also a reporting tool for your own safety."
	3	“I don't use apps to find fast-fuck. I've had that phase, but I don't feel like it anymore. Also it's very unsafe. I've heard stories of people being raptured, blackmailed, robbed. Scammer won't have the patience to keep talking to someone for a long time or meet over coffee.”

Discussion

Our hypothesis stated that users of gay dating apps would express lower levels of satisfaction than users of non-gay dating apps. However, the analysis showed that the mean rating score for gay dating apps (3.08) is higher than for general dating apps (2.48), indicating higher satisfaction among gay dating app users. A two-tailed t-test ($\alpha = 0.05$) revealed that this difference is statistically significant (T-statistic of 19.469 and a P-value of 3.82e-83). The null hypothesis that there is no significant difference in satisfaction scores was rejected. Instead, the analysis showed a statistically significant difference, with gay dating app users appearing more satisfied based on their App Store ratings.

The Sentiment analysis revealed similar results, with gay dating app users showing a slightly more positive sentiment towards gay dating apps (2.80) than non-gay dating app users show to general dating apps (2.28). The median sentiment for gay dating apps (3.0) is also higher than for non-gay dating apps (1.5). A two-tailed t-test ($\alpha = 0.05$) confirmed these results with a T-statistic of 18.60 and a P-value of 3.55e-76.

The hypothesis that gay dating app users would have lower satisfaction was based on data suggesting negative impacts of gay dating app usage. Time Well Spent found found in a survey that 77% of Grindr users feel miserable after using the app (Corner, 2018). Additionally, LGB individuals are more likely to experience sexual harassment from online applications – 69% of LGB individuals versus 52% of straight folks (Brown, 2020). Men of color experience more race-based sexual discrimination on dating apps; white users receive more messages and 15% of Grindr users openly express racism in their profiles (Rudder, 2014 as cited in Burkholder, 2019; Callander et al., 2015 as cited in Burkholder, 2019).

Nonetheless, while gay dating app users may face similar challenges as general dating app users, such as harassment, race-based discrimination, and negative feelings after using a dating app, gay dating apps may also offer some benefits that could enhance their satisfaction compared to general dating app users. One of the independent variables that we aimed to explore in this work was perceived social support. Using apps that are tailored for their community may increase the perceived social support of gay dating app users. These apps may also create an environment where being gay and bisexual is normalized and celebrated, and lead users to higher levels of self-expression and self-acceptance. A similar phenomenon has been observed recently with the popularity of TikTok. Duguay (2023) discusses how TikTok has been a space for people to experience a place where being queer is fully acknowledged and does not limit one's ability to imagine and create a future, what he calls queer "worldmaking".[20]

Another advantage of using gay dating apps is around the theme of Features and Functionality. Interviewee 1 said in his interview:

> "For example, Grindr having an aesthetic image more directed towards the gay public will generate greater attractiveness for this public than, for example, Tinder. I think that much beyond being for a specific niche, it's also about what it offers in terms of usability. For example, while on Tinder you swipe profiles to match with someone, on Grindr you can directly access a person whose photo or description you found interesting and from there you can like them and they can like you back or you can send them a message. So it's not just about being for a specific niche but also about what it offers in terms of usability and user experience which is tied to what the app tries to sell as a brand" (Interviewee 1, personal communication, p. 36, para 5).[21]

Interviewee 1 expressed satisfaction with the ability to quickly view a grid of people in their area without having to wait for a match before contacting them. This design is present in all three gay dating apps analyzed here, which could have contributed to satisfaction and positive sentiment for a portion of the app reviews analyzed here. Interviewee 3 expressed a similar sentiment towards the grid view. To him, the swiping aspect of general dating apps make the experience too game-like:

[20]#psychologicalexplanation
[21]Small adjustments were made so the quote makes sense in English.

"Swiping isn't something I like. It gamifies the experience a lot. Also, seeing all the profiles in a radius facilitates communication and profile visualization."

Interviewee 2, highlighted that he enjoyed Scruff's search by neighborhood function. In a big city like São Paulo, with 12 million inhabitants, being able to match people in your neighborhood means sharing a more similar cultural background. He also mentioned that he likes Grindr's hashtag function:

"In Grindr, you put your interests as hashtags, like on Twitter. For example, here in my profile, there are some interesting ones. For example, there's a hashtag here that says theater. I like theater, so if I click on this hashtag here, I'll see all the people near me who have this hashtag. That's really cool." (Interviewee 2, personal communication, p. 44, para 7-8).

One small design option praised by all the interviewees was the ability to add your preferred sexual role. The ability to express your sexual role in a profile field is only available on gay dating apps. The choice of omitting this function makes sense given that general dating apps have to cater to a much larger audience where sexual roles as top and bottom are not necesserily applicable to them, as it is the case for heterosexual users. Zheng et al., (2017 as cited in Zheng, 2021) found that 72% gay and bisexual men who identify as "tops" or "bottoms" expect their longterm romantic partner to be complementary to his own sexual role. Thus, the ability to clearly see if a partner is compatible with their own sexual role prior to engaging in conversation seems to be an important feature that is only present in gay dating apps, which in turn might increase the user's satisfaction. On this topic, Interviewee 3 confirms:

"Grindr also has the person's role. I think this information is useful before starting a conversation." (Interviewee 3, personal communication, p. 51, para 6).

We expected gay dating app users to show less satisfaction than general dating app users for yet another reason: the low success rate of forming a relationship through the app. Data shows that despite using dating apps twice as much, the success rate of entering a long-term relationship through an app is 15% for gay users compared to 62% for the overall user base (Leskin, 2020; Woodley, 2016; Ballard, 2021). Grindr and other gay dating apps are also highly associated with casual sexual relationships, as seen in the Figure 8 and Table. Licoppe, (2020) also researches and confirms the social association between Grindr and hookups. Considering the evolutionary pressures that lead for humans to pair bond, it seems intuitive that users would demonstrate a lower satisfaction level with apps that do not lead to relationships (Conroy-Beam et al., 2015).

These facts led us to our second prediction that users of gay dating apps would perceive these apps as less safe and less supportive of long-term relationships compared to users of general dating apps. However, our analysis of user sentiment did not confirm this prediction. In fact, we found that gay dating apps had slightly more positive sentiment expressed in their reviews, which was statistically significant. Our quality analysis provided mixed results in regards to this prediction. Some users expressed concerns about scams, blackmail, and other dangers in dating apps. Such as Interviewee 2 says:

> "Because I've heard stories about people. Like, who have been kidnapped, like, stories where all the cards that the person had were maxed out. Bank accounts were emptied and then the person was raped and drugged." (Interviewee 2, personal communication, p. 40, para 3).

Still, all interviewees mentioned that they appreciate the blocking and reporting features, which added a feeling of security on the app.

When it comes to long-term relationships, users acknowledged the social association between gay dating apps and hookups, and this is one of the reasons why the theme of "Preference for Detailed Profiles" was also recurrent. As Interviewee 1 highlights, it seems like there is the possibility to develop many different models of engagement with the app, from casual to more serious relationships. According to him, what people displayed in their profile will be crucial in determining their interest. Grindr, for example, has a field where users are able to write down what they are looking for, divided in different categories such as Fun right now, Dates, and Friends.

> "I believe that maybe it doesn't make that much of a difference, you know? I think there will always be people looking for more casual relationships and people looking for deeper relationships. I think it all depends on how this conversation starts and also what you put as your profile description."(Interviewee 1, personal communication, p. 35, para 6).

Another aspect that interviewee 1 highlights is how queer relationships might not necessarily follow their own timelines. He says that many times two users from Grindr might meet for a sexual encounter and then see if there is a possibility of a more stable relationship.

> "I believe that most people who use dating apps, at least specifically speaking of Grindr, for example, some more specific ones that are directed towards the public, I think gay, bi, have a very strong niche when it comes to relationships; let's say casual relationships. But there is also a search for the development of a relationship. There are people who are open to this, but I believe that at first, it is about meeting people who are willing to have a meeting and this meeting can be casual or not, or develop into some kind of deeper relationship." (Interviewee 1, personal communication, p. 35, para 2).

In conclusion, our study discovered that gay dating app users report higher satisfaction levels than non-gay dating app users, contradicting our initial hypothesis. The qualitative analysis indicates that distinctive features and functionality tailored to the LGBTQ+ community in gay dating apps may contribute to this increased satisfaction. However, further evidence is required to better comprehend users' perceptions regarding the support for long-term relationships in both gay and non-gay dating apps. Additional research should be conducted to delve deeper into these aspects and identify other factors that influence user satisfaction and sentiment towards dating apps.[22]

Limitations and Future Directions

Our study has several limitations that should be considered when interpreting the results. First, we were unable to differentiate users' sexual orientation based on App Store reviews. This information would be useful to ensure there is no overlap between the two groups (gay dating app users, and general dating app users), or alternatively, to compare the given statistics for gay and bi men using both gay dating apps and general dating apps. Future research should aim to collect more specific demographic data from users to address this limitation.

Alternative research methods and data sources could have been employed to gain a deeper understanding of user experiences and satisfaction levels. For instance, conducting in-depth interviews with more users from both groups or focus groups with users would provide richer insights into the reasons behind their preferences and satisfaction levels. Additionally, analyzing user-generated content within the apps, such as messages or profile information, could provide a more nuanced understanding of user sentiment and experiences.

In terms of statistical tests, our study primarily relied on independent sample t-tests. However, if there is an overlap between the two groups, it means that some individuals are

[22]#cs130-decisionbrief

present in both groups. In this case, an independent sample t-test may not be appropriate, as the assumption of independence between the two groups is violated. Instead, we could consider using a different statistical test that accounts for the dependence between the two groups. One option could be to use a mixed-effects model or a repeated measures ANOVA if the data meets the assumptions of these tests. Such tests are more complex to be performed but are also more robust in producing reliable statistical results.

Our study highlights the importance of considering the unique experiences of users within different dating app categories. Future research should aim to address the limitations mentioned above, incorporate alternative research methods, and explore additional statistical tests to provide a more comprehensive understanding of user satisfaction and sentiment in the rapidly evolving landscape of dating apps. Understanding why a group of users, such as gay men, might be more satisfied with a specific product category can offer relevant insight for those willing to enter the promising dating app market. It can also provide ways for current dating apps to improve their services to ensure that minorities are safe and supported in current solutions.

Learning Outcomes Appendix

LOs

1. #b112-socioCulturalStrat: Relationship between a market (company strategy) and culture. Why would we need one more gay dating app? Or, more broadly, why do we have so many gay dating apps based on culture? Grindr exists as a response to a sociocultural context: dating apps have been around for a long time, and gay people want to find those who are "like them ." Grindr is bridging the gay and straight world and making people feel included. I have also mentioned the social context of users not liking matching by distance.
2. #b110-marketAnalytics: I present the broad market research question and explore the profitability and growth potential of the dating app industry. I present growth data in terms of dollar values and percentages. I present growth drivers that have influenced the industry and those that will continue to do so. I bring revenue information and use an analogy from the audio industry to showcase the growth that dating subscriptions could face as the industry grows and social acceptance increases. I calculate the Compound Annual Growth Rate to corroborate the growth forecast.
3. #cs110-CodeReadability: I thoroughly commented on my python implementation of the web scraping algorithm so that any user could follow my code and reproduce my results. I added a docstring that explains the algorithm and the parameters. I followed naming conventions consistently. I did not raise an error because the only way to get an error in this code is by inputting the wrong id number for the desired app. Nonetheless, it would be impossible for the code to know whether that is true. Given the high number of apps in the app store, it is impossible to know the range of ids (what is the starting and ending

number).

4. #cs130-decisionbrief: In my analysis, I explored the hypothesis that gay dating app users would express lower levels of satisfaction than users of non-gay dating apps. However, the analysis revealed that the mean rating score and sentiment for gay dating apps are actually higher than for general dating apps, indicating higher satisfaction among gay dating app users. I provided evidence to suggest that the tailored features and functionality of gay dating apps, such as grid view and the ability to add sexual role, may have contributed to this satisfaction. I also discussed the potential benefits of using gay dating apps, such as increased social support and the normalization of being gay or bisexual. Finally, I addressed the expected lower satisfaction due to the low success rate of forming long-term relationships through gay dating apps and their association with casual sexual relationships.
5. cs110-pythonProgramming: I have applied the requirements for writing Python code by creating multiple classes that are used throughout my code. In my statistical analysis I created the class called "RatingAnalysis" that implements the required functionality of performing statistical tests and calculating descriptive statistics on two dataframes. I have used Python commands and instructions that demonstrate my deep knowledge of Python by utilizing packages such as pandas, scipy, and numpy. I have also provided well-written instructions on how to use my Python code by including docstrings, comments throughout the code and providing clear method names that describe the purpose of each function.
6. #curation: I have rewritten several sections to better reflect the new hypothesis focused on satisfaction rather than commitment. I have also opted to remove the literature review

altogether since it would not deepen the user satisfaction analysis. I moved the word association to be included in the data analysis so it makes more sense as a flow.

7. #navigation: I have worked consistently to deliver relevant parts of my work by each deadline. At each new deliverable, I have expanded on new work that contributes to the overall product. I have stayed accountable to professors and peers throughout the semester with many conversations and feedback iterations.
8. #outcomeanalysis: I have demonstrated a deep understanding of various skills necessary in the writing of this project from quantitative statistical and coding to qualitative and business analysis.
9. #qualitydeliverables: I have submitted quality work at each deliverable making sure to reflect and respond to the previous feedback. At each deliverable, I have added new and quality sections that have deepened my analysis.

HCs

1. #significance: I applied a t-test to compare satisfaction levels of gay and general dating app users. Levene's test showed unequal variances, so I used Welch's t-test. The p-value was smaller than the significance level (alpha = 0.05), indicating a significant difference between the two groups. I considered type I and type II errors and selected an appropriate significance level to minimize their probability. I also distinguished between practical and statistical significance. My analysis showed a statistically significant difference in satisfaction levels between gay and general dating app users. However, I considered the practical implications of this finding.
2. #fallacies: I correctly identify the existence of the post hoc logical fallacy. I explain how the fallacy violates formal rules of logic (using the alphabetic representation of the

syllogism). I also point out how other fallacies, such as the single-cause fallacy, might be related. I draw on evidence already presented in the report to correct the fallacy.

3. #variables: I accurately point out the variables to be collected in the following sections (Sexual orientation, use of dating apps, satisfaction, and perceived safety). I classify the variables and provide an example of possible relationships that could be created between the variables thinking of dating as our system. I point out why these variables will be relevant to our research and accurately identify and classify variables. This explanation further depended on my data analysis when I retrieved and classified variables of interest in the online dating app review dataset/web scraping. See Appendix F.
4. #algorithms: I identified a problem that would benefit from an algorithmic solution. In this case, I did not have market research on user associations with each app. Thus, an AI algorithm, such as GPT-3, was a good choice for the problem. Further, I break down the process of using GPT-3 into a well-explained algorithm that can be followed by any person just reading the instructions. I explain the details of the algorithm, such as the amounts chosen for temperature and maximum length, and explicitly the input that was chosen, so my work can be verified. I also thoroughly apply algorithms when writing python code. I create reusable code, in the format of classes, that follows a clear set of steps that is then instantiated as many times as necessary for the given objects.
5. #critique: I effectively critique aspects of Porter's Five Forces that are not complete representations of the market and thus represent a weakness of the model. I justify why I chose the framework, its ability to give an overview of an industry, and why the drawbacks do not deem the framework useless; it is intended to be a broad overview rather than a hyper focused analysis. I point to other pieces of data in the report that

complement our market analysis.

6. #constraints: I accurately identify obstacles (not having data sets with updated user reviews) and how to overcome them (use Python to scrape the App Store for reviews). I identify nuanced constraints in getting data that would fully support our analysis in the paradigm of choosing mainstream apps that do not have specific data on queer people and are more focused on relationships or getting data directly from gay dating apps mainly focused on hookups. I bring market data to show that comparisons between LGBTQIA+ experiences and non-LGBTQIA+ folks are not fitting and bring steps to satisfy our constraints.
7. #thesis: I compose a substantial (answer the how – how gay men feel, and why – why they feel that way), arguable (give an argument that can be disagreed upon), precise (clear and specific and points towards the arguments which will be laid out after), and relevant (is significant to the context at hand, contributing to the understanding of our problem and guiding towards the hypotheses).
8. #context: I analyze the context of dating apps throughout history. I show how there was always a market need to find matches in society. I analyze how the queer community was always at the forefront of new dating options due to a not-so-subtle but relevant aspect of the sociocultural context: homophobia (At times enforced by laws). I produce sophisticated interpretations of what that means to the current dating market.
9. #hypothesisdevelopment: I draw connections between the patterns and initial data presented about gay men's dissatisfaction with dating apps, the possible reasons for such, and the paradox of looking for love in apps marketed at hookups (such as Grindr). I generate a hypothesis to explain this phenomenon further and clearly explain the

connection between my hypothesis and the current data. I provide testable predictions to investigate my hypothesis further. See #testability.

10. #testability: I identify multiple sub-hypotheses about gay men's dissatisfaction with gay dating apps that could support or refute our hypothesis. I discuss why the predictions are testable in both principles by not violating important scientific considerations such as user privacy, and in practice, given the possibility of getting and processing user data. In the section named User reviews, I explain the limitations of getting complete and perfect data that would allow us to generate the best hypothesis test and justify why my data is still appropriate given the limitations.
11. #breakitdown: I decompose the problem of understanding the gay dating market into many tractable, clear, and well-defined components. I first analyze overall market metrics (revenue, growth), then break the market into smaller parts and focus on the gay dating market. For this one, I divide the problem into smaller parts: user safety and satisfaction, a hypothesis following market data on current gay dating apps, and a look at the factors influencing market competitiveness. Lastly, I point to a method for creating solutions based on the findings of each of these smaller modules.
12. #systemmapping: I defined an explanatory challenge (Understanding user satisfaction from looking at Grindr as a complex system). I use Grindr as a more tractable system to analyze and break the app down into its agents. I explain how the agents contribute to our explanatory challenge.
13. #psychologicalexplanation: I use psychological theories to identify, analyze, and propose explanations for dating app usage. I use different theories to complement a view of why queer users might engage in dating apps.

14. #descriptivestats: I made sure to carefully choose the appropriate descriptive statistics that best represented the data I was analyzing. I did this by considering the nature of the data and what I wanted to learn from it. I accurately calculated them using clear and detailed steps in python, which also helped minimize human errors. I applied multiple descriptive statistics to gain a more nuanced understanding of the trends and patterns present in the data. I have not only used mean, but also mode and median in my interpretations. I calculated the standard deviation and variance which were useful later in the significance analysis.
15. #dataviz: In creating the histogram and word clouds presented above, I have effectively generated detailed data visualizations that are appropriate for the data analyzed. For the histogram, I chose to use a bin size that allowed for a clear representation of the frequency of the data. I also included labels for the x and y axes to provide context and make the visualization more interpretable. In analyzing the histogram and word clouds, I provided appropriate justification and details, such as identifying the most frequent words and interpreting the distribution of ratings.

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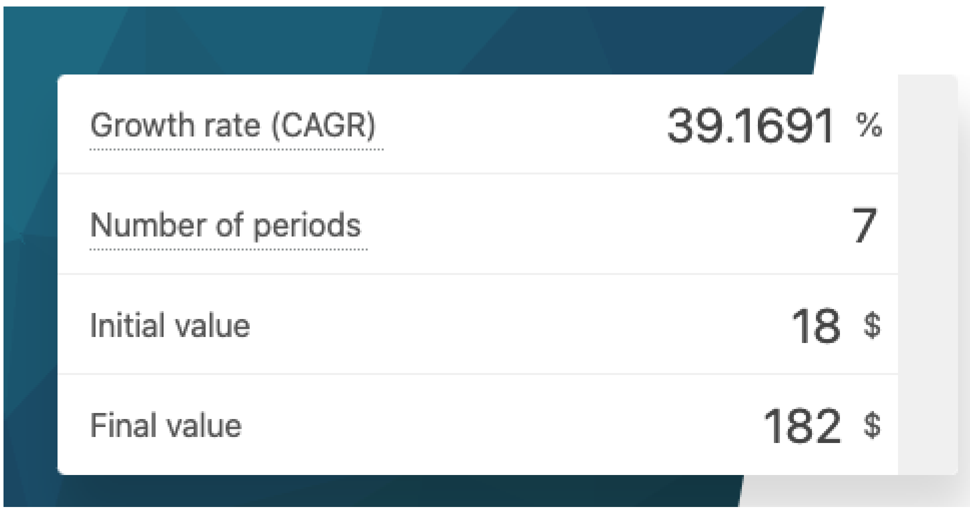
Appendix

Appendix A: Compound annual growth calculator

Inital value: 7 (Q1 2015)

Final Value: 182 (Q1 2022)



https://www.omnicalculator.com/finance/cagr

Appendix B: Word association algorithm

https://beta.openai.com/playground

1. Create an account at OpenAi.
2. Open the playground linked above.
3. I selected the model text-davinci-003
4. The temperature was set to 0.7
5. The Maximum length was set to 200 words.
6. All the other ones setting were kept as default.
7. What are the most common words associated with the app ____?
8. Copy the results of the search to a new tab and clean the search result.

9. Repeat steps 7 and 8 for all the dating apps.

Text-DaVinci-003 is the most updated and well-trained algorithm within OpenAi; thus, we chose it. The temperature was set to 0.7, meaning that the algorithm on a scale from 0-1 would give results moderately different at each search. However, more is needed to simulate randomness. The maximum length was set to 200 to guarantee that the algorithm would not suggest paragraph answers and lead to bias of me having to choose words out of it.

Appendix C: Python code to scrape reviews from the App Store

```
#pip install app-store-scraper

import pandas as pd
import numpy as np
from app_store_scraper import AppStore

class AppReviewsScraper:
    """
    A class to scrape app reviews from the Apple App Store.

    Parameters
    ----------
    country : str
        Abbreviation in English of the country you want to scrape the reviews.
    app_name : str
        The name of the app.
    app_id : int
        The app id on the app store. To find this id, just google app_name on
app store.
        The end of the url says id followed by the id number.
    how_many : int
        The number of reviews you want to scrape from the app store.

    Attributes
    ----------
    country : str
        Abbreviation in English of the country you want to scrape the reviews.
    app_name : str
```

```
        The name of the app.
    app_id : int
        The app id on the app store.
    how_many : int
        The number of reviews you want to scrape from the app store.
    app_store : AppStore
        An instance of the AppStore class from the app_store_scraper package.

    Methods
    -------
    scrape_reviews():
        Scrapes reviews for the given app from the App Store.
        Returns a Pandas DataFrame containing the reviews and their associated
information.

    export_to_csv(file_path):
        Exports the scraped reviews to a CSV file at the given file path.
    """
    def __init__(self, country, app_name, app_id, how_many):
        self.country = country
        self.app_name = app_name
        self.app_id = app_id
        self.how_many = how_many
        self.app_store = AppStore(country=self.country, app_name=self.app_name,
app_id=self.app_id)

    def scrape_reviews(self):
        self.app_store.review(how_many=self.how_many)
        reviews_df = pd.DataFrame(np.array(self.app_store.reviews),
columns=['review'])
        reviews_df =
reviews_df.join(pd.DataFrame(reviews_df.pop('review').tolist()))
        return reviews_df

    def export_to_csv(self, file_path):
        reviews_df = self.scrape_reviews()
        reviews_df.to_csv(file_path, index=False)

# instantiate the class for Grindr app reviews
grindr_scraper = AppReviewsScraper(country='us', app_name='grindr',
app_id='319881193', how_many=2000)

# scrape the reviews and export them to a CSV file
grindr_scraper.export_to_csv('grindr_reviews.csv')
```

```
# instantiate the class for Scruff app reviews
scruff_scraper = AppReviewsScraper(country='us', app_name='scruff',
app_id='380015247', how_many=2000)

# scrape the reviews and export them to a CSV file
scruff_scraper.export_to_csv('scruff_reviews.csv')

# instantiate the class for Hornet app reviews
hornet_scraper = AppReviewsScraper(country='us', app_name='hornet',
app_id='462678375', how_many=2000)

# scrape the reviews and export them to a CSV file
hornet_scraper.export_to_csv('hornet_reviews.csv')

# instantiate the class for tinder app reviews
tinder_scraper = AppReviewsScraper(country='us', app_name='tinder',
app_id='547702041', how_many=2000)

# scrape the reviews and export them to a CSV file
tinder_scraper.export_to_csv('tinder_reviews.csv')

# instantiate the class for badoo app reviews
badoo_scraper = AppReviewsScraper(country='us', app_name='badoo',
app_id='351331194', how_many=2000)

# scrape the reviews and export them to a CSV file
badoo_scraper.export_to_csv('badoo_reviews.csv')

# instantiate the class for Bumble app reviews
bumble_scraper = AppReviewsScraper(country='us', app_name='bumble',
app_id='930441707', how_many=2000)

# scrape the reviews and export them to a CSV file
bumble_scraper.export_to_csv('bumble_reviews.csv')
```

Appendix D: GitHub Public Directory With Coding Files And Datasets

https://github.com/dasilvagabriel/dating_analysis

Appendix E: Variables Collected From User Reviews

developerResponse: string - If there is a developer response to that specific review, it is computed here

Date: datetime - the date the review was published.

Rating: integer - the rating attributed to the app by the user on a scale from 1 to 5.

isEdited: boolean - if the rating was edited or not.

userName: string - the username of the customer writing the review.

review title: string - the review title chosen by the user.

Appendix F: Python code to generate User review histograms and Worcloud

This code was adapted from the tutorials of Selvaraj (2020) and GeeksforGeeks (2018)

```
#install and import the relevant libraries and packages
get_ipython().system('conda install pytorch torchvision torchaudio -c pytorch
-y')
get_ipython().system('pip install transformers requests beautifulsoup4 pandas
numpy')
get_ipython().system('pip install torchvision ')

import pandas as pd
import torch
import requests
from bs4 import BeautifulSoup
import re
from transformers import AutoTokenizer, AutoModelForSequenceClassification
import statistics
import plotly.express as px
from plotly.subplots import make_subplots
from IPython.display import display
import nltk
from wordcloud import WordCloud
import matplotlib.pyplot as plt


# In[10]:
```

```
class ProductReviews:
    """A class to represent a set of product reviews.
    Attributes:
    -----------
    df : pandas.DataFrame
        The dataframe containing the product reviews.

    Methods:
    --------
    create_histogram(title)
        Creates a histogram of the product ratings and displays it.
    mean()
        Calculates the mean of the product ratings.

    mode()
        Calculates the mode of the product ratings.

    median()
        Calculates the median of the product ratings.

    standard_deviation()
        Calculates the standard deviation of the product ratings.

    variance()
        Calculates the variance of the product ratings.

    """
    def __init__(self, csv_file):
        """Initialize a new ProductReviews object.

        Parameters:
        -----------
        csv_file : str
            The path to the CSV file containing the product reviews.

        """
        self.df = pd.read_csv(csv_file)

    def create_histogram(self, title, subplot_idx):
        """Create a histogram of the product ratings and display it.

        Parameters:
        -----------
        title : str
```

```
            The title to display above the histogram.
        subplot_idx: int
            The index of the subplot to plot the histogram in

        Returns:
        --------
        None

        """
        fig = px.histogram(self.df, x="rating")
        fig.update_traces(marker_color="steelblue",
marker_line_color='rgb(8,48,107)',
                          marker_line_width=1.5)
        fig.update_layout(title_text=title)

        row = subplot_idx // 3 + 1
        col = subplot_idx % 3 + 1

        return (fig, row, col)

    def mean(self):
        """Calculate the mean of the product ratings."""
        return round(statistics.mean(self.df['rating']), 2)

    def mode(self):
        """Calculate the mode of the product ratings."""
        return statistics.mode(self.df['rating'])

    def median(self):
        """Calculate the median of the product ratings."""
        return round(statistics.median(self.df['rating']), 2)

    def standard_deviation(self):
        """Calculate the standard deviation of the product ratings."""
        return round(statistics.stdev(self.df['rating']), 2)

    def variance(self):
        """Calculate the variance of the product ratings."""
        return round(statistics.variance(self.df['rating']), 2)


#Create instances of the ProductReviews class for each product
grindr_reviews = ProductReviews('grindr_reviews.csv')
scruff_reviews = ProductReviews('scruff_reviews.csv')
hornet_reviews = ProductReviews('hornet_reviews.csv')
```

```
tinder_reviews = ProductReviews('tinder_reviews.csv')
badoo_reviews = ProductReviews('badoo_reviews.csv')
bumble_reviews = ProductReviews('bumble_reviews.csv')

# Initialize the subplot grid
fig = make_subplots(rows=2, cols=3, subplot_titles=("Grindr Product Ratings",
"Scruff Product Ratings", "Hornet Product Ratings",
                                                    "Tinder Product Ratings",
"Badoo Product Ratings", "Bumble Product Ratings"))

#Use the create_histogram method of each instance to create a histogram of the
product ratings
histograms = [grindr_reviews.create_histogram('Grindr Product Ratings', 0),
              scruff_reviews.create_histogram('Scruff Product Ratings', 1),
              hornet_reviews.create_histogram('Hornet Product Ratings', 2),
              tinder_reviews.create_histogram('Tinder Product Ratings', 3),
              badoo_reviews.create_histogram('Badoo Product Ratings', 4),
              bumble_reviews.create_histogram('Bumble Product Ratings', 5)]

# Add each histogram to the subplot grid
for histogram in histograms:
    fig.add_trace(histogram[0]['data'][0], row=histogram[1], col=histogram[2])

# Update the subplot layout
fig.update_layout(height=600, width=900, title_text="Product Ratings")

# Display the subplot grid
fig.show()

stats_dict = {
    'Product': ['Grindr', 'Scruff', 'Hornet', 'Tinder', 'Badoo', 'Bumble'],
    'Mean': [grindr_reviews.mean(), scruff_reviews.mean(),
hornet_reviews.mean(), tinder_reviews.mean(), badoo_reviews.mean(),
bumble_reviews.mean()],
    'Mode': [grindr_reviews.mode(), scruff_reviews.mode(),
hornet_reviews.mode(), tinder_reviews.mode(), badoo_reviews.mode(),
bumble_reviews.mode()],
    'Median': [grindr_reviews.median(), scruff_reviews.median(),
hornet_reviews.median(), tinder_reviews.median(), badoo_reviews.median(),
bumble_reviews.median()],
    'Standard Deviation': [grindr_reviews.standard_deviation(),
scruff_reviews.standard_deviation(), hornet_reviews.standard_deviation(),
tinder_reviews.standard_deviation(), badoo_reviews.standard_deviation(),
bumble_reviews.standard_deviation()],
    'Variance': [grindr_reviews.variance(), scruff_reviews.variance(),
```

```
hornet_reviews.variance(), tinder_reviews.variance(), badoo_reviews.variance(),
bumble_reviews.variance()]
}

# Create a pandas DataFrame from the dictionary
stats_df = pd.DataFrame(stats_dict)

# Display the DataFrame
display(stats_df)


class WordCloudGenerator:
    def __init__(self, file_path, new_stopwords):
        self.df = pd.read_csv(file_path, encoding="latin-1")
        self.comment_words = ''
        self.stopwords = nltk.corpus.stopwords.words('english')
        self.stopwords.extend(new_stopwords)

    def generate_word_cloud(self, ax, title):
        word_count = {}
        # iterate through the csv file and split the string into single words
        for val in self.df.title:
            # typecast each val to string
            val = str(val)

            # split the value
            tokens = val.split()

            # Converts each token into lowercase
            for i in range(len(tokens)):
                tokens[i] = tokens[i].lower()

            self.comment_words += " ".join(tokens) + " "

        # define the parameters for the wordcloud graph
        wordcloud = WordCloud(width=1600, height=800,
                              background_color='white',
                              stopwords=self.stopwords,
                              min_font_size=10).generate(self.comment_words)

        # plot the WordCloud image
        ax.imshow(wordcloud)
        ax.axis("off")
        ax.set_title(title)
```

```
new_stopwords = ["grindr", "dona", "t", "ita", "ia", "a", "m",
                 "donâ", "t", "itâ", "iâ", "â", "app", "canâ",
                 "get", "even", "really", "said", "also", "phone", "wonâ",
                 "thatâ", "youâ", "know", "scruff", "like", "would", "still",
                 "much", "use", "apps", "guy", "guys", "people", "didnâ",
"look",
                 "see", "many", "u", "could", "way", "something", "i'm", "say",
                 "one", "though", "new", "doesnâ"]

fig, axs = plt.subplots(nrows=2, ncols=3, figsize=(16, 8), facecolor=None,
                        gridspec_kw={'hspace': 0.1, 'wspace': 0.1})

grindr_wc = WordCloudGenerator("grindr_reviews.csv", new_stopwords)
grindr_wc.generate_word_cloud(axs[0][0], "Grindr Reviews")

scruff_wc = WordCloudGenerator("scruff_reviews.csv", new_stopwords)
scruff_wc.generate_word_cloud(axs[0][1], "Scruff Reviews")

hornet_wc = WordCloudGenerator("hornet_reviews.csv", new_stopwords)
hornet_wc.generate_word_cloud(axs[0][2], "Hornet Reviews")

tinder_wc = WordCloudGenerator("tinder_reviews.csv", new_stopwords)
tinder_wc.generate_word_cloud(axs[1][0], "Tinder Reviews")

badoo_wc = WordCloudGenerator("badoo_reviews.csv", new_stopwords)
badoo_wc.generate_word_cloud(axs[1][1], "Badoo Reviews")

bumble_wc = WordCloudGenerator("bumble_reviews.csv", new_stopwords)
bumble_wc.generate_word_cloud(axs[1][2], "Bumble Reviews")

plt.tight_layout(pad=0)
plt.savefig('wordcloud.png', dpi=300)
plt.show()
```

Appendix G: Python code for sentiment analysis

```
class SentimentAnalyzer:
    """
    Class for sentiment analysis using BERT-based model.
    Args:
    model_name (str): Name of the pre-trained BERT-based model to be used.
```

```
Default is 'nlptown/bert-base-multilingual-uncased-sentiment'.

    Attributes:
    tokenizer: Instance of the AutoTokenizer class from transformers package
for tokenizing input text.
    model: Instance of the AutoModelForSequenceClassification class from
transformers package for sentiment analysis.

    Methods:
    sentiment_score(review): Method for calculating sentiment score of a given
review text using the pre-trained model.
    """
    def __init__(self,
model_name='nlptown/bert-base-multilingual-uncased-sentiment'):
        self.tokenizer = AutoTokenizer.from_pretrained(model_name)
        self.model =
AutoModelForSequenceClassification.from_pretrained(model_name)

    def sentiment_score(self, review):
        """
        Method to calculate sentiment score of a given review text.

        Args:
        review (str): Text of the review to be analyzed.

        Returns:
        Integer: Sentiment score of the input review text (1-5).
        """
        tokens = self.tokenizer.encode(review, return_tensors='pt')
        result = self.model(tokens)
        return int(torch.argmax(result.logits)) + 1

class ReviewSentimentAnalyzer:
    """
    Class for sentiment analysis of a collection of reviews using BERT-based
model.
    Args:
    model_name (str): Name of the pre-trained BERT-based model to be used.
Default is 'nlptown/bert-base-multilingual-uncased-sentiment'.

    Attributes:
    analyzer: Instance of the SentimentAnalyzer class for sentiment analysis of
individual reviews.

    Methods:
```

```
    analyze_reviews(review_csv_file_path): Method for analyzing sentiment of a
collection of reviews given in a CSV file.
    """

    def __init__(self,
model_name='nlptown/bert-base-multilingual-uncased-sentiment'):
        self.analyzer = SentimentAnalyzer(model_name)

    def analyze_reviews(self, review_csv_file_path):
        """
        Method for analyzing sentiment of a collection of reviews given in a
CSV file.

        Args:
        review_csv_file_path (str): File path of the CSV file containing the
reviews.

        Returns:
        DataFrame: Pandas DataFrame object containing the reviews along with
their sentiment scores.
        """
        df = pd.read_csv(review_csv_file_path)
        df['sentiment'] = df['review'].apply(lambda x:
self.analyzer.sentiment_score(x[:512]))
        return df

class SentimentStatistics:
    """
    Class for calculating statistics from sentiment ratings.
    Args:
    sentiment_ratings (list): List of integer sentiment ratings (1-5).

    Attributes:
    sentiment_ratings: List of integer sentiment ratings (1-5).

    Methods:
    mean(): Method for calculating the mean of the sentiment ratings.
    mode(): Method for calculating the mode of the sentiment ratings.
    median(): Method for calculating the median of the sentiment ratings.
    std(): Method for calculating the standard deviation of the sentiment
ratings.
    variance(): Method for calculating the variance of the sentiment ratings.
    """
    def __init__(self, sentiment_ratings):
        self.sentiment_ratings = sentiment_ratings
```

```
def mean(self):
    """
    Method to calculate the mean of the sentiment ratings.

    Returns:
    float: Mean of the sentiment ratings.
    """
    return round(statistics.mean(self.sentiment_ratings), 2)

def mode(self):
    """
    Method to calculate the mode of the sentiment ratings.

    Returns:
    tuple: Mode of the sentiment ratings.
    """
    return round(statistics.mode(self.sentiment_ratings), 2)

def median(self):
    """
    Method to calculate the median of the sentiment ratings.

    Returns:
    float: Median of the sentiment ratings.
    """
    return round(statistics.median(self.sentiment_ratings), 2)

def std(self):
    """
    Method to calculate the standard deviation of the sentiment ratings.

    Returns:
    float: Standard deviation of the sentiment ratings.
    """
    return round(statistics.stdev(self.sentiment_ratings), 2)

def variance(self):
    """
    Method to calculate the variance of the sentiment ratings.

    Returns:
    float: Variance of the sentiment ratings.
    """
    return round(statistics.variance(self.sentiment_ratings), 2)
```

```
# In[ ]:


tokenizer =
AutoTokenizer.from_pretrained('nlptown/bert-base-multilingual-uncased-sentiment
')
model =
AutoModelForSequenceClassification.from_pretrained('nlptown/bert-base-multiling
ual-uncased-sentiment')
analyzer =
SentimentAnalyzer('nlptown/bert-base-multilingual-uncased-sentiment')

#Load reviews from a CSV file into a pandas dataframe
hornet_reviews = pd.read_csv('hornet_reviews.csv')
#Add a new column called 'sentiment' to the dataframe by applying the
sentiment_score method to the 'review' column
#The sentiment_score method uses a BERT model to predict the sentiment of the
text, but only uses the first 512 characters
hornet_reviews['sentiment'] = df['review'].apply(lambda x:
sentiment_score(x[:512]))
#Save the dataframe with the added sentiment column to a new CSV file
#The index column is excluded by setting index=False
hornet_reviews.to_csv('sentiment_hornet.csv', index=False)

grindr_reviews = pd.read_csv('grindr_reviews.csv')
grindr_reviews['sentiment'] = grindr_reviews['review'].apply(lambda x:
analyzer.sentiment_score(x[:512]))
grindr_reviews.to_csv('sentiment_grindr.csv', index=False)

scruff_reviews = pd.read_csv('scruff_reviews.csv')
scruff_reviews['sentiment'] = scruff_reviews['review'].apply(lambda x:
analyzer.sentiment_score(x[:512]))
scruff_reviews.to_csv('sentiment_scruff.csv', index=False)

tinder_reviews = pd.read_csv('tinder_reviews.csv')
tinder_reviews['sentiment'] = tinder_reviews['review'].apply(lambda x:
analyzer.sentiment_score(x[:512]))
tinder_reviews.to_csv('sentiment_tinder.csv', index=False)

badoo_reviews = pd.read_csv('badoo_reviews.csv')
badoo_reviews['sentiment'] = badoo_reviews['review'].apply(lambda x:
analyzer.sentiment_score(x[:512]))
badoo_reviews.to_csv('sentiment_badoo.csv', index=False)
```

```
bumble_reviews = pd.read_csv('bumble_reviews.csv')
bumble_reviews['sentiment'] = bumble_reviews['review'].apply(lambda x:
analyzer.sentiment_score(x[:512]))
bumble_reviews.to_csv('sentiment_bumble.csv', index=False)


# In[16]:


# Define a list of products
products = ['Hornet', 'Grindr', 'Scruff', 'Badoo', 'Tinder', 'Bumble']

# Create an empty DataFrame to store the statistics
stats_df = pd.DataFrame(columns=['Product', 'Mean', 'Mode', 'Median', 'Standard
Deviation', 'Variance'])

# Iterate over the products and calculate the statistics for each one
for product in products:
    sentiment_ratings =
pd.read_csv(f'sentiment_{product.lower()}.csv')['sentiment'].tolist()
    product_stats = SentimentStatistics(sentiment_ratings)
    stats = {
        'Product': product,
        'Mean': product_stats.mean(),
        'Mode': product_stats.mode(),
        'Median': product_stats.median(),
        'Standard Deviation': product_stats.std(),
        'Variance': product_stats.variance()
    }
    stats_df = pd.concat([stats_df, pd.DataFrame(stats, index=[0])],
ignore_index=True)

# Print the table of statistics
display(stats_df)
```

Appendix H: T-test

Null hypothesis (H0): There is no difference in satisfaction scores between gay dating app users and non-gay dating app users ($\mu1 = \mu2$).

Alternative hypothesis (H1): There is a difference in satisfaction scores between gay dating app users and non-gay dating app users ($\mu 1 \neq \mu 2$).

Mean satisfaction score for gay dating apps = (2.44 + 3.29 + 3.51) / 3 = 3.08

Mean satisfaction score for non-gay dating apps = (1.54 + 3.56 + 2.34) / 3 = 2.48

Next, we calculate the pooled standard deviation. The sample size for each group is 3, since there is 3 dating apps in each product category (gay dating apps and general dating apps). The pooled standard deviation is calculated as:

Sp = √(((3-1)*2.72 + (3-1)*2.24) / (3+3-2)) = √(8.16/4) = 1.43

Now, we will perform an independent samples t-test to assess the statistical significance of the difference in mean satisfaction scores between the two groups.

Appendix I: User Interview Transcriptions

Link to full document

In the first page there is a guide to how the document is organized.

Questions from user interviews:

- How do you think people normally look for romantic partners?
- What kind of connection do you think people look for in dating apps?
- Do you think it's hard for folks looking to find committed partners to find people in dating apps?
- Do you use apps targeted at gay folks?
- What features do you like from dating apps?
- What features do you dislike?
- What do you wish dating apps had in general?

- What do you wish dating apps didn't have?

Appendix J: Python Code For Statistical Analysis

```
def calculate_descriptive_statistics(df, column_name):
    """
    This script calculates the descriptive statistics for rating data from
merged CSV files of gay dating apps,
    general dating apps, gay dating apps sentiment, and general dating apps
sentiment.

    Functions:
        calculate_descriptive_statistics(df): Calculates the mean, mode,
median, standard deviation,
                                              and variance for the rating
column in the given DataFrame.

    The script reads merged CSV files, calculates descriptive statistics for
each dataset, and then
    prints the results.
    """
    mean = round(df[column_name].mean(), 2)
    mode = df[column_name].mode().values[0]
    median = round(df[column_name].median(), 2)
    std_dev = round(df[column_name].std(), 2)
    variance = round(df[column_name].var(), 2)

    return {
        'Mean': mean,
        'Mode': mode,
        'Median': median,
        'Standard Deviation': std_dev,
        'Variance': variance
    }

# Calculate descriptive statistics for the the chosen column
gay_dating_apps_stats = calculate_descriptive_statistics(gay_dating_apps_df,
'rating')
general_dating_apps_stats =
calculate_descriptive_statistics(general_dating_apps_df, 'rating')
gay_apps_sentiment_stats =
calculate_descriptive_statistics(gay_apps_sentiment_df, 'sentiment')
general_apps_sentiment_stats =
calculate_descriptive_statistics(general_apps_sentiment_df, 'sentiment')
```

```
# Print the results
print("Descriptive statistics for gay dating apps:")
for stat, value in gay_dating_apps_stats.items():
    print(f"{stat}: {value}")

print("\nDescriptive statistics for general dating apps:")
for stat, value in general_dating_apps_stats.items():
    print(f"{stat}: {value}")

print("\nDescriptive statistics for gay dating apps sentiment:")
for stat, value in gay_apps_sentiment_stats.items():
    print(f"{stat}: {value}")

print("\nDescriptive statistics for general dating apps sentiment:")
for stat, value in general_apps_sentiment_stats.items():
    print(f"{stat}: {value}")
```

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

class RatingAnalysis:
    """
    A class for performing statistical analysis on two datasets with a column
chosen by the user.

    Args:
        data_file1 (str): The path to the first dataset CSV file.
        data_file2 (str): The path to the second dataset CSV file.

    Attributes:
        data_df1 (pandas.DataFrame): The first dataset as a pandas DataFrame.
        data_df2 (pandas.DataFrame): The second dataset as a pandas DataFrame.

    Methods:
        read_data(file_path): A static method that reads a CSV file and returns
it as a pandas DataFrame.
        two_sample_t_test(): Computes the t-test for the means of two
independent samples.
        two_sample_t_test_unequal_var(): Computes the t-test for the means of
two independent samples with unequal variances.
```

```
        cohen_d(): Computes Cohen's d effect size.
        levene_test(): Computes Levene's test for equal variances.
        perform_analysis(): Performs all the statistical analyses and returns a
dictionary with the results.

    Example usage:
        # Read the merged CSV files and create dataframes
        gay_dating_apps_df = pd.read_csv('gay_dating_apps_merged.csv')
        general_dating_apps_df = pd.read_csv('general_dating_apps_merged.csv')

        # Create an instance of the RatingAnalysis class for the two datasets
        rating_analysis = RatingAnalysis('gay_dating_apps_merged.csv',
'general_dating_apps_merged.csv')

        # Get the statistics for the rating analysis
        rating_stats = rating_analysis.perform_analysis()

        # Print the statistics
        print("Statistics for Rating Analysis:")
        for stat, value in rating_stats.items():
            print(f"{stat}: {value}")
    """
    def __init__(self, data_file1, data_file2, column_name):
        self.data_df1 = self.read_data(data_file1)
        self.data_df2 = self.read_data(data_file2)
        self.column_name = column_name

    @staticmethod
    def read_data(file_path):
        return pd.read_csv(file_path)

    def two_sample_t_test(self):
        t_statistic, p_value = stats.ttest_ind(self.data_df1[self.column_name],
self.data_df2[self.column_name])
        return t_statistic, p_value

    def two_sample_t_test_unequal_var(self):
        levene_statistic, levene_p_value = self.levene_test()
        if levene_p_value > 0.05:
            return None
        else:
            print("The variances are not equal.")

        t_statistic, p_value = stats.ttest_ind(self.data_df1[self.column_name],
self.data_df2[self.column_name], equal_var=False)
```

```
        return t_statistic, p_value

    def cohen_d(self):
        mean_diff = np.mean(self.data_df1[self.column_name]) -
np.mean(self.data_df2[self.column_name])
        n1, n2 = len(self.data_df1[self.column_name]),
len(self.data_df2[self.column_name])
        var1, var2 = np.var(self.data_df1[self.column_name], ddof=1),
np.var(self.data_df2[self.column_name], ddof=1)

        pooled_variance = ((n1 - 1) * var1 + (n2 - 1) * var2) / (n1 + n2 - 2)
        d = mean_diff / np.sqrt(pooled_variance)

        return d

    def levene_test(self):
        levene_statistic, levene_p_value =
stats.levene(self.data_df1[self.column_name], self.data_df2[self.column_name])
        if levene_p_value > 0.05:
            return None
        else:
            return levene_statistic, levene_p_value


    def plot_histograms(self):
        fig, ax = plt.subplots(1, 2, figsize=(12, 4))
        sns.histplot(self.data_df1[self.column_name], ax=ax[0], kde=True)
        ax[0].set_title(f'Histogram for {self.column_name} (Data 1)')
        ax[0].set_xlabel(self.column_name)
        ax[0].set_ylabel('Frequency')

        sns.histplot(self.data_df2[self.column_name], ax=ax[1], kde=True)
        ax[1].set_title(f'Histogram for {self.column_name} (Data 2)')
        ax[1].set_xlabel(self.column_name)
        ax[1].set_ylabel('Frequency')

        plt.show()

    def perform_analysis(self):
        t_statistic, p_value = self.two_sample_t_test()
        welch_statistic, welch_p_value = self.two_sample_t_test_unequal_var()
        cohen_d_value = self.cohen_d()
        levene_statistic, levene_p_value = self.levene_test()

        results = {
```

```
            'T-statistic': t_statistic,
            'P-value': p_value,
            'Welch T-statistic': welch_statistic,
            'Welch P-value': welch_p_value,
            'Cohen\'s d': cohen_d_value,
            'Levene Statistic': levene_statistic,
            'Levene P-value': levene_p_value
        }

        self.plot_histograms()
        return results

rating_analysis = RatingAnalysis('gay_dating_apps_merged.csv',
'general_dating_apps_merged.csv', 'rating')
sentiment_analysis = RatingAnalysis('gay_dating_apps_sentiment_merged.csv',
'general_dating_apps_sentiment_merged.csv', 'sentiment')

rating_stats = rating_analysis.perform_analysis()
sentiment_stats = sentiment_analysis.perform_analysis()

# Print the statistics
print("Statistics for Rating Analysis:")
for stat, value in rating_stats.items():
    print(f"{stat}: {value}")

print("\nStatistics for Sentiment Analysis:")
for stat, value in sentiment_stats.items():
    print(f"{stat}: {value}")
```

Appendix K: Notes On The Use Of Gay, Queer, LGBTQ

While the aim of the analysis was to focus on the experiences of gay men, it is important to note that some of the statistics presented may not be exclusive to this group. It is also important to recognize the nuance involved in terminology when it comes to sexual orientation and gender identity. In this analysis, sometimes the term "gay" was used to refer to gay and bisexual men for the sake of being parsimonious, but it is important to acknowledge that this term may not encompass the full range of experiences and identities within the LGBTQIA+

community.

Furthermore, when possible, the use of the term MSM (men who have sex with men) was avoided in this analysis because it overly focuses on the sexual aspect of same-sex relationships rather than the affection and emotional connections involved.

"Queer" has historically been used as a derogatory term to refer to individuals who do not conform to general standards of gender and sexuality. However, in recent years, many people within the LGBTQIA+ community have reclaimed the term and use it as an umbrella term to encompass a wide range of non-heterosexual and non-cisgender identities. In this work, the term Queer was used to refer to the large LGBTQIA+ community, including sexual and gender diversity.

While the term "LGBTQIA+" is used here, it is not an exhaustive list of all sexual orientations and gender identities. The community continues to evolve and expand, and some individuals may choose to use different terminology or identify with other labels.

Appendix L: AI Use Disclaimer

I have used AI tools for the word cloud association, as noted above. I have also used it as a grammar, conciseness and clarity checker for my writing.