A Tale of Two Platforms: A Comparative Analysis of Language Use in Consumer Complaints on Reddit and Spotify Community

by

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Abstract

Consumer complaints play a crucial role for companies in understanding customer needs and spotting areas of improvement. In the digital era, online platforms have become popular venues for users to voice their concerns. According to Communication Accommodation Theory (CAT) and recipient design, consumers may have different recipients in mind when writing a complaint and tailor their language accordingly. This thesis aims to examine language variations in consumer complaints on an independent platform and a corporate platform, exploring how consumers adjust their language based on the intended recipients of their complaints. Comments under complaint posts from Reddit's dedicated subreddit, r/Spotify, and from the Spotify Community were extracted and analyzed using the Linguistic Inquiry and Word Count (LIWC), a text analysis tool. This comparative analysis identified and compared various linguistic categories within the consumer complaints from the perspectives of formality, emotion, and assertion. The results showed that complaints on the corporate platform (1) used more formal language, (2) contained more negative emotional tones and emotion words, and (3) exhibited more assertiveness compared to those on the independent platform. Understanding the distinct linguistic features in consumer complaints on different platforms can help companies tailor their responses and address customer concerns effectively. This research contributes to the growing field of online consumer behavior by uncovering how language is employed within different online communities depending on the message recipient. Furthermore, it demonstrates the potential of LIWC as a valuable tool for analyzing unstructured consumer-generated content in diverse digital platforms, offering insights into user sentiment and experiences.

Keywords: online consumer complaint, language use, LIWC, comparative study, consumer behavior.

1. Introduction

Consumer complaints serve as valuable sources of feedback for businesses, allowing them to identify areas for improvement and enhance customer satisfaction. Before the advent of the Internet and social media, consumer complaints took place in private interactions, such as face-to-face conversations, written letters, and phone calls (Lee & Cude, 2012). As online platforms continue to gain prominence, they have become significant spaces for consumers to voice their concerns and complaints about products and services (Levy et al., 2012; Ward & Ostrom, 2006). With the diverse range of online platforms available, each with its unique characteristics and user dynamics, it becomes crucial to understand how the choice of platforms influences the language used in consumer complaints (Cheung & Thadani, 2012; Smith et al., 2012). Understanding these language variations helps researchers grasp how consumers adapt their communication to convey their complaints effectively. Additionally, it enables businesses to better manage their online reputation by addressing complaints in an appropriate and timely manner.

Guided by Communication Accommodation Theory (CAT), this thesis aims to explore the impact of online platform types on language use in online consumer complaints using Linguistic Inquiry and Word Count (LIWC), a text analysis software. Specifically, the study compares the language patterns exhibited in complaints related to the new user interface (UI) features of the Spotify mobile app, a popular music streaming service application. The complaints were collected from two popular online platforms: Reddit and the official Spotify Community website. By conducting an in-depth linguistic analysis, this research aims to identify and compare linguistic patterns in consumer complaints across the two types of online platforms and discuss the underlying reasons for these differences based on CAT.

This study adopts the following structure. In Section 2, the theoretical background is presented, with a specific focus on four key areas: (1) CAT, (2) consumer complaint platforms, (3) consumer reactions to UI changes, and (4) a review of the metrics used to assess the linguistic patterns of customer complaints. Section 3 details the methods of the text analysis and data analysis, while Section 4 provides the results obtained from testing the main hypotheses. Finally, a discussion section presents a summary of the main findings, theoretical contributions, the managerial implications of the study, the limitations, and directions for future research.

2. Literature review

2.1 Online consumer complaint platforms

Consumer complaint is a behavioral outcome of a perceived discrepancy between expected and actual product or service performance (Fincham, 1992; Kitapci et al., 2019; Kowalski, 1996; Singh, 1988). The discrepancy results in dissatisfaction, which is subsequently manifested through complaints (Heung & Lam, 2003). Complaining is a persuasive form of interpersonal communication to express frustrations and dissatisfactions to achieve intrapsychic (e.g., to make the consumers themselves feel better) or interpersonal goals (e.g., to request a refund) (Kowalski, 1996). Meanwhile, it also serves as an important communicative tool to redress grievances or call for company's remedial action (Alberts, 1998; Forneil & Westbrook, 1979). In other words, consumers can express their complaints either to bring about change or simply to feel better (Kowalski, 1996).

Online consumer complaints are complaints communicated through digital platforms or online channels (Hong & Lee, 2007). Discussion forums, review websites, blogs, company websites, social media platforms, and other online outlets – nowadays, online environments give consumers massive choices of channels to communicate with other consumers or firms. The characteristics of the platforms also influence consumers' interaction with each other or the company (e.g., Kundu & Chakraborti, 2020; Xu & Lee, 2020). These interactions are shaped by factors such as the platform interface design, communication features, and user engagement mechanisms (Law & Hsu, 2006).

There is currently no universally agreed-upon categorization framework for online complaint platforms (Kundu & Chakraborti, 2020). In general, depending on the platform creator, online complaint platforms can be classified as either marketer-generated or non-marketer-generated (Lee & Youn, 2009). For example, a shopping website is initiated by the marketer, whereas an independent review website (e.g., Tripadvisor) is not established by restaurants or museums seeking to promote their services (Kundu & Chakraborti, 2020). Kiecker and Cowles (2002) added message sender and internet environment as criteria and categorized electronic Word-of-Mouth (eWOM) platforms into four types: (a) spontaneous (initiated by own means, e.g., personal email account), (b) quasi-spontaneous (created by the marketers, carried out by consumers, e.g., brand official website), (c) independent (third-party sponsored, e.g., online forums) and (d) corporate-sponsored (marketers pay for selling or promotions, e.g., e-commerce websites) (Kiecker & Cowles, 2002; Kundu & Chakraborti, 2020; Tsao & Hsieh, 2015).

To study user-generated content instead of corporate-generated content, this research focuses on type (b) and (c) platforms. The key distinction between these two types of platforms lies solely in the initiator or creator of the website. In line with the purposes of this research, this study adopted the classifications established by Kiecker and Cowles (2002) and applied by Tsao and Hsieh (2015), which divide consumer complaint platforms into two categories: corporate and independent. Corporate platforms refer to communication that involves consumer reviews posted on websites operated by businesses for marketing their products or services (Tsao & Hsieh, 2015), such as the Spotify Community (https://community.spotify.com/). The Spotify Community is an online forum or discussion platform provided by Spotify for its users. It is a dedicated space where Spotify users can connect with each other, ask questions, provide feedback, and discuss various topics related to Spotify, music, playlists, and more. Platforms as such are established and operated by the companies themselves, providing a dedicated space for customers to share their feedback and engage in discussions.

In contrast, independent platforms are public online forums where individuals with shared interests or expertise gather without any monetary transactions involved (Tsao & Hsieh, 2015). As an example of an independent platform, Reddit is known for its diverse communities, "subreddits," and user-generated content. Users can discuss and share their experiences or grievances related to products, services, or companies in brand-related subreddits. These discussions can provide an avenue for consumers to seek advice, share feedback, or voice their complaints, potentially gaining attention from both fellow users and representatives of the companies in question. Independent platforms such as Reddit are not affiliated with any specific company.

A report by TNS NIPO (2011) reveals that 30% of consumers choose to post their complaints on corporate-generated platforms. In contrast, the remaining 70% of online complaints are submitted on non-corporate-generated platforms. The two types of platforms both host space for users to publicize their complaints, yet they exhibit one distinct difference (Golmohammadi et al., 2021; Xu & Lee, 2020). On corporate platforms, consumer complaints are exposed to both fellow consumers and the company's customer service team. For instance, Spotify's team actively engages with consumers to answer their questions and offer solutions to their problems with the app. On Reddit, interaction is primarily expected to occur among users without direct involvement from the company. Thus, on corporate platforms, consumers are aware that the team will read their posts and comments. They may hope the team will adopt their feedback and adjust their products accordingly (Xu & Lee, 2020). In contrast, Reddit users typically do not anticipate company involvement; instead, they often express their emotions and seek validation from others.

2.2 CAT, recipient design, and online consumer complaint

The theoretical background of this study lies in the Communication Accommodation Theory (CAT) (Giles, 1979). CAT describes individuals' behavioral adaptations to accommodate and adjust their communications depending on the environment (Giles, 2016). Individuals modify their verbal and nonverbal behavior based on their perceptions of social norms and the context of interaction (Gasiorek, 2016; Infante et al., 2009). These accommodation strategies are used to signal social identity, establish rapport, and achieve various communicative goals (Gasiorek, 2016).

Various constructs and theories across social science disciplines have attempted to explain communication adjustment, each addressing specific aspects of these phenomena (Gasiorek, 2016). Scholars have approached communication adjustment by considering its antecedents and consequences and exploring the behavior at various linguistic levels (Gasiorek, 2016). Several researchers proposed *recipient design* (e.g., Sacks et al., 1974; Schegloff, 1972; 1996). This construct claims that speakers "design talk with knowledge of the addressee or recipient in mind" (Gasiorek, 2016, *p*. 32). The result of this context sensitivity is the adjustment regarding factors such as word selection and topic selection (Sacks et al., 1974). For example, when a speaker delivers a presentation to interested laypeople, they tend to choose simple and accessible words to avoid confusion. When the audience is professionals, the speaker tends to use academic terms (Gasiorek, 2016). While this design operates in oral conversations, it also applies to written communication (Soliz et al., 2021). For example, Hilte et al. (2022) found that adolescents were found to adjust their writing style to the stereotypical writing style of the opposite sex in mixed-gender talk during online texting. When engaging in mixed-gender communication, as compared to single-gender communication, boys used more expressive language while girls used less.

This thesis is interested in how consumer communication style change when the recipients differ. The communication style in this thesis is reflected in the linguistic characteristics of online consumer complaints. The environments in which consumers' communication accommodation occurs are the platforms, which are social networks containing both social and technical aspects (Uhrig et al., 2010). The social elements include the participants on the platform, the imaginative recipient of their message, and their social relationships (Busch et al., 2016). The two platforms examined, Reddit and the Spotify Community, both offer a feature where users can post a thread without a word limit, and others can comment below and interact with each other by replying to either the comment or the original post (Law & Hsu, 2006). Thus, the technical elements will not be the focus of this study.

2.3 Analyzing linguistic patterns on different online platforms

In the context of online complaints, consumers adjust their communication styles to the characteristics of online interaction defined by the complaint channel and tailor their language to the recipients. Comparative studies revealed that the nature of the platform would determine the language patterns of the eWOM message. Online complaints occur (1) between consumers and their peer consumers and (2) between consumers and managers (Chen et al., 2019; Xu & Lee, 2020). Xu and Lee (2020) compared the linguistic characteristics of online consumer reviews of hotels from three platforms. They found that when the messages are facing a general audience on social media, the language was the least readable and diverse, yet the most subjective and had the most words and negative emotions; when the consumers are writing to the hotels directly on their direct-sale platform, their language was the least subjective and had the fewest words and negative emotions, and the language was most readable and diverse. Language on the third-party booking platform exhibits moderate levels of subjectivity, readability, and diversity.

Kundu and Chakraborti (2022) focused on dedicated review websites, social networking sites, and e-commerce platforms. The results showed that the dedicated review website (MouthShut.com) contained the highest percentage of positive reviews and the lowest percentage of negative reviews. The social networking site (Twitter) contained the highest number of negative reviews. The e-commerce website, on the other hand, yielded results that fell between the two extremes. Different motives behind online consumer review creation reflected the focus on different topics on three sites. The authors summarized four general motives: self-enhancement, sharing feelings, social concern, and consumer empowerment. Amazon has the highest number of motives covered, and the review portal MouthShut.com shows the least number of motives covered in the reviews.

Smith et al. (2012) compared sentiment toward brands in language use of brand-related user-generated content (UGC) on Twitter, Facebook, and YouTube. Although it was initially hypothesized that sentiment towards brands in brand-related UGC is similar across all three social media sites, the variance in sentiment can reflect the social norms, values, and purposes of the sites. YouTube, with its emphasis on self-promotion, features significantly fewer negative sentiments compared to Twitter and Facebook. Twitter and YouTube are commonly used for discussions and news sharing, making them convenient channels for consumer-marketer communication. Consumers express honest compliments or heartfelt negative comments based on their experiences with the product or service.

In the current research of eWOM, the predominant focus lies on consumer reviews and comments in a broad sense, encompassing both positive and negative feedback provided by consumers. Meanwhile, the industry-specific attention within this field has been largely confined to the hotel and tourism industry. This study aims to address this gap by narrowing the focus to negative reviews, specifically complaints, in order to provide valuable insights into how companies can manage consumer dissatisfaction with their products or services.

2.4 Consumer reactions to changes in UI design

A well-designed user interface requires constant updates to maintain its aesthetics, enhance its usability, and achieve optimal functionality (Bolsh, 1995). According to Bolsh (1995), UI design modifications can elicit both positive and negative responses from consumers. Positive reactions include enhanced user engagement, improved usability, and increased satisfaction, leading to higher retention rates and app loyalty. Necessary updates can lead to a better user experience and increased consumer satisfaction. However, consumers are naturally inclined to resist change because change can introduce unfamiliar elements, leading to a perception of losing control and security (Prochaska & Prochaska, 1999). Negative reactions encompass user frustration, resistance to change, and potential abandonment of the app. It necessitates consumers forgoing their interaction habits with the application or website interface and adapting to new features. Furthermore, the success of UI design changes relies on factors such as the clarity of communication regarding updates, the perceived value of the alterations, and the alignment with user preferences (Ziamou, 2002).

Human-computer interaction literature pinpointed the pivotal role of functionality in shaping consumers' responses to new interface (Akrimi, 2016). Ziamou (2002) claimed that marketers might face two major challenges when launching a new interface: identifying the optimal functionality for the novel technology and effectively communicating with consumers to reduce performance uncertainty and increase adoption intentions. Consumers show reduced uncertainty about the performance of a new interface and increased adoption intentions for a new interface when it's introduced with new functionality, as opposed to pre-existing features. Additionally, Semerádová & Weinlich (2020) highlighted the role of visual aesthetics in influencing consumer reactions, with visually appealing UI designs eliciting more favorable responses.

Overall, the findings underscore the need for app developers to carefully consider consumer preferences, communication strategies, the interface's functionality, and aesthetic elements while implementing changes to UI design on service apps to ensure positive user experiences and app retention. In the topic studied in this thesis, both new functionality and visual changes were implemented in the new user interface of the Spotify app. Based on the comments on online platforms, it is evident that consumers exhibited uncertainty and disapproval in response to these changes.

2.5 Development of key metrics and hypotheses

This study aims to investigate two online platforms to identify potential differences in linguistic patterns in consumer complaints. According to the concept of recipient design, consumers consider their intended recipients when writing complaints on various online platforms, reflected by linguistic patterns in their text. In this thesis, I examined linguistic patterns from three aspects: linguistic style (formality), emotional aspect (emotion), and cognitive aspect (assertion).

2.5.1 Formality

This category considered four variables: "WC" (total word count), "WPS" (average words per sentence), "Big Words" (percentage of words that are seven letters or longer), and "Swear Words." An independent platform gathers people of the same interests and allows them to build a relationship via frequent and active interaction (Xu & Lee, 2020). Considering the close social distance between consumers on independent platforms, I hypothesize that their linguistic patterns will appear more casual, yet when confronting customer service on official corporate websites, consumers might feel the pressure to use formal language due to the larger social distance (Xu & Lee, 2021).

WC (total word count): This variable counts the total number of words present in the analyzed text (Boyd et al., 2022). A higher word count may suggest a more formal style of writing or communication. Formal texts often tend to be more detailed, elaborate, and descriptive, leading to a larger number of words.

WPS (average words per sentence): The average words per sentence metric offers insights into the syntactic structure and complexity of the text. In formal language, sentences are generally longer and more complex, consisting of multiple clauses or subclauses (Beers & Nagy, 2007).

Big Words (percentage of words that are seven letters or longer): Formal language often employs a broader vocabulary, including more complex or sophisticated words. Consequently, a higher percentage of longer words in a text might indicate a more formal language style. Using complex words or a higher word-per-sentence ratio might indicate a more thoughtful and elaborative expression (Spitzley et al., 2022).

Swear Words: The latest version of the LIWC manual considered swear words as likely to express positive sentiment as negative ones, especially in informal contexts. However, the data set deals with complaints only. Thus, the swear words in these data are supposedly only used to intensify their negative sentiment. In LIWC dictionaries, all swear words were excluded from the emotional tone categories and subcategories. Swearing is related to emotional expression (Stephens & Zile, 2017). In informal settings, individuals tend to use more profanity compared to formal environments. For instance, places frequently visited by students, such as dormitories and pubs, were reported to have higher instances of swearing, whereas academic offices and campus service locations were rated as less likely locations for profanity (Jay & Janschewitz, 2008).

Based on these variables, Hypothesis 1 was formulated: Consumers will write more formal complaint messages on the corporate website than on the independent website.

2.5.2 Emotion

This category considered two major variables, the summary variable "Emotional Tone" and "Emotion." Emotions play a significant role in driving community interactions, thereby influencing consumer behaviors, as consumers seek avenues to vent, share, and connect with others on an emotional level (Kundu & Chakraborti, 2020). I also included the subordinate categories related to specific negative emotions available on LIWC: "ton_neg" (Negative Tone), "emo_neg" (Emotional Negativity), "emo_anx" (Emotional Anxiety), "emo_ang" (Emotional Anger), and "emo_sad" (Emotional Sadness).

Emotional Tone: Emotional tone is a psycholinguistic variable that counts both positive and negative emotion words and combines the results into a single variable (Boyd et al., 2022; Cohn et al., 2004). Values above 50 indicate a positive tone, whereas values below 50 are associated with a negative tone, representing feelings of anxiety, sadness, and hostility (Boyd et al., 2022). Robertson et al. (2021) established that low-rated reviews (i.e., negative reviews) tended to present negative emotions such as anxiety, sadness, and hostility.

Emotion: This variable counts all the words expressing emotion. LIWC provided measurements for various aspects of emotions, including overall negative emotions, negative emotional tones, and specific sentiments such as anxiety, anger, and sadness (Boyd et al., 2022). Given the availability of these measures, additional analyses were conducted to investigate the differences in subcategory variables. Since the focus of this study is on complaints, the presence of negative emotion words becomes particularly relevant and meaningful for drawing conclusions. The superordinate emotion categories include more words than their subordinate categories. For example, the “emo_neg” (emotional negativity) category contains many undifferentiated negative emotion words extending beyond the total of the emotional words for anxiety, anger, and sadness in their subordinate categories (Boyd et al., 2022). Emotion plays a significant role in achieving communication goals across various contexts, such as persuasion (Stiff & Mongeau, 2016), negotiation (Andrade & Ho, 2009), and conflict resolution (Halperin & Schwartz, 2010). Consequently, it is reasonable to expect that consumers will incorporate emotional language into their complaint messages as well.

Regarding the emotional perspective, it was challenging to predict the direction of the results. On the one hand, when consumers use the Spotify Community as a platform to communicate directly with the team, they may employ emotional appeals to make their comments more persuasive (Stiff & Mongeau, 2016). By incorporating negative emotions into their complaints, consumers aim to evoke a stronger response and urgency from the team in addressing their concerns. This emotional approach can potentially enhance the effectiveness of their complaints by gaining attention and eliciting the desired actions from the company.

On the other hand, according to Ward & Ostrom (2006), consumers might frame their complaints using negative emotions such as anger, frustration, and tiredness to persuade their fellow consumers and the public to shun and oppose firms that have failed their expectations for the product or service. When dissatisfied consumers express their complaints on Reddit, they are likely to employ emotion-laden words strategically to sway others into canceling their membership, thus amplifying the impact of their negative experiences. Furthermore, during interactions with fellow consumers, they may actively seek empathy, understanding, and a space to vent their emotions (Yin et al., 2014), strengthening the communal support and reinforcing the negative sentiment associated with their complaints.

Thus, two non-directional hypotheses were formulated:

Hypothesis 2A: Consumers will express more emotions when writing a complaint message on the corporate platform than on the independent platform.

Hypothesis 2B: Consumers will express more emotions when writing a complaint message on the independent platform than on the corporate platform.

2.5.3 Assertion

This category considered five variables, the summary variable, “Clout” (the power or influence of the text), “we” (the usage of first-person plural pronouns). “tentative” (uncertainty or hesitation in the text), “certitude” (the level of certainty or confidence), and “discrepancy” (the difference between expectations and reality). This category was established to account for potential variations in power dynamics between consumer-to-consumer interactions and consumer-to-company interactions. Galassi and Galassi (1978) described a few behavioral dimensions of assertiveness: (1) standing up for one’s rights; (2) initiating and refusing requests; (3) giving and receiving compliments; (4) initiating, maintaining, and terminating conversations; (5) expressing love and affection; (6) expressing personal opinions, including disagreement; and (7) expressing justified anger and annoyance (Richins, 1986). In the context of consumers defending their interest in the company, dimensions 1, 2, 4, 6, and 7 are relevant for consumer complaint behavior and a consumer-to-company relationship. I hypothesized that complaints directed toward other consumers are likely to exhibit assertive features through the use of a relatable and conversational tone, while complaints directed toward companies tend to be more assertive, confident, and focused on obtaining a resolution.

Tentative: The variable “tentative” refers to linguistic cues that convey uncertainty or hesitancy. It captures expressions of doubt or speculation in text. Example words are “maybe,” “perhaps,” and “guess” (Boyd et al., 2022). The variable allows for the analysis of the extent to which consumers express uncertainty or hesitation in their complaints or interactions, providing insights into their level of confidence.

Certitude: Boyd et al. (2022) noted that “certitude” appears to reflect a degree of bravado, “boasting of certainty that often reveals an insecurity or lack of truly verifiable, concrete information” (*p*. 17). Examples are: “I love you, really” or “I’m positive that I’ve studied enough.” (Boyd et al., 2022, *p*. 17). Consumers might employ such language to assert their grievances strongly and emphasize the validity and strength of their claims. It also indicates the intensity of their dissatisfaction or the need for resolution.

Clout: The Clout variable in LIWC reflects social status and confidence in written text (Boyd et al., 2022). The inclusion of words is based on the research findings that higher social power is associated with increased use of first-person plural pronouns and social words (e.g., lead, influence, connect, and engage) (Jordan et al., 2010; Kacewicz et al., 2013). These findings suggest that individuals with higher status focus on collectivity and direct their attention outward. By using such words, consumers may intend to indicate a conscious effort to assert their voice and potentially guide the outcome of the complaint.

Discrepancy: This variable focuses on linguistic cues that reflect the difference between expectations and reality (Boyd et al., 2022). It captures expressions of dissatisfaction, disappointment, or incongruity in text. In the analysis of complaints, the variable “discrepancy” allows for the examination of consumers’ expressions of dissatisfaction, highlighting the gaps between their expectations and the actual products or services received.

Based on these variables, Hypothesis 3 was established: Consumers will show more assertion in their language on the corporate platform than on the independent platform.

3. Methods

3.1 Data collection

The dataset for this research consists of consumer complaints about the latest features introduced to the Spotify home page User Interface (UI). The topic was selected because Spotify received backlash due to recent UI updates. The post on the Spotify Community (https://community.spotify.com/t5/App-Features/New-Home-Feed-Interface/td-p/5521360) quickly caused heated discussion among Spotify users, generating more than two thousand comments. Meanwhile, there has been a post on r/Spotify titled “Complaint Megathread” (https://www.reddit.com/r/spotify/comments/wc7sjj/complaint_megathread/) where users can share complaints and questions. It gathered more than 5.1 thousand comments, and a large proportion of them were about the new UI features. The substantial body of comments provides abundant materials to analyze and summarize the linguistic patterns within the texts.

I collected the complaints using the PRAW (Python Reddit API Wrapper) library to access the Reddit API (Proferes et al., 2021) and the Requests library to access the Spotify Community API (see Appendix for codes). The "community manager" @Loneliest_Cabin from the Spotify team launched an official response to all the comments under the post on the Spotify Community and closed it at 9:45 am (CET) on May 3rd. Thus, I extracted all the comments from both platforms until that time to exclude comments in response to @Loneliest_Cabin's comment. Only the comment text bodies were extracted, preserving both the text and emojis within the comment body.

3.2 Data cleaning

To clean the data, I removed irrelevant content such as duplicates, spam, non-English comments, official responses from the Spotify team on both platforms, and bot comments on Reddit. Some Reddit users believe that posts and comments under r/Spotify are moderated by the Spotify team. Thus, they promoted another independent subreddit, r/truespotify, which operates without the team's involvement. As this information is unrelated to the complaint, the comments promoting r/truespotify were filtered out from the text. Additionally, as the Reddit discussions included various topics, including cybersecurity, requests for user authentication, and old features, I further filtered out content that was not related to the newly introduced UI features.

The Reddit data cleaning process included the following steps by order:

1. Removal of duplicates
2. Removal of URLs
3. Removal of comments marked as [deleted] and [removed]
4. Removal of comments that do not contain at least one of the following keywords:
   a) Home page, homepage, discovery, discover weekly, shuffle, podcast, interface, layout, heart button, heart, like button, playlist button, like song, liked songs, search bar
   b) Tiktok, tik-tok
   c) UI, UX, ui, ux, design, update, feature
5. Removal of bot comments
6. Removal of response by the Spotify team
7. Removal of promotion for r/truespotify
8. Removal of comments on irrelevant topics: experiences being hacked, security, privacy, authentication (2FA), verification, and features and problems that have already existed before the new UI update.

The Spotify Community data cleaning process included the following steps:

1. Removal of duplicates
2. Removal of URLs
3. Removal of the three responses by the Spotify team
4. Removal of mentioning users' ID (starting with @)
5. Quotes from other users' comments

Steps 1-4 for Reddit (1-2 for Spotify) were implemented using Python and R, while steps 5-8 for Reddit (3-5 for Spotify) were implemented by manually searching for keywords in Microsoft Word. Eventually, the data cleaning yielded 4439 and 2298 comments from the Reddit and Spotify Community datasets, respectively.

3.3 Linguistic analysis

Unstructured online review text data is widely recognized as a rich source of information that reflects consumers' evaluations of products or services (Xiang et al., 2017; Zhan et al., 2009). In current consumer complaint literature, experiments and surveys have been the most employed methods (see Kitapci et al., 2019), despite the vast research resources available in the online environment. The seemingly overwhelming volume of online data poses a challenge for firms to read them one by one, yet with the help of computerized text analysis tools, firms can quantify and predict customer (Ferreira et al., 2023). For example, Ferreira et al. (2023) extracted reviews of three healthcare insurance companies from an online review platform. The findings proved that Linguistic Inquiry and Word Count (LIWC), one of the computerized text analyses, can predict consumers' evaluations of their customer-firm interactions even without a quantitative measurement, for example, a star-rating system.

Linguistic Inquiry and Word Count (LIWC) is a text analysis software that calculates the frequency and proportions of words falling into specific linguistic categories (Pennebaker et al., 2003). Compared to other computerized text analysis tools, LIWC stands out for its user-friendly nature and affordable cost, making it appealing to service firms looking to analyze customer feedback (Ferreira et al., 2023). It utilizes a language processing component and over 100 built-in dictionaries of words to analyze text data (Tausczik and Pennebaker, 2010). Each dictionary comprises a collection of words that define a particular category. LIWC compares each word in text data to the predetermined list of words in the LIWC-22 dictionaries and counts the number of words falling into each category (Boyd et al., 2022). This information will be presented as the percentage of words within a specific text (Ferreira et al., 2023). The categorization of the words provides insights into linguistic patterns (e.g., use of pronouns and emotion words) and psychological states.

In this case, comments from Reddit and the Spotify Community were saved into two separate Excel files. Each comment was placed in an individual cell under the same column. This way, LIWC could read the text in each cell and generate percentage statistics for each piece of comment separately.

3.4 Data analysis

A preliminary inspection of data revealed unequal variances and the violation of a normal distribution between the two groups in most variables. Thus, a bootstrapped Welch's *t*-test on SPSS was selected as the appropriate statistical test. Welch's *t*-test relaxes the assumption of equal variances and provides robustness against violations of this assumption (Delacre et al., 2017). Bootstrap resampling can provide a more robust approach than a standard *t*-test when the data does not follow a normal distribution, as it makes fewer assumptions about the underlying distribution (Wehrens et al., 2000). The bootstrapped Welch's *t*-test on SPSS was conducted to compare the means of the 16 selected LIWC categories between Reddit and the Spotify Community to identify significant differences in the linguistic features present in consumer complaints on the two platforms.

Since this study involves conducting multiple *t*-tests between two platforms, the chance of committing Type I errors (false positives) increases (Armstrong, 2014). To control Type I errors, a Bonferroni correction was conducted. The initial significance level was divided by the number of comparisons. In this case, I divided 0.05 by 15, which resulted in an α value of .003. Subsequently, when the significance level is below .003, the difference between the linguistic patterns of the two platforms is considered significant.

4. Results

4.1 Formality

Welch's *t*-tests were conducted to compare the mean scores of 4439 Reddit and 2298 Spotify Community (SC) comments on the chosen 16 variables. Given the large sample sizes, variances between the two datasets are not equal; confidence intervals and measures of significance were generally uninformative; most statistical tests were significant at $p < .001$ (Evans et al., 2021). After the application of Bonferroni correction, Welch's *t*-tests still yielded mostly significant results. Therefore, I combined this information with effect sizes.

As shown in Table 1, the results indicate significant differences between the two groups across the four variables. Specifically, consumers on SC wrote significantly more words ($t(2710.23) = 24.41$, $p < .001$, $d = .79$) and longer sentences ($t(3222.27) = 12.93$, $p < .001$, $d = .38$) and used more words containing seven or more letters ($t(5775.54) = 5.61$, $p < .001$, $d = -.13$) compared to consumers on Reddit. The message length on SC ($M = 69.72$, $SD = 75.46$) was more than twice that of Reddit ($M = 29.63$, $SD = 31.19$). Complaints on SC ($M = 17.84$, $SD = 14.01$) had sentences with an average of approximately four more words compared to Reddit ($M = 13.71$, $SD = 8.62$). The effect size for the difference in the use of big words was relatively small ($d = -.13$), although the difference is significant. Regarding the use of big words, the percentage data from the two groups differed by around 1% (SC: $M = 17.53$, $SD = 8.27$; Reddit: $M = 16.21$, $SD = 10.73$). Interestingly, Reddit users ($M = 1.15$, $SD = 4.51$) used swear words far more than SC users ($M = .09$, $SD = 1.17$) ($t(5496.46) = -14.79$, $p < .001$, $d = -.29$).

In summary, complaints on the Spotify Community (SC) tend to have a higher word count, longer sentences, and employ more complex vocabularies compared to complaints. On the other hand, complaints on Reddit were found to be shorter in length, featuring shorter sentences and fewer complex words. Notably, consumers tend to employ swear words significantly more on Reddit than on SC. These findings provide support for Hypothesis 1.

Table 1
T-test results comparing Formality variables

	SC		Reddit			
Variables	*M*	*SD*	*M*	*SD*	*p*	*d*
WC	69.72	75.46	29.63	31.19	< .001	-.79
WPS	17.84	14.01	13.71	8.62	< .001	-.38
BigWords	17.53	8.26	16.21	10.73	< .001	-.13
Swear words	.09	1.17	1.15	4.51	< .001	.29

4.2 Emotion

As shown in Table 2, the analysis of the summary variable, Emotional Tone, did not yield significant results ($t(4982.67) = -2.63$, $p = .009$, $d = -.07$). Interestingly, data from both platforms suggest an overall more negative tone in the language used (SC: $M = 41.04$, $SD = 33.73$; Reddit: $M = 43.39$, $SD = 36.53$). (Please note that an Emotional Tone score below 50 indicates a negative tone, with lower scores reflecting an increasingly negative emotional tone.) The lack of significance may be due to the inclusion of words indicating both positive and negative emotion tones in the summary variable. It is proved by the measurement of negative tone alone ($t(5278.99) = -4.36$, $p < .001$, $d = .11$), with SC complaints ($M = 2.54$, $SD = 4.01$) containing more words indicating a negative tone on average than Reddit complaints ($M = 2.06$, $SD = 4.65$). Regarding the variable "emotion," SC comments ($M = 2.09$, $SD = 3.53$) exhibited a higher score compared to Reddit comments ($M = 1.70$, $SD = 4.37$). This suggests that complaints expressed on SC contained a greater frequency of emotion words.

Regarding negative emotion, SC ($M = .64$ $SD = 1.47$) presented higher percentages of words falling in this category than Reddit ($M = .55$ $SD = 2.72$). Users on SC showed more anxiety in their language ($t(6355.24) = -14.79$, $p < .001$, $d = -.29$). The language expressing anger and sadness did not show any difference between the two platforms.

In general, SC users utilize a negative emotional tone and negative emotion words more frequently. Hypothesis 2A was supported.

Table 2
T-test results comparing Emotion variables

	SC		Reddit			
Variables	*M*	*SD*	*M*	*SD*	*p*	*d*
Tone	41.04	33.73	43.38	36.53	.009	-.07
ton_neg	2.54	4.01	2.06	4.65	< .001	.11
Emotion	2.09	3.53	2.06	4.65	< .001	.09
emo_neg	-.20	1.47	.55	2.72	< .001	.09
emo_ang	.47	1.52	.50	2.31	.303	-.01
emo_anx	.05	.39	.03	.36	.002	.08
emo_sad	.10	.90	.11	1.24	.683	-.01

4.3 Assertion

To assess assertion levels in the comments, variables related to tentativeness and certitude were examined. The *t*-test results showed no significant difference in tentativeness between the two platforms ($t(5754.96) = -1.45$, $p = .074$, $d = .03$). However, SC users ($M = 1.10$, $SD = 2.49$) demonstrated more certitude compared to Reddit users ($M = 0.86$, $SD = 3.41$) ($t(5999.14) = -3.37$, $p < .001$, $d = .08$). Data on the "discrepancy" variable also revealed that

SC consumers (*M* = 2.24, *SD* = 2.67) proposed more changes to the new UI updates than Reddit consumers (*M* = 1.92, *SD* = 3.40) ($t(5683.28) = -4.17$, $p < .001$, $d = .10$).

Regarding the "Clout" summary variable, although the *p*-value indicates a significant difference ($t(4704.29) = 0.09$, $p < .001$, $d = .002$), the actual difference between SC (*M* = 24.80, *SD* = 29.79) and Reddit (*M* = 23.73, *SD* = 30.94) is relatively small. Additionally, as the use of the first-person plural pronoun "we" is an important part of the "Clout" variable score, another *t*-test was conducted. SC users (*M* = 0.54, *SD* = 1.54) used "we" to refer to the consumer community significantly more frequently than Reddit users (*M* = 0.19, *SD* = 1.17) ($t(3702.99) = 9.50$, $p < .001$, $d = .27$).

In summary, the findings indicate that SC users exhibited more assertion in their complaints compared to Reddit users, supporting Hypothesis 3.

Table 3
T-test results comparing Assertion variables

	SC		Reddit			
Variables	*M*	*SD*	*M*	*SD*	*p*	*d*
Clout	23.80	29.79	23.74	30.94	< .001	.002
Tent	2.73	3.15	2.60	4.08	.074	.03
Certitude	1.10	2.49	.86	3.41	<.001	.08
We	.54	1.54	.19	1.17	< .001	.27
Discrep	2.23	2.67	1.92	3.40	< .001	.10

5. Discussion

Complaint content reflects product or service weaknesses and customer needs. However, in addition to "what" is expressed, "how" these complaints are expressed also holds significance for a company's relationship with consumers. This section presents the discussion of the results, the theoretical and managerial contributions of the study to existing knowledge, along with its limitations and suggestions for future research.

The goal of this study is to identify and compare linguistic patterns in consumer complaints across two different online platforms. Drawing from Communication Accommodation Theory and recipient design, the study examines three aspects of linguistic patterns that reflect consumers' linguistic adaptation when communicating with different recipients on online platforms. The results of Welch's *t*-tests revealed the following findings: (1) complaints on the corporate platform used more formal language compared to those on an independent platform, (2) complaints on the corporate platform contained more negative emotional tones and emotion words compared to those on an independent platform, and (3) complaints on the corporate platform exhibited more assertiveness compared to those on an independent platform. Communication Accommodation Theory provides a valuable lens to examine variations in language use across different online platforms. In general, this study aligns with the recipient design concept of the Communication Accommodation Theory, suggesting that consumers have a specific recipient in mind when composing their complaint messages and adapting their communication style accordingly (Gasiorek, 2016).

Regarding formality, the findings on word count and words per sentence differ from previous research conducted by Xu and Lee (2020), who found that consumers write longer messages on social media compared to corporate websites. In this study, consumers exerted more effort in writing reviews on the corporate website, as indicated by the longer length of their reviews. Consumers who only posted short messages may be less involved in the community compared to those who contributed more extensive content (Verbene et al., 2019). This active engagement within the community demonstrates that consumers treated the platform seriously and had corresponding expectations. Consumers may anticipate that the service will be changed in line with their complaints, so a clear and elaborated message will help in the communication. Furthermore, consumers tend to use longer and more complex vocabulary when communicating with the company. The length and complexity of words are often related to cognitive complexity (Lewis & Frank, 2016), where individuals may use more sophisticated language to convey complex ideas or demonstrate their knowledge of a subject. This choice can be influenced by the desire to maintain face (Xu & Lee, 2020). The fear of appearing incompetent or unknowledgeable in front of the company can drive consumers to opt for language that they believe reflects their level of competence and expertise. Similarly, Xu and Lee (2020) discovered that consumers used more diverse words to describe and evaluate hotel services on the corporate website while relying on repeated words to convey their feelings on social media. The language used on social media platforms is easier and more conversational to read and understand as the overall environment is more casual and relaxed compared to corporate websites.

The discrepancy in swear word usage reflects the formality of the language use as well as the difference in social norms between the two platforms. On independent platforms, users may perceive greater anonymity and freedom to express their frustrations without direct consequences from the company. This perceived anonymity can lead some users to feel more comfortable using strong language, including swearing, as a means of venting their dissatisfaction (Voggeser et al., 2018; Vranjes et al., 2020). In contrast, when posting on a corporate website, consumers may be more aware that their comments are likely to be seen by company representatives or other customers. This awareness may influence individuals to adopt a more restrained and formal tone, choosing to express their complaints using less explicit or offensive language.

Regarding emotions, when consumers directly address the company on the corporate platform, they employ emotional appeal to emphasize their frustration with a new UI update. By doing so, they aim to raise awareness within the company regarding the significance of the issue and urge timely improvements (Varela-Neira et al., 2010). Previous research revealed that consumers often turn to social media or blogs as a platform to vent their negative experiences when they feel they have no other means to express their emotions toward a company (Svari & Olsen, 2012). Yet this study showed that when a corporate website is open to hearing consumers' voices, consumers engage actively and reveal their genuine emotions to the company. This highlights the significance of establishing a direct channel for consumers to provide feedback to the company. By offering such a channel, companies can showcase their commitment to acknowledging and addressing consumer concerns, proving the importance they place on customer feedback (Varela-Neira et al., 2010). This, in turn, encourages consumers to actively engage and make efforts to have their voices heard, with the hope of resolving the issues they have encountered.

Regarding assertion, SC users exhibited more assertions in their complaints compared to Reddit users. Consumers on both platforms expressed similar levels of hesitation or uncertainty in their comments. However, SC users displayed a higher level of confidence or conviction in their complaints. Meanwhile, SC users were more inclined to request changes or express dissatisfaction with the product or service compared to Reddit users. They were more proactive in seeking improvements or addressing issues they encountered, highlighting a greater level of engagement and assertiveness. The Internet provides consumers with digital platforms to share information and opinions as a tool for consumer empowerment (Litvin et al., 2008). In fact, consumer empowerment has also been regarded as a motivation for consumers to share opinions online (Bronner & De Hoog, 2011). Although the overall "Clout" variable did not yield any significant results between the two groups, the use of the pronoun "we" showed that SC users have a stronger sense of community and identify themselves more closely with the collective consumer group. This approach helps convey a sense of unity and collective voice, which can be more effective when engaging with the company's representatives. Perhaps, when facing an issue with the company, the users could come together and unite as a cohesive group to confront the company, resulting in an "us versus them" dynamic.

Previous studies have consistently highlighted the value of social media as a platform for marketers to gather consumer opinions and facilitate consumer interactions (e.g., Smith et al., 2012). However, this research has uncovered another direction of the finding: the corporate website is also a valuable space for consumers to engage directly with the company. Consumers demonstrate a genuine interest in seeing tangible changes implemented by expressing a desire for their voices to be heard through their language use. This underscores the importance of providing consumers with avenues to communicate their concerns and expectations directly to the company, especially establishing an official corporate website as a platform for consumer-company interactions.

5.1 Theoretical contributions

This is the first comparative study that analyzes the language use in online consumer complaints on two platforms using LIWC. The use of LIWC as an analysis tool provides a standardized and quantitative approach to examining linguistic patterns in unstructured consumer-generated content in diverse digital platforms (Boyd et al., 2022). By utilizing LIWC, this study enhances our understanding of the specific linguistic features and patterns present in customer feedback, thereby contributing to the broader field of linguistics. This contributes to the methodological advancement in the field of online consumer behavior research and offers a replicable approach for future studies in similar contexts.

Meanwhile, this study also expanded the application of CAT and recipient design to the realm of consumer complaint handling. Recipient design focuses on how speakers shape their communication to match the expectations and characteristics of the intended audience (Gasiorek, 2016). Companies can receive consumer complaints through various platforms. The finding that consumers adapt their language to suit the specific platform indicates that individuals are conscious of the platform's nature and its typical audience. By adopting the recipient design perspective, this study explores how consumers accommodate their language use in complaint interactions based on the recipient (the company and its customer service team versus netizens in general) and context, shedding light on the dynamics of linguistic convergence and divergence in communication.

5.2 Managerial contributions

The results indicated that individuals are mindful of the recipients of their complaints when they share them on publicly accessible online platforms. The longer and more formal complaints on the corporate website suggest that customers make more efforts to write comments and treat the official website more seriously. They may have higher expectations when communicating directly with the company. This indicates the importance of providing comprehensive and professional responses to address their concerns.

The presence of more negative emotional tones and emotion words signals a high emotional intensity among customers when communicating directly with the companies. The emotional complaints highlight consumers' need to improve the product or service, but it is also detrimental to the reputation of the business of the company (Kundu & Chakraborti, 2020). Effective customer complaint management requires managers to prioritize the emotional aspects of the feedback and respond with empathy.

In addition, the observed assertion in complaints on the corporate website implies a perceived power imbalance between customers and the company. To create a balanced and respectful communication environment, managers should be sensitive to these power imbalances and avoid using their authority in ways that may intimidate or dismiss customer concerns (Xia, 2013). Instead, they should foster an atmosphere of mutual respect and understanding where customers' perspectives are valued and acknowledged.

Overall, the differences between complaints on the corporate website and independent platforms indicate the need for tailored complaint-handling strategies. Besides the official corporate website, Reddit also attracts massive traffic and active consumer engagement. Companies should incorporate different platforms for feedback collection and develop platform-specific approaches for addressing complaints, considering customers' distinct characteristics in language use and expectations on each platform (Smith et al., 2012).

5.3 Limitations

The limitations of this research are threefold. Firstly, programs such as LIWC analyze text at the word level, which causes them to overlook context, irony, sarcasm, and idioms (Evans et al., 2021; Moore et al., 2021). The misinterpretation of the word's contextual meaning might lead to inaccurate data. While it may not capture all nuances, LIWC can efficiently analyze massive volumes of unstructured data available online and generate quantitative insights into linguistic patterns (Ferreira et al., 2023). Despite its crude calculation approach, using LIWC is more time-efficient and practical than manually coding every word in a corpus with thousands of text pieces. Given the wide range of text mining techniques available, future comparative research can verify the robustness of the results by employing alternative data processing techniques (Geng et al., 2020).

Secondly, the effect sizes observed in this study are generally not substantial, except for a few variables such as word count, words per sentence, and swear words. However, this small effect size can be attributed to the significant variances observed across all measurements (Bakker et al., 2019). The presence of significant variances within the data, serving as the denominator for Cohen's *d*, can lead to small effect sizes. Controlling this factor was challenging in this thesis as the comments were collected without selection or manipulation. The variances observed reflect how consumers leave comments and interact with one another in a naturalistic setting. Additionally, Cheung and Slavin (2016) reported that average effect sizes in studies with sample sizes up to 100 were approximately 3.5 times greater than in studies with larger samples (2000+): 0.38 versus 0.11. Therefore, despite the small effect size, the findings of this study still carry real-life significance.

Thirdly, the data source in this study only consisted of consumer complaints about one specific topic on two online platforms. Different platforms attract diverse demographics and might have unique features that could influence the way consumers express their complaints. While the findings of this study offer insights into the influence of recipient and platform type on the linguistic patterns of consumer complaints, it is possible that data from other types of online platforms (such as social media platforms like Twitter and Facebook or dedicated review websites like Tripadvisor) could provide different perspectives. Future research should explore additional platforms to understand how different factors influence the linguistic patterns of consumer complaints. By considering platform features and design (e.g., word limit and content presentation), audience, and culture, as well as anonymity and publicity, researchers can gain insights into how consumers interact differently on various platforms, leading to diverse language use in their complaints.

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Appendix

Codes for Scraping and Filtering Comments on Reddit and the Spotify Community

For display purposes, in the following codes, the files to be processed were uniformly named "input.txt," and the files produced by the program were named "output.txt." The original input and output files were uploaded to Research Information Services (RIS).

Step 0a: Scrape comments from Reddit

```
import praw
import math

# authenticate to Reddit API
reddit = praw.Reddit(client_id='EskwcO6JSqqeGHCFgdhSuw',
                     client_secret='hlP3FHqbqnmGjOkasYj7l71kQwfyNQ',
                     user_agent='final')

# specify the subreddit and thread ID
subreddit = reddit.subreddit('spotify')
thread_id = 'wc7sjj'

# get the submission object for the thread
submission = reddit.submission(id=thread_id)

# define a recursive function to print out comment tree with indentation
def print_comment_tree(comment, indent=0, file=None):
    print('  ' * indent + comment.body, file=file)
    for reply in comment.replies:
        print_comment_tree(reply, indent+1, file=file)

# flatten comment tree and sort by score (highest first)
submission.comment_sort = 'top'
submission.comments.replace_more(limit=None)
comments = submission.comments.list()
comments = sorted(comments, key=lambda x: x.score, reverse=True)

# print out the comment tree to files
chunk_size = 40
num_files = math.ceil(len(comments) / chunk_size)
for i in range(num_files):
    start_idx = i * chunk_size
    end_idx = (i+1) * chunk_size
    chunk_comments = comments[start_idx:end_idx]
    with open(f'output_{i+1}.txt', 'w') as f:
        for j, comment in enumerate(chunk_comments):
            print(f'Comment {j+start_idx+1}:', file=f)
            print_comment_tree(comment, file=f)
            print('\n', file=f)
```

Step 0b: Scrape comments from the Spotify Community

```
import requests
from bs4 import BeautifulSoup

# Define the base URL and number of pages to scrape
base_url = 'https://community.spotify.com/t5/App-Features/New-Home-Feed-
```

```
Interface/td-p/5521360/page/'
num_pages = 117

# Loop through each page and scrape the comments
for i in range(1, num_pages+1):
    # Send a GET request to the URL
    url = base_url + str(i)
    response = requests.get(url)

    # Parse the HTML content using BeautifulSoup
    soup = BeautifulSoup(response.content, 'html.parser')

    # Find the HTML elements that contain the comments
    comments = soup.find_all('div', class_='lia-message-body-content')

    # Save the comments to a text file for this page
    with open(f'comments_page{i}.txt', 'w') as f:
        for comment in comments:
            f.write(comment.get_text() + '\n')

    # Print a message indicating that the comments for this page have
been saved
    print(f'Saved comments for page {i}')
```

Step 1: Remove duplicates from the Reddit data:

```
# read the file
data <- readLines("input.txt")

# remove duplicates
unique_data <- unique(data)

# write the new data to a new file
writeLines(clean_data, "output.txt")
```

Step 2: Remove comments containing [deleted] and [removed] from the Reddit data:

```
# read the file
data <- readLines("input.txt")

# remove "[deleted]" and "[removed]"
clean_data <- gsub("\\[deleted\\]|\\[removed\\]", "", unique_data)

# write the new data to a new file
writeLines(clean_data, "output.txt")
```

Step 3: Remove URLs for both datasets:

```
# Read the text file
text <- readLines("input.txt")

# Define a regular expression pattern to match URLs
```

```
url_pattern <- "http[s]?://(?:[a-zA-Z]|[0-9]|[$-
_@.&+]|[!*\\(\\),]|(?:%[0-9a-fA-F][0-9a-fA-F]))+"

# Remove URLs from the text
clean_text <- gsub(url_pattern, "", text)

# Write the cleaned text to a new file
writeLines(clean_text, "output.txt")
```

Step 4: Filter out irrelevant comments according to keywords for the Reddit data

```
# Read in the input file
input_file <- readLines("input.txt")

# Define the keywords to search for
keywords <- c("Home page", "homepage", "discovery", "discover weekly",
"shuffle",
              "podcast", "interface", "layout", "heart button", "heart",
"like button",
              "playlist button", "like song", "liked songs", "search
bar", "Tiktok",
              "tik-tok", "UI", "UX", "ui", "design", "update", "feature")

# Define a function to check if a unit contains any of the keywords
check_keywords <- function(unit) {
  any(sapply(keywords, grepl, unit, ignore.case = TRUE))
}

# Initialize an empty vector to hold the filtered units
filtered_units <- c()

# Initialize an empty vector to hold the current unit's lines
current_unit_lines <- c()

# Iterate through each line in the input file and filter out units that
don't contain keywords
for (line in input_file) {
  if (grepl("^Comment \\d+:$", line)) {  # Start of a new unit
    if (check_keywords(paste(current_unit_lines, collapse = "\n"))) {  #
If the previous unit contains keywords, add it to the output
      filtered_units <- c(filtered_units, current_unit_lines)
    }
    current_unit_lines <- c(line)
  } else {
    current_unit_lines <- c(current_unit_lines, line)
  }
}

# Add the last unit to the output if it contains keywords
if (check_keywords(paste(current_unit_lines, collapse = "\n"))) {
  filtered_units <- c(filtered_units, current_unit_lines)
}

# Write the filtered units to a new file
writeLines(filtered_units, "output.txt")
```