

Gaming Sentiment: The Relationship of Comment Sentiment and Subscriber Growth Rate

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ABSTRACT

The following research paper explores the potential relationship between comment sentiment and subscriber growth rate on YouTube gaming channels. This study aims to discover if the effect that YouTube comments have on users' perceptiveness of video content extends to their decision in subscribing to those channels. A sentiment analysis was utilized using Python programming in order to derive the data from various YouTube comment sections. This was compared with the monthly subscriber growth of each channel studied. Results indicate that there is no correlation between comment sentiment and subscriber growth rate for YouTube gaming channels. This implies that gaming content creators should not be wary of the positive or negative comments within their video comment threads and should focus on other areas to grow their channel. However, further research is required in order to verify the results of this study.

Introduction

YouTube is one of the most famous video sharing platforms of this era. With over two billion active users, the website has managed to captivate one-third of the entire Internet with its content (YouTube, 2020). This immense audience has attracted even more content creators who hope to make a name for themselves. Not only do those successful on YouTube gain fame, they also gain careers. Taking advantage of its enormous user base, YouTube exposes users to ads on content creators' videos. While the company does still take a portion of the money paid by advertisers, content creators can still make money off of these ads. PewDiePie, one of the top YouTubers in the world, rakes in millions of dollars from ad revenue due to his high view rates and his subscriber base of over 100 million (Social Blade, 2020). His viewers are enticed by the channel's one goal: to play video games.

Gaming has seen a meteoric rise in popularity over the past decade. People like PewDiePie have made gaming their career, creating YouTube channels and posting videos regularly. These content creators for gaming channels, who are sometimes referred to as commentators, need to consider their audience when creating content to maximize their views. In order to accomplish this, they need subscribers.

Subscribers are what breathe life into a commentator's channel. Postigo (2016) deems subscribers as the social currency of YouTube because they bring in consistent views to channels. When users subscribe to a channel, they will receive video updates from that channel's content creator (p. 7). This allows subscribers to keep track of their favorite channels, which helps commentators bring in constant views that eventually turn into stable ad revenue. As channels generate these views from engaged users, they are able to create a flourishing community that represents the views of those that are subscribed and those that are unsubscribed. These points of view are generated in the comments section of each video produced by a channel.

The YouTube comment section has become a frequently used feature to provide feedback on videos or to engage in discussions with other users. The heart of a channel's community is represented here, with various users forming their opinions and engaging in discussions on what they just watched. The comments section has provided an essential experience to YouTube because after watching a video, people seek related information to what they just

watched (Choi & Segev, 2020). Since the most convenient place to find this related information is the comments section, many users are exposed to the opinions and discussions of other engaged users. However, as a video attains more views, the popularity of that video increases as well. This causes the comments to increase significantly as well because the more popular the video, the more likely users will comment below (Hoiles, Krishnamurthy, & Pattanayak, 2020). Users will likely not bother with potentially reading hundreds of comments, so it is safe to assume that the majority of users would read up to the first 25 to 50 comments at the top of the thread. These comments are the most important comments of the video because they are the first viewpoints that users will see. Users may even be influenced by what these comments have to say.

A study done by Peter Schultes, a graduate student at the University of Passau, investigated the relationship between comment types and its influence on viewers' perception of a video. By classifying comments into three categories (substantial, inferior, and discussion), Schultes was able to derive these types of comments from a variety of categories on YouTube, including gaming. Through an analysis of the effect that these comment types have on the likes and dislikes of a video, the process determined that in general, comments have an influence on viewers' perception of a video (Schultes et al., 2013). Additionally, Schultes confirmed that users often communicate their own emotions through comments. This means that viewers' perceptions can be changed by the whims of an emotional comments section. In the gaming category of YouTube, this happens to be the case. Schultes's data indicated that 26% of the comments in the gaming category of YouTube, which consisted of shoutouts and offensive posts, showed strong emotional feelings. Emotional sentiment is not limited to these comments, which means that ample sentiment is shown in the other 74%. Gaming channels have the capability to take the abundant sentiment shown in their comment sections and use it to their advantage.

As stated before, commentators need subscribers to grow their channel. In order to gain subscribers, these content creators need to create engaging videos that viewers would enjoy. In his paper describing the benefits of digital labor, Hector Postigo, an associate professor at Temple University, states that happy viewers subscribe and unhappy viewers do not subscribe to YouTube channels (Postigo, 2016). If this is the case, then commentators can take advantage of this concept by promoting positive sentiment within their comments section. By inducing positive emotions within their comment sections, commentators can influence viewers into perceiving their videos positively as well. This results in "happy" viewers, which makes them more likely to subscribe.

However, this approach needs to be verified before it can be put to use by commentators. Identifying sentiment within YouTube comments is key to validating this method; in order to accomplish this, a sentiment analysis is required. Sentiment analysis can be defined as a text classification system in which a machine obtains sentiment from a text as any other human would when reading it (Das, 2017). Numerous studies have utilized a sentiment analysis program to accomplish their goals. Jaime Mendes Gouveia Batalha Reis, a graduate student from NOVA Information Management School, created a sentiment analysis device that studied the comments of Twitch, one of the largest live streaming platforms for video games. Reis derived sentiment from livestream comments during events such as the opening ceremony of Blizzcon 2018. The overall sentiment from the livestream comments were segmented according to the time in which new announcements were made. For example, the highest positive sentiment was received during the surprise announcement of the "Warcraft 3 Remastered" game. The most negative sentiment was received from the "Diablo Immortal" announcement because the fans expectations for the game were not met (Reis, 2020). This use of sentiment analysis was important in acquiring the attitude and overall feedback of the livestream's viewers during separate times, which can prove useful to Blizzard Entertainment, the organization that ran Blizzcon 2018. Similar to how Reis's sentiment analysis can prove to be useful to Blizzard, a sentiment analysis of YouTube comments can prove to be useful to content creators as well.

Studies in the past have conducted a sentiment analysis on YouTube comments. In his study, Stefan Siersdorfer, who works at the L3S Research Center, analyzed the sentiment of YouTube comments and compared it to community feedback, which constitutes the "Likes" and "Dislikes" of a video. After conducting a sentiment analysis and using prediction models on 6.1 million comments contained in 67,290 videos, Siersdorfer et al. concluded that community feedback is dependent on the sentiment of comments (Siersdorfer et al., 2010). These results indicate that

a sentiment analysis of YouTube comments is feasible and can provide insights into various relationships. While Siersdorfer et al. mainly investigated the community within YouTube channels, other studies have investigated on a more large-scale using comment sentiment. Amar Krishna, a graduate research assistant from Iowa State University, conducted a sentiment analysis on YouTube comments in order to discover a potential influence on real world events. Through their data analysis of more than 4 million comments across more than 3,000 videos, Krishna et al. concluded that the sentiment expressed in YouTube comments is closely related to real world events. This conclusion was based on the sentiment of YouTube comments with the key phrase “Dow Jones.” The sentiment of these comments related closely to the real time fluctuations of the Dow Jones index (Krishna et al., 2013). Even though this was only one of the three topics that Krishna pursued in his research, it provides further validation to the idea that there are more relationships stemming from the sentiment of YouTube comments.

Despite the numerous studies conducted on YouTube comments, there has yet to be a study that focuses on the relationship between comment sentiment and subscribership. Studies such as those of Siersdorfer et al. focused more internally on community feedback and studies such as those of Krishna et al. focused more externally on real world events. Little research has been conducted on comment sentiment in relation to an aspect that would benefit content creators, who create the videos containing those comments. Investigating the relationship between comment sentiment and subscriber growth within a content creator's videos would provide invaluable insights. Those that are serious about expanding their channel, which include commentators, could potentially grow their career from knowing more about the relationship between comment sentiment and subscriber growth.

This just begs the question: Does YouTube comment sentiment affect gaming channels' subscriber growth rate? My research aims to address this question. Through a sentiment analysis of the comments contained in their respective gaming channels, I plan to compare these results to the subscriber growth rates within specific periods of time. These results will help to verify if viewers are indeed positively influenced by positive sentiment expressed in comments and vice versa. My study differs extensively from the studies related to YouTube comment sentiment because it researches the decision for viewers to subscribe based on the comments they viewed. My research is also exclusive to gaming channels, which is unlike other studies. Finally, my research analyzes the sentiment of the first page of comments on videos. Since this study is aimed towards the users themselves, the first page of comments are the most relevant because these are the comments that are exposed to the majority of viewers. My approach is promising in providing the insights into whether viewers are influenced by the sentiment of comments when subscribing to gaming channels.

Method

In order to compare the sentiment that viewers have towards a channel's videos to subscriber growth rate, a content analysis was required. Specifically, a sentiment analysis of the comments on a channel's individual videos was needed. Similar studies have studied the sentiment of individual videos for a macro purpose. For example, a peer-review study conducted a sentiment analysis on user comments from specific YouTube videos to derive the most relevant videos through search parameters (Bhuiyan et al., 2017). Similarly, within my study, a sentiment analysis was conducted on specific videos of YouTube channels over the span of an entire year. Thirty channels were selected, which were separated into three categories based on the main game the channel covered. In an effort to combat confounding variables, all channels selected had a subscriber base between 100,000 to 400,000. For each channel, up to a maximum of 120 videos were individually analyzed and separated by the month they were uploaded to YouTube.

This procedure revolved around using a coding language. Utilizing a coding language was an important aspect to my research because it hastened the process of collecting data. Collecting comments on each video in a year for each channel required too much manual work. With a coding language, I simply created a program that automated the process of collecting comments and calculating its sentiment. The coding language that was used to create this program was Python. Python is a strong general-purpose programming language that is especially helpful in data

science. Its easy-to-use syntax allowed me to execute code in a much more efficient way than any other language (See Appendix A for full code).

The three games that were studied were Minecraft, Rainbow Six Siege, and League of Legends. All three of these games are significantly different from each other. Minecraft is an open world, sandbox video game that puts an emphasis on building and creativity. The game is deemed appropriate for those ages 6 and up (Short, 2012). Rainbow Six Siege is a first person shooter (FPS) game that puts an emphasis on tactics. The video game has some gore and warns players that may have epilepsy beforehand (Asadi & Hemadi, 2018). League of Legends is a multiplayer online battle arena (MOBA) game that puts an emphasis on team-based gameplay and strategy through objective capturing and NPC management (Ferrari, 2013). These games cover a wide base of the different genres of video games, which help to verify the method and research question (See Appendix B for channels studied).

When selecting the ideal channels to study, the website, *Channel Crawler*, was utilized. *Channel Crawler* allows the user to set specific parameters in order to search for specific YouTube channels. This allowed for the selection of channels for each game to be efficient and accurate. A total of ten channels were selected from *Channel Crawler* for each game category.

Figure 1
Search Parameters

The screenshot shows the search interface of Channel Crawler. It features several input fields and filters:

- Channel Name:** An empty text input field.
- Category:** A dropdown menu with "Gaming" selected and a search icon.
- Topics:** A dropdown menu with "Search" selected.
- Language:** A dropdown menu with "English" selected and a search icon.
- Countries:** A dropdown menu with "Search" selected.
- Creation Date:** Two input fields labeled "Min" and "Max" followed by "days ago".
- Subscribers:** Two input fields with values "100000" and "400000".
- Total Views:** Two input fields labeled "Min" and "Max".
- Total Videos:** Two input fields labeled "Min" and "Max".
- Latest Video:** Two input fields labeled "Min" and "Max" followed by "days ago".
- Keywords:** A text input field containing "Minecraft".

At the bottom, there is a red "Search" button and a white "Add Channel" button. A tip below the keywords field reads: "(Tip: enter i.e. -minecraft to exclude Minecraft channels from your search)".

Note. The image depicts the search parameters on the website *Channel Crawler* when selecting YouTube channels specializing in the game Minecraft.

To obtain comments from videos, I utilized an application programming interface — commonly referred to as an API — offered by YouTube. The YouTube API allows for the incorporation of functions ordinarily executed on the YouTube website into one’s own interface or project (YouTube, n.d.). After creating a developer account on Google, I was able to use my developer key to access all the videos and comments posted on YouTube’s website. I used Python programming in order to utilize the YouTube API because Python is able to easily link the comment extraction process to the sentiment analysis process. My Python algorithm for comment extraction worked as follows:

1. Accessing the YouTube API through my developer key.
2. Call the commentThread function to obtain the first page of comments for a video. For each video, copy and paste the Video ID found in the URL to the API parameters for the function.
3. Write each comment onto a local CSV (Comma-separated values) file. Each comment would be contained as a single line on the file.

An amount of 10 videos were studied for each month due to the collection process requiring an abundance of manual work through copying and pasting Video ID’s. If there are more than 10 videos posted during a month for

a channel, a systematic sampling approach will be taken in which every other video will be analyzed. The reason for this approach was to capture the sentiment of the channel throughout the entire month. At most, a channel will have 120 videos analyzed for all 12 months. This was a significant limitation to the study, as analyzing less videos can yield less accuracy of data.

In order to conduct a sentiment analysis on each comment, I used a Python library called VADER Sentiment. Compared to other text analysis tools, VADER was chosen because it performs at a higher, more accurate level. A peer-review study on the performance rates of different sentiment analysis tools revealed that VADER performed better than eleven other highly acclaimed analysis tools (Hutto & Gilbert, 2014). Through inputting raw text, VADER can return a positive and negative score. A score of 0.0 in the positive section translates to no positive sentiment detected and a score of 1.0 translates to extremely positive sentiment. A score of 0.0 in the negative section translates to no negative sentiment detected and a score of 1.0 translates to extremely negative sentiment. In the CSV file containing all the comments collected for a video, each line was separately assessed with the sentiment analysis machine because each line represented one comment. When determining the final sentiment score for each comment, the following formula was utilized: $Final\ Sentiment\ Score = Positive\ Score - Negative\ Score$

A final sentiment score above zero means that the comment has more positive sentiment and a score below zero means that the comment contains more negative sentiment. The overall sentiment score for each video was calculated through the following formula:

$$Overall\ Sentiment\ Score = \frac{sum(Final\ Sentiment\ Scores)}{Number\ of\ Comments}$$

In very rare cases, a comment may contain no positive or negative sentiment. These comments were excluded from the calculation of the overall sentiment score because the focus of this study revolves around the effect of positive and negative sentiment on users' decision to subscribe. This study based any sentiment scores without positive or negative sentiment as null, having no influence on the user. Using these scores in the overall sentiment score was deemed to impair the results of the data because it would affect the calculations of the results, yet continue to indicate no positive or negative sentiment displayed.

Figure 2
Sample Sentiment Data

Channel: Sirud						
YEAR 2020	January	February	March	April	May	June
Video #1 Sent.	0.27107	0.28025	0.17630	0.19913	0.31064	0.03741
Video #2 Sent.	0.10113	0.29167	0.00867	0.16969	0.26982	0.12767
Video #3 Sent.	0.24017	0.19060	0.33915	0.23947	0.29040	0.37830
Video #4 Sent.	0.37714	0.26809	0.35557	0.24760	0.21830	0.27320
Video #5 Sent.	0.01629	-0.10310	0.28245	0.19536	0.15307	0.19983
Video #6 Sent.	0.28390	0.19800	0.23013	0.12082	0.21838	0.11113
Video #7 Sent.	0.17864	0.24150	0.23600	0.07973	0.49071	0.11380
Video #8 Sent.	-0.14683	0.22080	0.18289	0.28550	0.35727	0.08036
Video #9 Sent.	0.05862	0.30615	0.29500	0.26631	0.31800	0.26867
Video #10 Sent.	0.09000	0.08750	0.23017	0.13975	0.13645	0.15550
Avg Sentiment	0.14701	0.19815	0.23363	0.19434	0.27631	0.17459

Note. This image depicts data collected on the comment sentiment from Sirud, a Minecraft channel, studied through the months January through June.

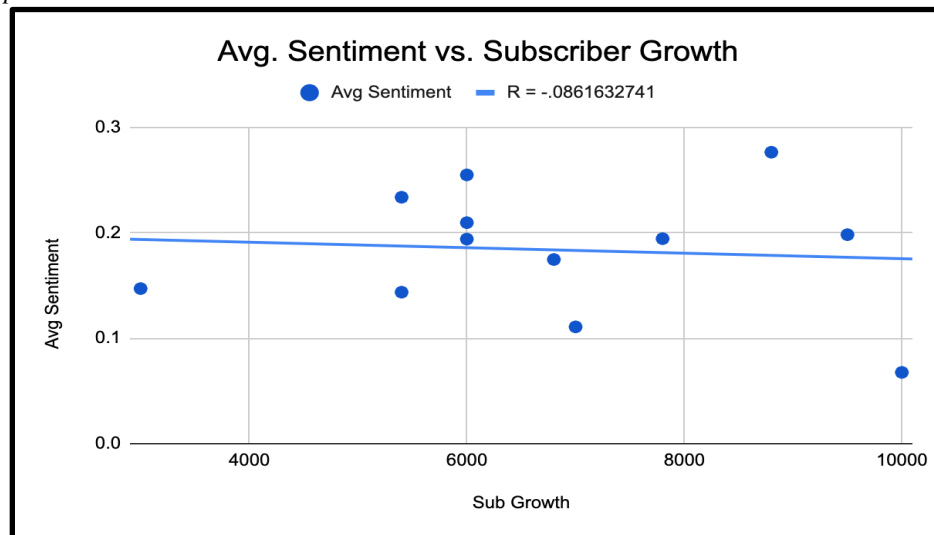
After gathering the sentiment from all 30 channels over the span of the year 2020, the subscriber growth for each channel was collected. I used the website, *SocialBlade*, to accomplish this task. *SocialBlade* is a social media analytics website that is separate from YouTube. The website tracks and collects intricate statistics on YouTube channels regarding factors such as subscriber base and views (Tan et al., 2018). Within *SocialBlade*, there are statistics on subscriber growth on a monthly basis for every channel. These statistics were used to compare the number of subscribers gained for each month with the mean of the overall sentiment scores for each month. This procedure was accomplished for each channel.

Results

After completing the data collection process, some deviations were seen from the data collected. While the intention was to collect sentiment from ten videos per month for each channel, some channels did not have sufficient videos posted each month. At times, content creators posted 15 videos in a month, but other times they posted around three to five videos in a month. Furthermore, there were rare cases in which there were not enough comments to fill up the first page of a comment thread, which was the intended area of the data collection process. In these instances, only a few comments were analyzed instead of a full page of comments, which consists of about 20 comments.

Functions from Google Sheets were utilized in calculating the results of this study. An initial analysis of the channel data sets collected revealed a low association between comment sentiment and subscriber growth rate. Through the comparison of each channel based on average monthly comment sentiment and monthly subscriber growth, mostly low Pearson correlation coefficient values were computed. For example, Sirud, one of the Minecraft channels studied, displayed a correlation coefficient of approximately -0.0862, which is consistent with many of the other channels studied. However, some channels displayed a high individual correlation with comment sentiment and subscriber growth. Channels studied such as Avomance, a Minecraft channel, and Virkayu, a League of Legends channel, produced correlation coefficients with magnitudes above 0.7.

Graph 1. Sample Correlation Data

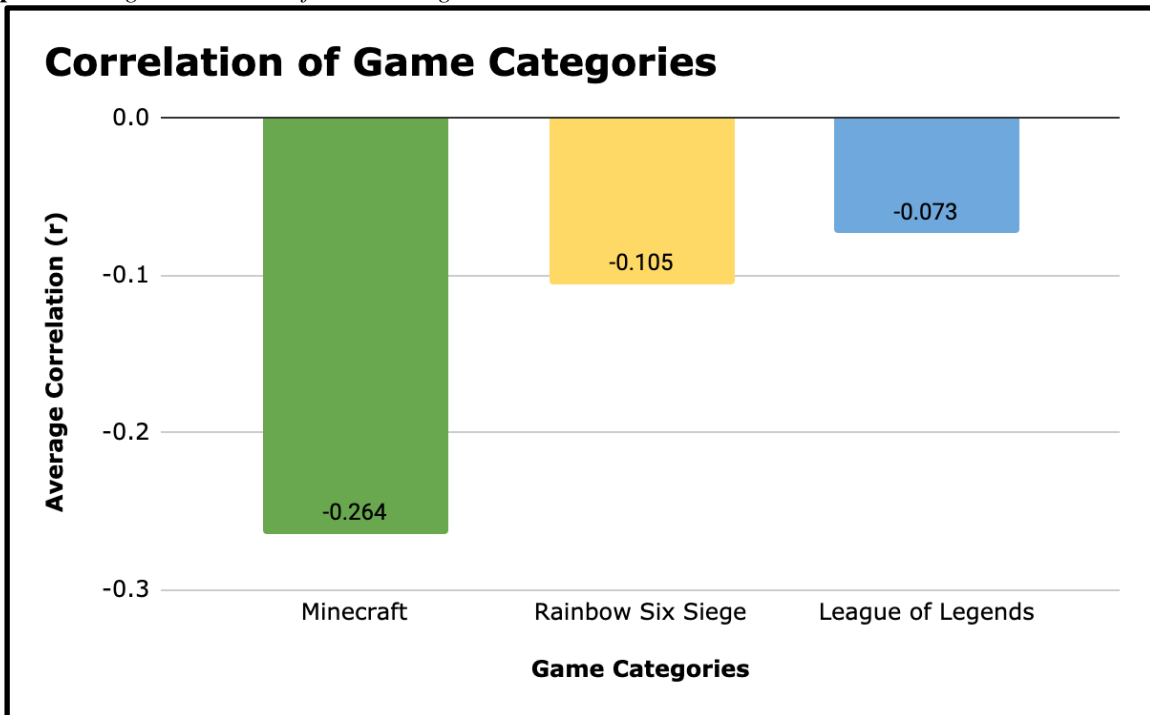


Note. This image depicts sample data from Sirud, a Minecraft channel.

Afterwards, the average correlation was calculated for each game category. In order to calculate the average correlation for each game category studied, a Fisher Z Transformation was utilized. When calculating the mean of correlation coefficients, they needed to be transformed into different values, as the coefficients cannot be averaged together alone. A Fisher Z Transformation allows for correlation coefficients to be converted into z-scores. After

calculating the mean of the z-scores, the value is converted back into a correlation coefficient using an inverse Fisher Z Transformation.

Graph 2. Average Correlation of Game Categories

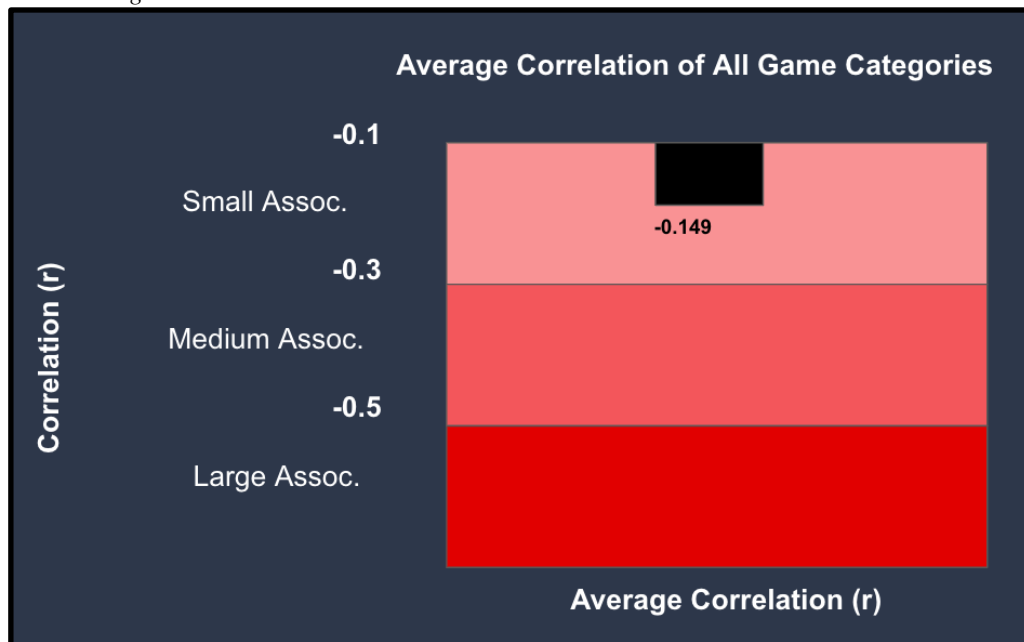


Note. This image depicts the average correlation coefficients of each game category studied.

Cohen’s d was used when determining the strength of association between comment sentiment and subscriber growth. Cohen’s d gives an operational definition for effect size, which allows for the conclusion of whether a correlation coefficient has a small, moderate, or large association (Becker, 2000). The average correlation coefficient of each game category displays a low association according to Cohen’s d. The average correlation coefficients for all game categories were negative, but this is not enough to conclude a relationship due to the low magnitude of the values. The correlation coefficient for Minecraft, which is approximately -0.264, has the highest magnitude among those of the game categories studied, yet this value still falls under the low association category by Cohen’s d. As a final assurance to the study, the three correlation coefficients were used to calculate an average correlation for all three game categories.

The resulting correlation coefficient of -0.149 shows that there is indeed a small association. The comment sentiment from YouTube gaming channels’ videos show little relationship with the subscriber growth of those channels.

Graph 3. Total Average Correlation



Note. This graph depicts the average correlation coefficient of all three game categories studied.

Discussion

Implications

From the results, it can be concluded that there is little to no association between comment sentiment and subscriber growth of gaming channels. Despite the consistent negative correlation coefficients calculated among the data sets, the average correlation coefficients show that the magnitude is not high enough to conclude a relationship. Furthermore, from a logical perspective, the negative correlations appear contradictory. Typically, when a user posts a positive comment, other users should be encouraged to perceive the video or channel in an optimistic way; however, the results of this study indicated the opposite. Thus, no correlation can be determined between comment sentiment and subscriber growth rate.

Evidence shows that content creators should not worry about the negative or positive comments they receive in their video's comment threads. While it was discussed that comments do have an impact on how users perceive a video, the data shows that the comments' sentiment do not seem to sway users into subscribing or not. The factors for why people subscribe lie elsewhere, as becoming a subscriber to a channel is an indicator of a long term viewer for a particular channel. One video displaying positive comments does not seem to influence users into making this commitment.

The success of a YouTube channel lies within the content creator. Exceptional content that is produced on YouTube may garner a lot of attention and subscribers for channels, but the comments under that content still pose a variety of emotionally charged language. Even though the results of this study imply that content creators should not worry about the sentiment of these comments, they should still be taken into consideration.

Limitations

Despite the conclusions made from the results, there are limitations worth discussing that may have affected the results of the study. One aspect that is common within most gaming comments is slang. Slang refers to phrases that are not a

part of the standardized language, yet they carry an emotionally charged meaning, which conveys the user's reaction (Tereshchenko, 2019). Slang is widely used in gaming communities. Content creators may adopt the usage of slang, which encourages their users to comment in terms of slang as well. Many sentiment analyzers, including VADER Sentiment, do not contain dictionaries that accommodate the usage of slang. This can result in an altered interpretation of the comments analyzed by the program used in the method, which affects the accuracy of the data.

Another limitation to consider is the very nature of the top comments posted under videos. In some cases during the method process, pinned comments were analyzed. Comments can be pinned to the top of a thread at the channel creator's choosing. Pinning certain comments at the top may display an artificial positive or negative sentiment of the video, which might not translate into precise data when the program analyzes them. Compared to the natural top comments in a thread, pinned comments may provide a hindrance to the true reaction to the video by users.

The amount of videos uploaded by channels is another limitation to consider. Throughout all game categories studied, some channels in the dataset had little to no videos uploaded in a month. Despite the set maximum of ten videos studied per month for a channel, some channels could not meet this amount. This inconsistency provided a lack of sentiment to collect for these channels, which caused large deviances in the average sentiment collected for the month. Large deviances in the average sentiment affects the correlation coefficient of these channels, which ends up altering the average correlation value of each game category.

These limitations were not considered earlier in the research process due to the abundance of work that was required in the coding aspect of the method. Initially, it was expected that comment sentiment would increase as subscriber growth increased, but there were inconsistencies in the data that proved otherwise. However, no signs of low correlation were seen when collecting the comment sentiment. The results and limitations of this study were only realized until after the method process had been completed. It can be considered that the low correlation between comment sentiment and subscriber growth was caused by these obstructions. Thus, it can be concluded that future research needs to be conducted. Other studies should look towards sentiment analyzers that are better suited to interpreting slang and YouTube channels without pinned comments.

Conclusion

The relationship between comment sentiment and subscriber growth rate still has an abundance of potential for research. The high correlation coefficients of select individual channels provide evidence that more research must be conducted in order to reach a thorough conclusion.

Future studies should aim to address the limitations considered in this study due to the low correlation calculated in the results. More games should be studied with a greater array of channels, as the three video games studied do not provide a wide enough insight into the genre. Games such as Fortnite, Hearthstone, and Rocket League are in completely different game classifications, which implies that there are more communities with different sentiments towards the games they play. Refining the method process will serve to verify the results of this study and provide even more valuable information to the content creators that spend their days reading comments, making videos, and playing games.

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Appendix A

```
import os
import googleapiclient.discovery
def main():
    api_service_name = "youtube"
    api_version = "v3"
    DEVELOPER_KEY = "AIzaSyCQ_LnQf76PfvPLsAehMonS56r7p-zsoBE"
    youtube = googleapiclient.discovery.build(
        api_service_name, api_version, developerKey=DEVELOPER_KEY)
    request = youtube.commentThreads().list(
        part="snippet",
        order="relevance",
        textFormat="plainText",
        videoId="vXGdNyrewiE"
    )
    response = request.execute()
    for ele in response['items']:
        testfile = open("testing.txt", "a", encoding="utf8", errors='ignore')
        testfile.write(ele['snippet']['topLevelComment']['snippet']['textOriginal'] + "\n")
    testfile.close()
    from vaderSentiment.vaderSentiment import SentimentIntensityAnalyzer
    analyzer = SentimentIntensityAnalyzer()
    with open("testing.txt", encoding="utf8", errors='ignore') as f:
        my_list = []
        for line in f.read().split("\n"):
            z = analyzer.polarity_scores(line)
            difference = (z['pos'] - z['neg'])
            if difference != 0.0:
                my_list.append(difference)
        result = sum(my_list)/len(my_list)
        print(my_list)
        print(result)
        file = open("testing.txt", "r+")
        file.truncate(0)
        file.close()
if __name__ == "__main__":
    main()
```

Appendix B

Minecraft Channels (search range - 100,000 - 400,000 subscribers)

1. JWhisp - 258k
2. SuchSpeed - 234k
3. PatarHD - 122k
4. Sirud - 180k
5. Target3DGaming - 223k
6. Avomance - 236k
7. Zyph - 192k
8. Lucky Creeper - 180k
9. ZombieMatty - 245k
10. Rays Works - 274k

Rainbow Six Siege Channels (search range - 100,000 - 400,000 subscribers)

1. Disrupt Gaming - 159k
2. KingGeorge2 - 161k
3. The DangleBerries - 201k
4. DBL Online - 149k
5. Snedger - 249k
6. BananaGaming - 228k
7. Braction - 194k
8. Bedasaja - 218k
9. Revolt Robbie - 117k
10. Lt. Custard - 313k

League of Legends Channels (search range - 100,000 - 400,000 subscribers)

1. Virkayu - 164k
2. Redox Teamfight Tactics TFT - 131k
3. KingStix - 225k
4. Foggedftw2 - 294k
5. TFBlade - 381k
6. TC Zwag - 304k
7. xPetu - 159k
8. PekinWoof - 130k
9. Ganker LoL - 225k
10. Prof Akali Gameplay - 141k