Abstract

This paper examines the role of social media and influencers in the advertising of clothing to identify trends. Two main approaches were used: a survey to allow for individual input into the thought process of consumers and the use of social media data to examine aggregated market strategies. Results from these approaches included that most individuals felt they had been influenced into buying products and that clothing retailers had increased their advertisements in 2024. Inferences from these results are limited, as difficulties arose in finding useful social media data and applicable products for respondents to discuss. Nevertheless, the dynamics underscored by the advertisements and survey suggest that influencers can emphasize authenticity and that urgency in shopping habits will continue to be a viable marketing strategy.

Background

The fast fashion industry has allowed for shorter production time which can lessen the life cycle of fashion clothing. This stimulates consumers to engage in more frequent purchases and impulsive buying. Additionally, fast fashion marketing techniques create pressure on consumers to buy products through a sense of scarcity made through small batches and limited availability (Chunling 2020). The emergence of social media influencers and consumers created a unique opportunity for businesses to incite its consumers through celebrity endorsements or social media influencers.

With the use of social media influencers, consumer behavior can be aided through a faster decision-making process. This also creates an influence phenomenon with the use of virtual relationships to promote products. Endorsements are more common today via social media and enhance consumer's perception regarding product purchases. In the article by Léa, Malek, and Runnvall (2018), they used qualitative research methods such as focus group studies, to understand the use of social media influencers and its effect on its viewers, more specifically, Generation Z. They studied the decision-making model and Engle-Kollat-Blackwell (EKB) models to understand the decision-making process and its impact on fast-fashion. From this, they concluded that younger generations differ from the traditional EKB model in the lack of identification of need prior to a purchase and a greater effect from online influence. This change creates opportunities for brands and influencers to move into new roles in purchasing.

Brands and textile companies have a variety of opportunities to use social media and influencers to promote products. In an article by Liu in 2022, they used convenience sampling to understand the textile fashion industry and celebrity endorsement strategies to influence consumer's buying intentions. They found that the desirable characteristics for celebrity endorsements were trustworthiness, attractiveness, credibility and expertise. These traits can influence the consumer's decisions and influence impulsive behavior. Authenticity, or trustworthiness and attractiveness can modify consumer purchase choices or interest. Credibility is seen to consumers as the perception of the brand and expertise is how the competencies of the celebrity can inspire consumers to buy the recommended product. Changes in the approaches used by companies and individuals to attract customers on different platforms means that social media use can be informational for understanding shopping habits and the market dynamics under such a new approach. With this background, the project will be focused on understanding the relationship between social media, influencers, and shopping habits.

Research Question

The project seeks to answer the question "How does social media marketing and influencer content impact consumer attitudes towards fast fashion choices?" With this, we will focus on how social media marketing and influencer's content can persuade consumers to purchase or increase knowledge of certain brands. The goal is to examine the perceptions of consumers as a factor of their marketing, which is our independent variable. Our project has a two-pronged approach that examines both the conscious opinions of individuals looking at products and making purchasing decisions, as well as the latent effect of marketing on products seen through social media platforms.

Methodology

The data project uses a mixed-method approach of web scraping and surveying. We used Qualtrics to create and send out surveys to people, including open-ended questions. Social media data was created to view content of brand deals, paid promotion content, and influencer's trends towards marketing using the APIs of two platforms: TikTok and YouTube.

Survey:

The survey consisted of 16 questions and two TikTok videos. The videos were based on the top click-through rate and number of likes, taken from the publicly accessible Top Ads Dashboard. Filters were applied to find these videos including narrowing to videos in the United States and in English, as well as specifying categories for videos as men's and women's apparel and accessories. Sorting the videos to find the top of each category included using the highest click-through rate, which is how often people click the shopping cart or view the product under a TikTok video, and using likes to allow for another metric of popularity among the videos. One video was used for women and one for men. We found that based on gender, the content in the video and the products shown were drastically different. Women's videos seemed to show more of an influencer's face and voice to showcase products. Men's videos seemed to show more of the products or used a form of meme, jokes that are copied and spread rapidly through social media.

The questions asked for the survey were demographics, type of social media use and time spent on those specific platforms, purchases they make, and their likeliness of whether or not they feel influenced to buy these products. The demographics questions were: “Choose one or more races that you consider yourself to be: White or Casucasian, Black or African American, American Indian/Native American or Alaska Native, Asian, Native Hawaiian or Other Pacific Islander, Other, Prefer Not to Say”, “Are you of Spanish, Hispanic or Latino origin? Yes, No”, “How old are you? Under 18, 18-24 years old, 25-34 years old, 35-44 years old, 45-54 years old, 55+ years old”, “How do you describe yourself? Male, Female, Non-binary/third gender, prefer to self-describe, prefer not to say”. These questions were taken from the Qualtrics library and were certified questions and response answers. The type of social media and usage was asked through a matrix question with the times of Under 1 hour, 1-2 hours, 2-3 hours, 3-4 hours, 5+ hours or Not Applicable. The types of social media were Instagram, Facebook, Twitter, YouTube, TikTok, Snapchat, and LinkedIn. We asked “Do you view videos about products on any of these applications? No, Maybe, Yes” to ensure that the people answering the rest of the questions have viewed product videos. If a respondent answered “No”, they were taken to the end of the survey. There were two questions pertaining to purchases: “Do you make purchases on any of these applications? No, Maybe, Yes”, “How many times a month do you purchase through those applications based on content you’ve seen? Never, Once a month, 2-3 times a month, 4-6 times a month”. The next three questions were based on influence, effectiveness and believability: “Do you feel influenced into buying products you see? Strongly disagree, somewhat disagree, neither agree nor disagree, somewhat agree, strongly agree”, “How effective do you think they are? Not effective at all, slightly effective, moderately effective, very effective, extremely effective”, How believable is the content you see on products? Extremely unbelievable, somewhat unbelievable, neither believable nor unbelievable, somewhat believable, extremely believable". The videos were shown to participants and they were asked three questions based on the video: "How likely are you to buy the product based on the video? Extremely unlikely, somewhat likely, neither likely nor unlikely, somewhat likely, extremely likely", "Why or why not?", "What characteristics in the video do you see that makes you feel drawn or less drawn to the product?". When the video was shown, we included a timer that participants cannot see to ensure that every participant watched the whole length of the video. If a participant did not they would have been excluded from the survey. Fortunately, all participants watched the duration of the video.

Social Media Data:

For social media, we used a combination of social media scraping to identify products and using APIs to identify video success. First, we used TikTok to identify popular products, keywords, trends, and their viewership metrics. Using their approval process, we received access to their "research.adlib.basic" data set as well as their Commercial Content API, which allowed for requests to query information about ads and their success. Firstly, the publicly accessible Ads Dashboard and Insights Dashboard were used to identify key terms on trends and public interest. These words were then used to find brands or specific advertisements that were popular using TikTok's ad query through their Commercial Content API. TikTok also has a Research API that allows for the querying of overall videos that was not used, but could provide an avenue for further data collection efforts. With this data, brands and advertisements were examined for trends, information, and analytics.

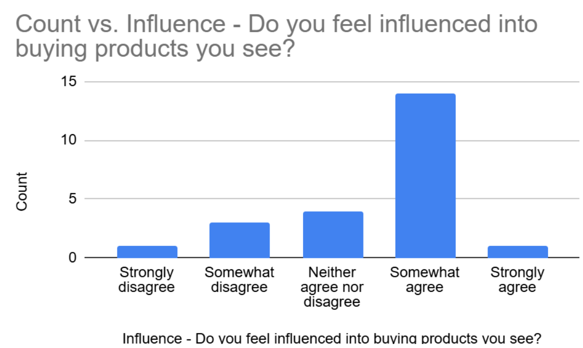
Then, we used Youtube Data API v3 to perform searches for videos from influencers and fast fashion products. We collected data on publishing dates and top channels in order to find similarities between different brands that would support the notion of creators influencing consumer decisions. This resulted in new data to analyze for the effect of product placements. We also used the API to find common themes within the videos in order to further our research on the impact of fast fashion.

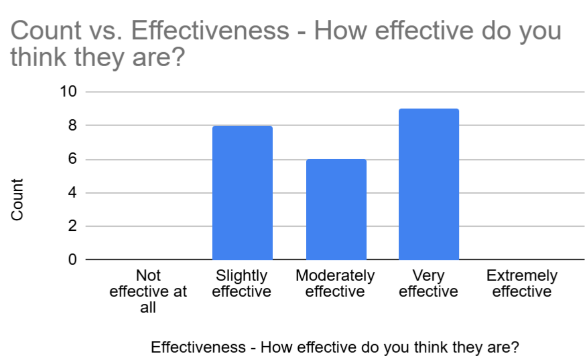
Analysis

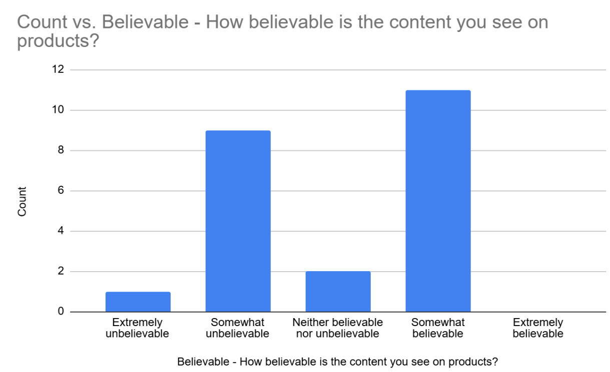
Survey:

We were able to get 23 people to complete the survey. Eight participants were caucasian, two were Black/African American, one was American Indian/Native American or Alaska Native, nine were Asian and five were other. Eight participants were Spanish, Hispanic or Latino origin and 15 were not. 78%, 18, of the participants were 18-24 years old and 22%, five, participants were 25-34 years old. The social media applications that had the most time usage were TikTok and Instagram. For Instagram, 47.83% of users used the app for 1-2 hours daily. FaceBook was used by 47.83% of the participants for under one hour, daily but most participants, 52.17%, did not use the application. X, formerly Twitter, was used by 34.78% for under an hour, but most participants, 47.83%, do not use the application. YouTube was mostly unused by participants, 39.13%. For the ones that did use, 26.09% of participants used YouTube for less than an hour, daily. TikTok was mostly used for 2-3 hours or 3-4 hours daily with 21.74% of the participants using it. Snapchat was used for under an hour, daily with 56.52%. LinkedIn is used for under an hour with 47.83% participants using LinkedIn. 39.13% participants do not use LinkedIn. Of our participants, one person said they do not watch videos on any applications, and were then taken to the end of the survey; the rest said they do. 11 participants said they do not make purchases on social media applications, two people said maybe and 10 people said they did. 12 people have never made purchases, 10 people make purchases about once a month and one person makes purchases 2-3 times a month.

When asking participants about influence, effectiveness or believability, we used summary statistics to understand the feelings surrounding these questions with a Likert scale of one to five. When asking participants if they feel influenced into buying products, 14 people said they somewhat agree. The mean was 3.63. It seems that most participants feel they are influenced by products on social media videos. Most participants feel the videos range from slightly effective to very effective. Eight people said slightly effective, six people said moderately effective, and nine people said very effective. The mean was 3.18; most people felt their videos were moderately effective. Most participants felt the videos were somewhat believable. The mean for this count was 3.13.







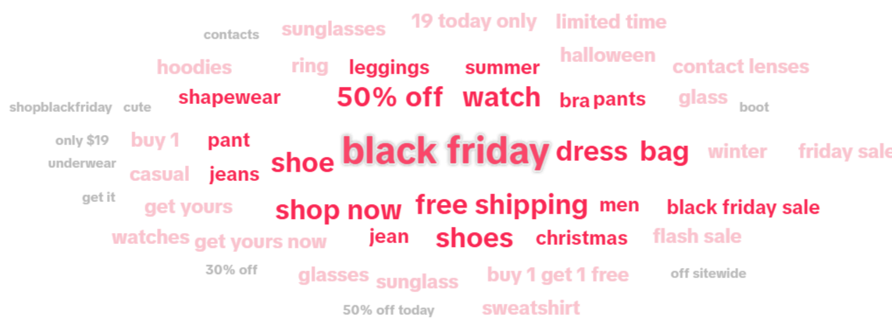
The second part of the survey consisted of a video that participants watched and three questions based on the video. These questions were text entry responses and we used qualitative analysis to understand the patterns and thoughts people had regarding the videos and what they viewed about videos. By asking about what characteristics they see in our chosen video, this can help us to see what they see in more general videos and how they think about product-sponsored videos. Applications use an algorithm to show people videos or products they would enjoy seeing based on past interactions of videos. Since we were selecting a general video, we did not expect people to like to dislike the video; we cared more about what they thought and the characteristics they see in the video. In order to understand this, we asked two questions to build up: “How likely are you to buy the product?” and “Why or why not?”. With the likeness question, most people said they were extremely unlikely to buy the product and the mean of the question was 1.95 on a likert scale of one to five. One was rated as extremely unlikely and five being extremely likely. The why or why not question received 63.64%, or 14, of participants saying the product was not their style, did not like how it looks or that they do not wear that type of clothing or any type of variation of that sense. Two people said they do not shop online. Some other responses were that “I do not trust the reviews because most of the time the creator is getting paid to make it”, “I have enough clothes”, “Not currently a want” and “Looks like a good product”.

Exploring the characteristics people see, eight people mention interactions within the video such as the person and how they interact with the product, or how the product is shown. Six people mention the actions of the creator such as “The interaction of the person talking to us and showing the dress from all angles and the benefit”. This reaction tells us that people can experience a connection between people through videos. The participant mentions that the person is “talking to us” which shows how influencers can aid with connection to increase consumer spending. Another participant mentioned, “I like seeing the average person showing them off instead of a model, so that would make me slightly more inclined to purchase”. This shows how the authenticity of the influencers would increase consumer spending. However, someone else said the video was “too sponsorish”. This is another call to authenticity but this participant feels the video is not authentic. Different views of authenticity can support or decrease the consumer's spending or feelings towards the product. Eight people mentioned some variation of the product, quality, how the product looks based on the video or their feelings regarding the product shown. Some mention they didn't like seeing it all, or it wasn't their style after seeing it. Two people mention the voice of the creator. One participant says "Even though I didn't like the dress, the author did a good job at making the dress appealing because of her high pitched energetic voice and the fact she did a 360 twirl". This plays into the consumer's energy and the characteristics people see to make them enjoy sponsored videos. This can also play a role in trustworthiness because of the way this participant mentions how the influencer made the dress more appealing with the traits of the voice and the twirl. One person said "the consumer's energy", which explains the characteristics they directly saw from the influencer.

This question and the responses allowed us to see how people viewed influencers and the characteristics they see in short videos that could change their attitudes toward a product. However, some people only see the product and never mentioned how the influencer interacted with the product. This shows that some of our participants viewed only the product on display. The characteristics that we did see were authenticity, trustworthiness and credibility which aligns with past studies done on influencer's traits and strategies that influence consumer buying intentions.

<u>Social Media Data</u>:

The data from the TikTok Insights Dashboard provided publicly accessible information on trends and commonly used phrases. This provided an indication of words, shown below in a word cloud, that would make good search terms for input into the API to query specific ads and as an overview of marketing tactics on the application. Many of the popular terms in the apparel category focused on sales, such as free shipping, packaged deals for multiple items, and overall discounts. The emphasis on sales suggests that the creation of time-sensitive incentives to purchase may be a common strategy used by brands on the platform. Other items from this approach, however, were not immediately useful as keywords and trends tended to be broad concepts or items, rather than specific branded pieces.



Using the Commercial Content API or the Research API itself provided data on the most common ads on the platform. However, this data was not very informative, as even using search terms from common keywords or filtering, most ads were not specific to branded clothing. Additionally, the ad dataset accessible was only for full ad campaigns, rather than the more common sponsorships available on the platform. This led to many of the ads returned being for alternative items, such as detergent for clothes or advertisements for poorly related products like mobile games. Filters including time and viewership were not effective in narrowing the scope to create usable data, and limitations on queries additionally hampered the ability to retrieve large numbers of ads to use. As such, conclusions from this data about brand or consumer behavior are limited. However, the limited nature of clothing advertisements comparable to other industries may support the idea that fashion retailers may partner with influencers more directly to promote items, such as through giveaways or sponsorships instead of direct advertisements.

Using the YouTube Data API v3 also proved more challenging than initially thought. We were able to scrape data centered around videos mentioning the top 10 apparel brands on TikTok shop in 2024. These brands were: Shein, TJ Maxx, Ross Stores, Marshalls, Nike, Burlington, Old Navy, Five Below, Macys, and Footlocker. Consumers have spent a combined 4.6 trillion dollars on apparel from the TikTok Shop buying goods from these brands. The data we scraped from YouTube included the publishing date, video ID, channel ID, title, description, and channel name. We had to modify our code to add the term 'clothing brand' after each initial search term because some terms such as Ross and Five Below were bringing in videos that were not pertinent to our research. Using this we were able to create a word frequency distribution table that was then used to create a word cloud. Analysis of the word cloud allowed us to find similarities between different brands and look for keywords such as "cheap" or "quality" that would help us understand the specific aspects of fast fashion that make it so desirable.

Figure 1: Ross Word Cloud

Figure 2: TJ Maxx Word Cloud

Similar words that we found across a multitude of brands included phrases such as: 'couture', 'less', 'clothes', 'haul', and 'spree'. These indicate that one of the many impacts of fast fashion has been the different types of styles available at a low cost which has resulted in consumers buying as much as they can at once. ‘Hauls’ and ‘Sprees’ have become much more popular in the age of influencers as many of them opt to post videos of them trying on a vast array of products while reviewing them.

To further examine influencer behavior, we looked at publishing data and top channels of each search term to find similarities that could point to one specific influencer holding a market share on consumer choices. Results showed that there were several creators reviewing multiple brands including ‘Simply Gen’, ‘Angie Grace’, and ‘Jennifer Lynn’. After creating a word cloud with each creator’s name we could look at specific traits that their channels held that contributed to high viewer interaction.

Figure 3: Simply Gen Word Cloud

Figure 4: Angie Grace Word Cloud

Figure 5: Jennifer Lynn Word Cloud

We also scraped data on the publishing dates of videos and we were able to find that there was a huge increase in videos associated with these brands in 2024 when compared to previous years. Interestingly, some of the brands that had a large foothold in American fashion such as Macy’s and Nike had more videos published in prior years than their counterparts but were easily outdone over the past couple months by companies like Shein, TJ Maxx and Ross. Evidence points to price differences as the reason why many of these stores sell cheap, low quality goods that give the same look as higher end ones.

Conclusion

Overall, conclusions from such a small scope are limited. However, some major takeaways include the increase in videos in 2024 on YouTube, suggesting the support for a market of cheaper goods from companies. Additionally, associated words from both TikTok and Youtube suggest that increased consumption is part of the dialogue on both platforms, with the prevalence of terms like “hauls” and discount terms promoting such. Despite this, using social media as an advertising strategy to partner with influencers and sell clothing resulted in mixed views from those in our survey, with differing views on the believability of such products and the direct impact of engaging with an advertisement. Nevertheless, most people felt that such advertisements were effective, even if the specific ones used in the survey were not. Characteristics identified from open statements included the energy and authenticity of influencers advertising products directly. While no conclusive information emerged from the data, the support for increased sales and the acceptance of online shopping on social media platforms in the survey suggest that the relationship between sales, influencers, and social media platforms is important to explore and will continue to be valuable to brands looking to expand their customer base.

Limitations

The survey allowed us to understand and analyze what people thought of video products and how they view videos. However, TikTok uses an individualized algorithm to populate videos for people and using one video for every participant does not allow us to fully understand what people see in terms of content or purchasing power when it comes to the video. Some people explained that they do not like the product at all as they do not think it is a reasonable purchase for them. If there was a chance to ask questions pertaining to the videos they see from their algorithm, answers might have looked different for each person in regards to what they see in characteristics or how they view their product-sponsored videos. Our survey was still able to receive results to understand general opinions on videos, but it was unable to allow for variation of products from person to person, other than a male versus female perspective.

If there were more time for the study, a focus study would allow us to understand what people think about video products on TikTok and their ideas surrounding products and content. It would allow us to understand their views on influencers and the fast fashion industry more deeply and allow for participants to bounce thoughts and ideas about influencers and consumer attitudes.

Limitations of the social media data include the small size of the dataset available. TikTok's public dataset is of paid advertisements on the site; however many brands may have a developed presence that removes the need to pay for advertisements to receive views. Moreover, advertisements available for analysis are purely from the brands themselves, as the data does not include placements or sponsorships that are not in the form of advertisements. This limits the applicability of the data, as information on the videos seen presents an incomplete picture of the content viewed or advertised on the platform.

Additionally, much of the TikTok advertisement data was not directly applicable or useful as information. Because of the popularity of advertising, filtering to isolate brands was not effective and many other companies identified were not clothing brands. Moreover, limitations on the ability to query data resulted in few ads being identified, preventing quantitative analysis of advertisement results. These obstacles, if improved, would allow for broader inferencing from the data and larger conclusions to be drawn. Potential ways to include this could be using the ad ids to identify further ad details. Additionally, using the Research API and dataset instead of the

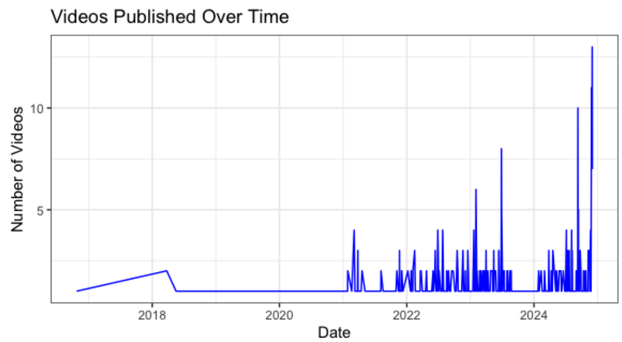
Commercial Content API to explore non-ad videos, such as those with sponsorships or partnerships could allow for the generation of more useful data.

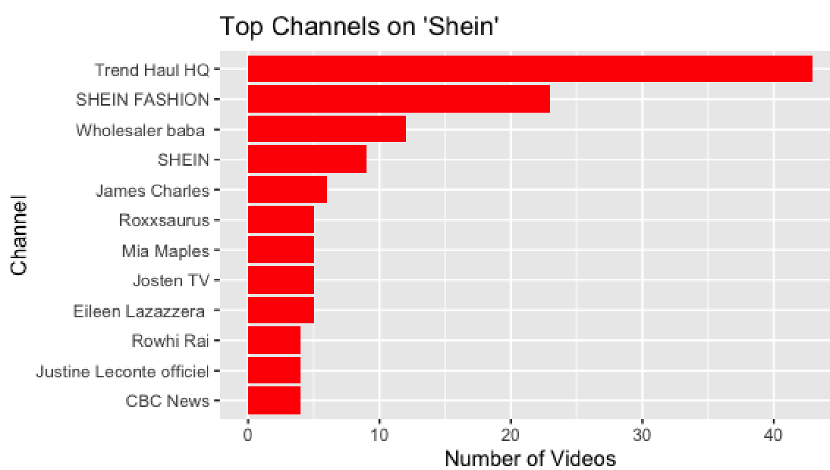
Using the Youtube Data API v3 had a couple of limitations as well. We attempted to create a filter for videos that were paid promotions but fetching the data for just one search term pushed us past our quota limit so we had to work with just publishing data, title, channel and video ID, and description. Another problem with the paid promotion filter was that it was picking up videos that had phrases in the title such as, "NOT Paid Promotion" but the filter would include it making some of the data inaccurate. We weren't able to obtain access to Youtube Paid Promotion but this would possibly be something that would be available to us if we had more time. Youtube also doesn't have the functionality to track how many people clicked product links found in descriptions or comments which would have allowed us to see which influencers were able to generate consumer interest and themes found in their videos.

Appendix

Appendix A: Shein Data

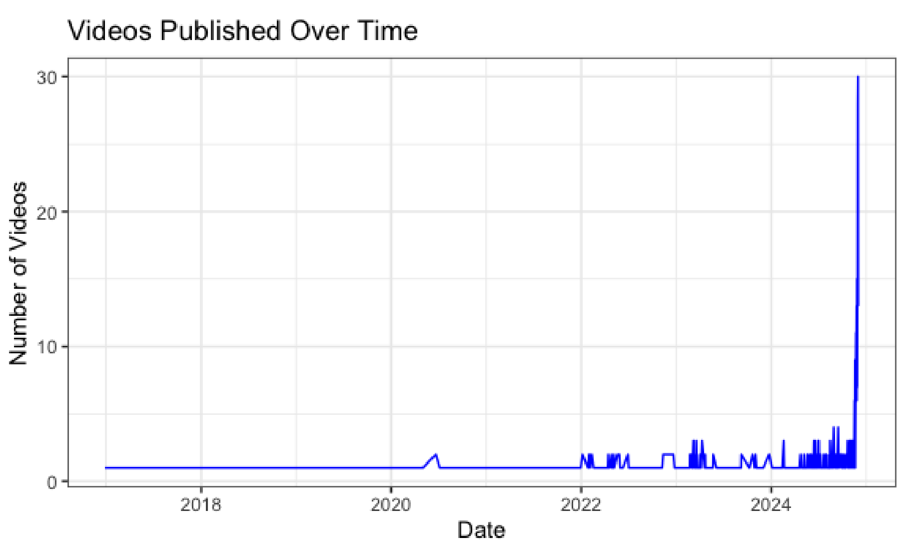
Shein Word Cloud

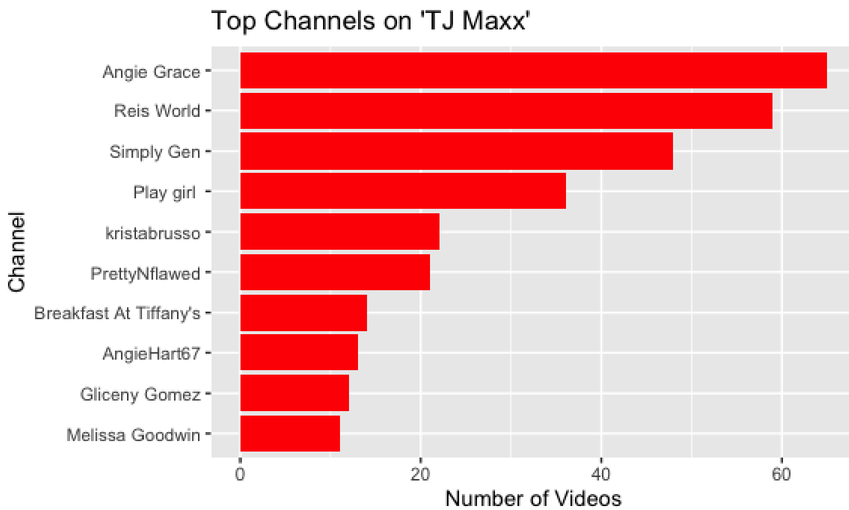




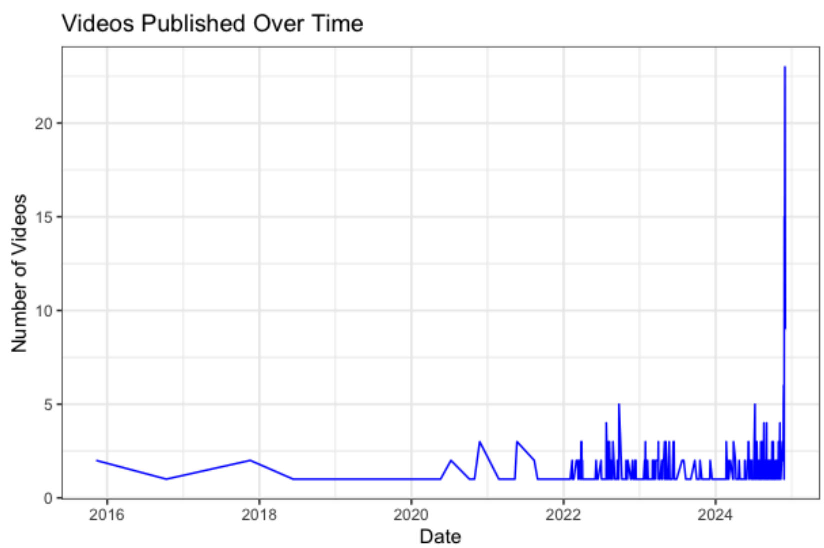
Appendix B: TJ Maxx Data

TJ Maxx Word Cloud

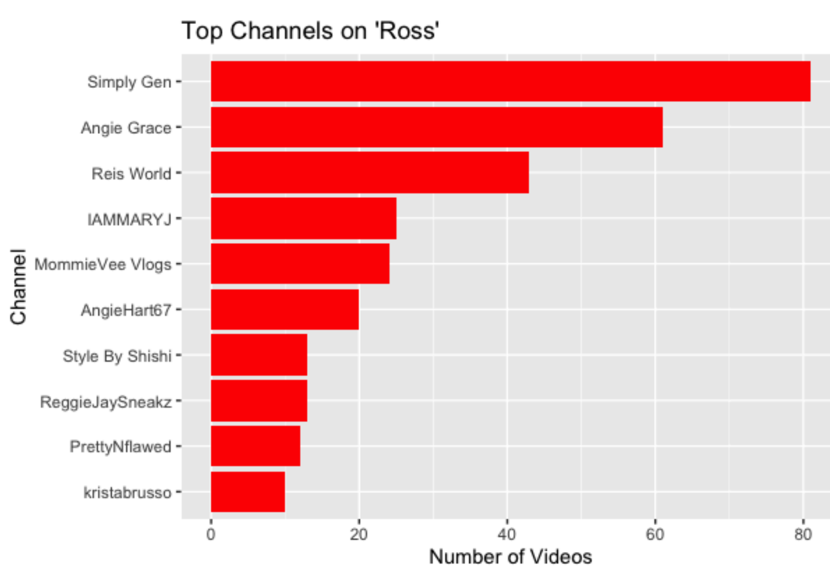




<u>Appendix C:</u> Ross Stores Data

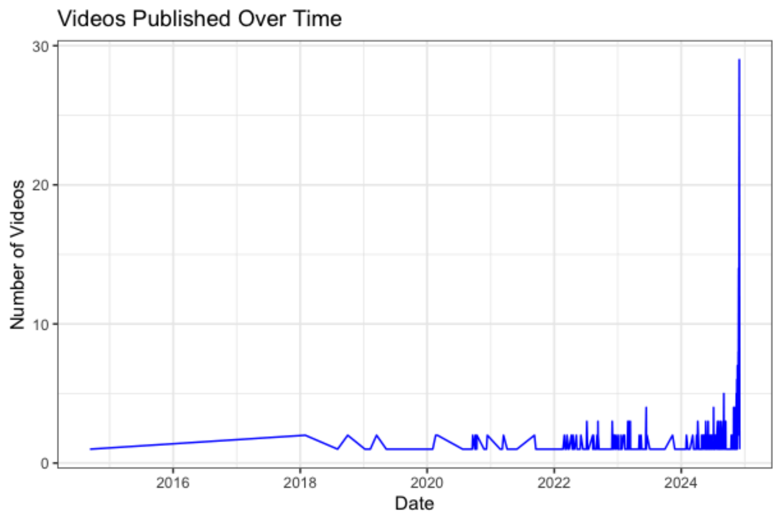


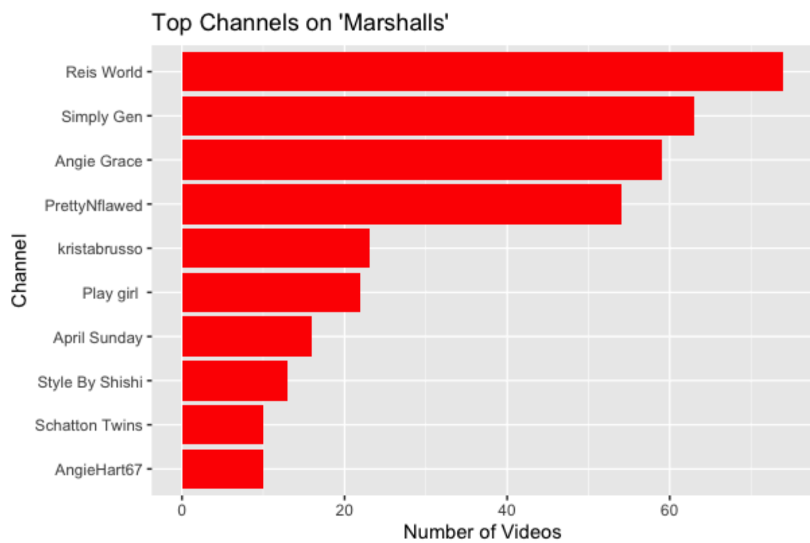
Ross Word Cloud



Appendix D: Marshalls Data

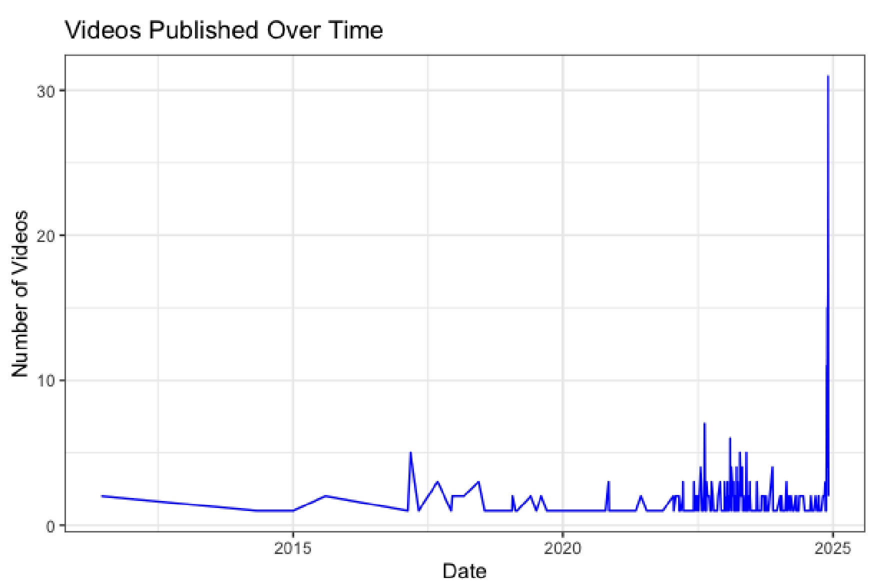
Marshalls Word Cloud

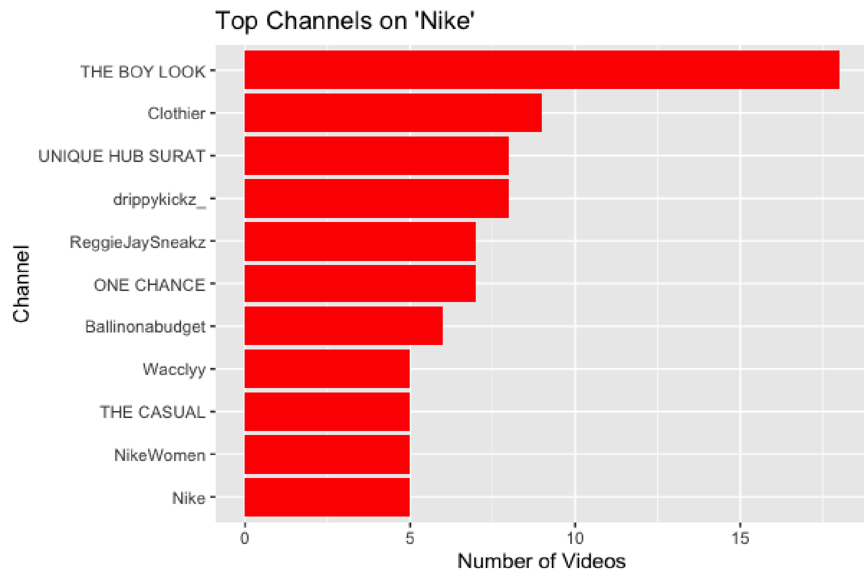




Appendix E: Nike Data

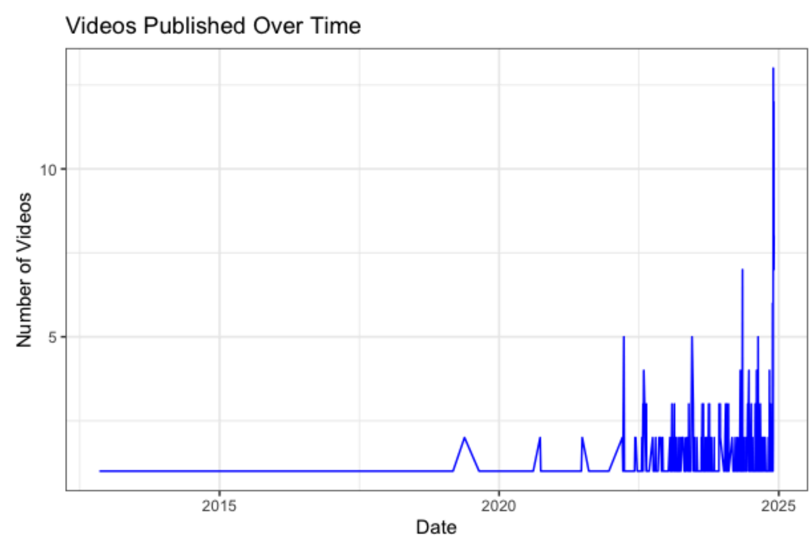
Nike Word Cloud

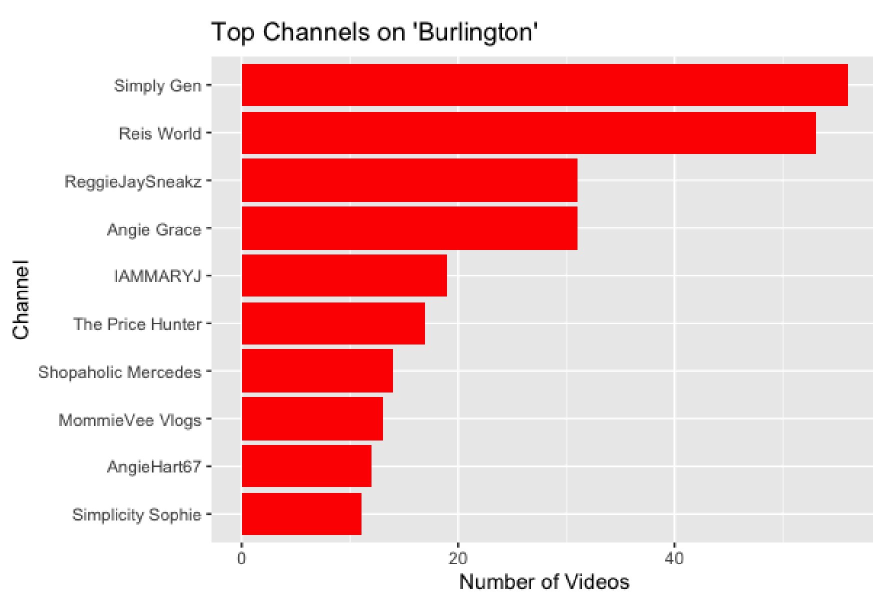




Appendix F: Burlington Data

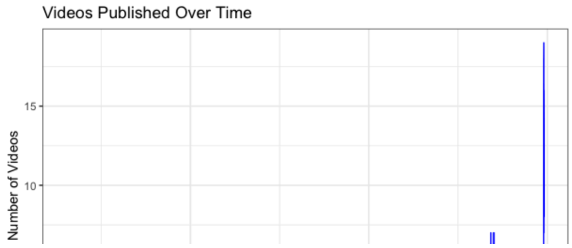
Burlington Word Cloud

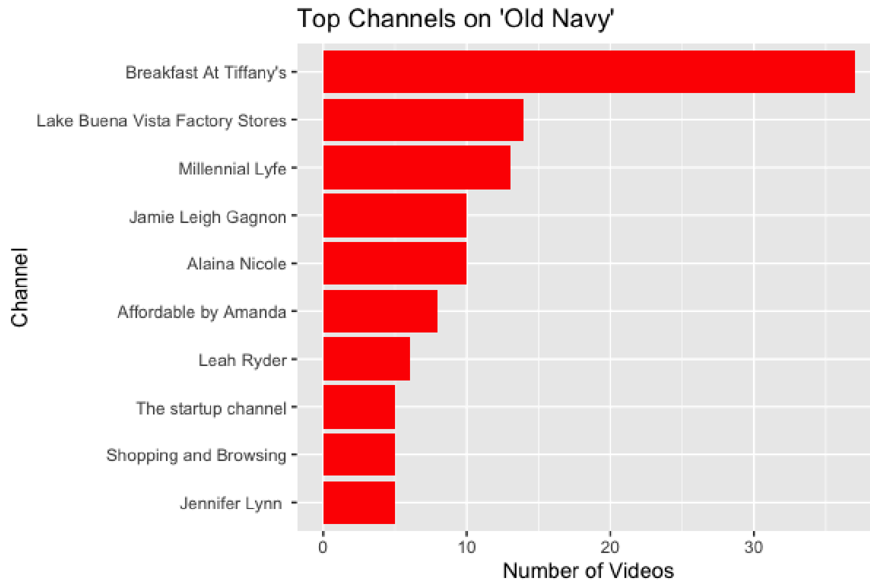




Appendix G: Old Navy Data

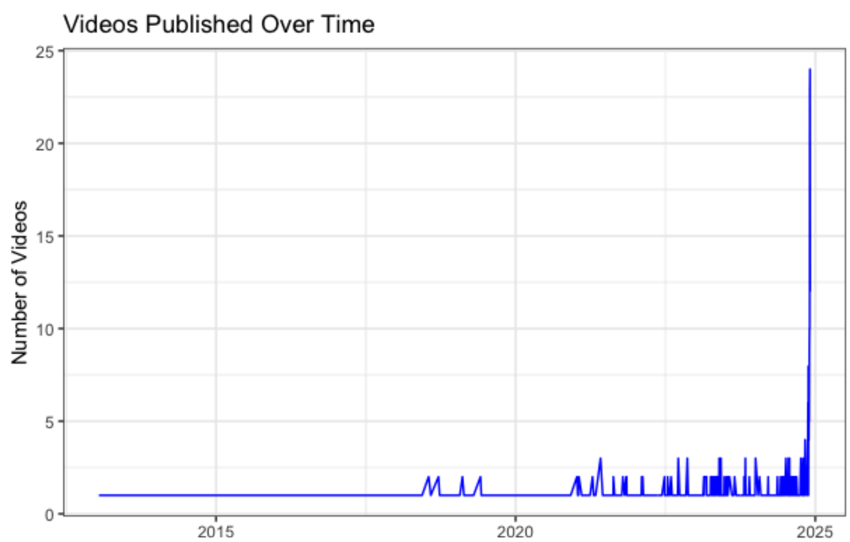
Old Navy Word Cloud

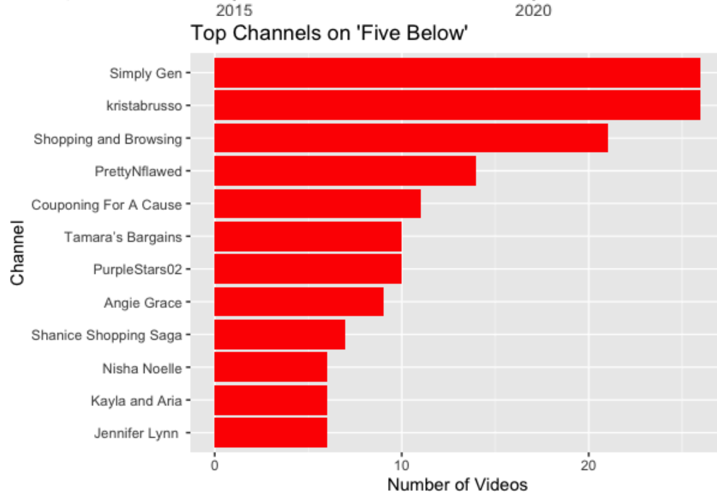




Appendix H: Five Below Data

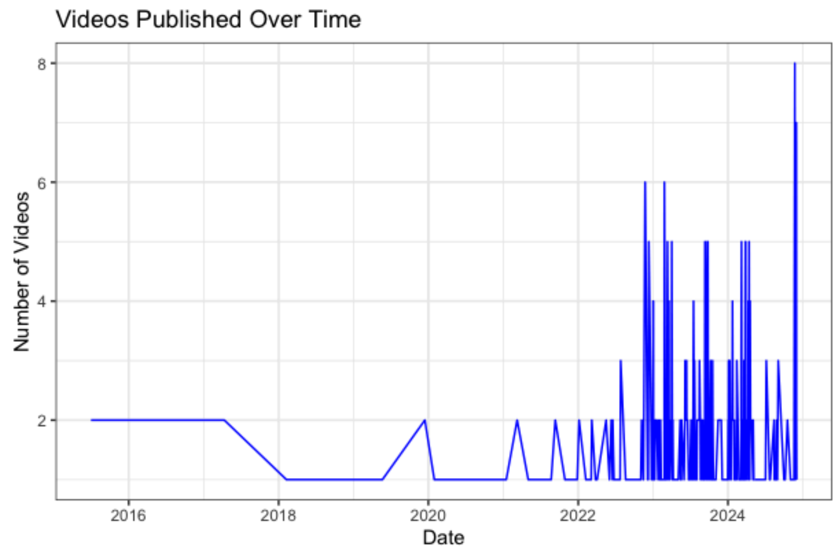
Five Below Word Cloud

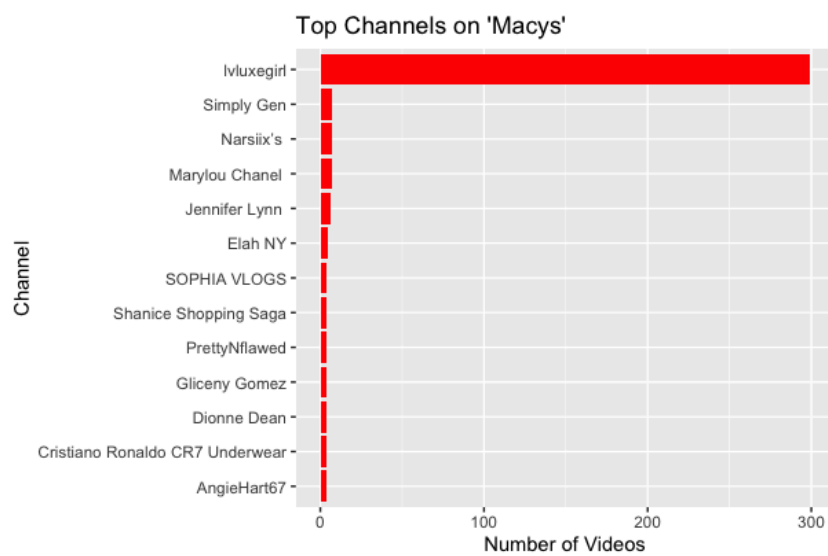




Appendix I: Macys Data

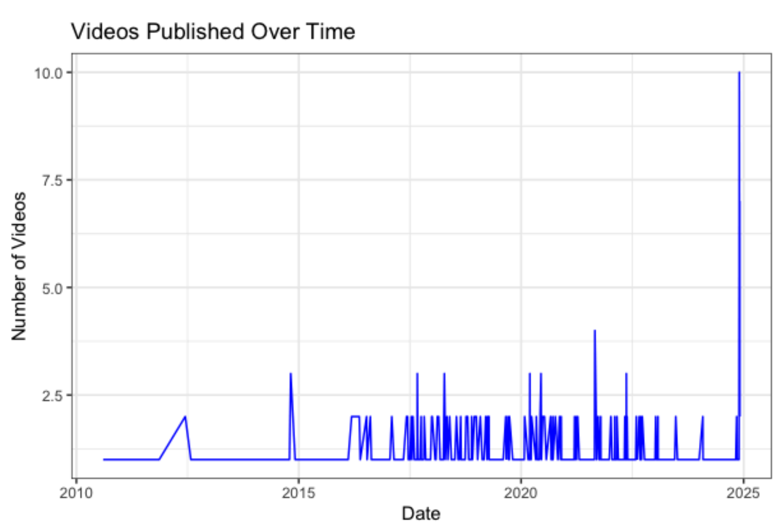
Macys Word Cloud

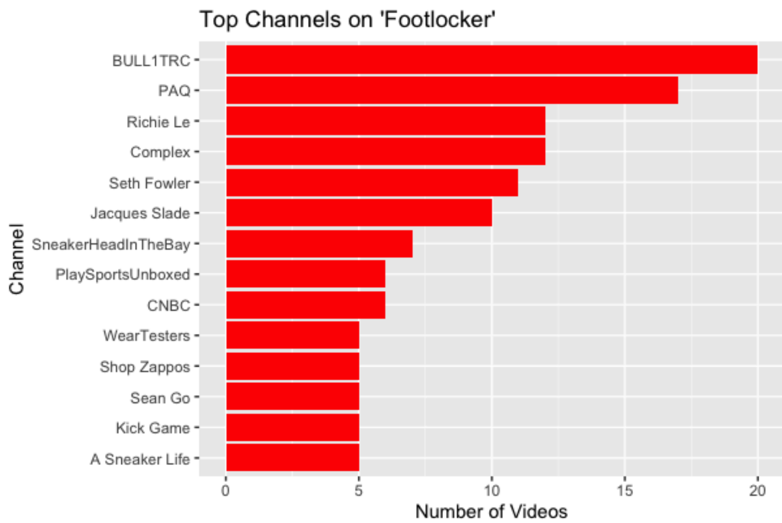




Appendix J: Footlocker Data

Footlocker Word Cloud





Appendix K: Youtube Data API v3 Code

```
## Collecting Social Media data: YouTube
install.packages("tuber")
install.packages("tidyverse")
install.packages("lubridate")
install.packages("stringi")
install.packages("wordcloud")
install.packages("gridExtra")
install.packages("httr")
install.packages("tm")
install.packages("httpuv")
library("httpuv")
library(tuber)
library(tidyverse)
library(lubridate)
library(stringi)
library(wordcloud)
library(gridExtra)
library(httr)
library(tm)

yt_oauth("499646706541-p3mmqu3sobj10hqbd8nh63rm9khburdn.apps.goo
gleusercontent.com", "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",
token = "")

#### Search for videos related to "Fashion brand"
main_term <- "Lululemon shorts"
yt_fashion <- yt_search(term = paste(main_term, "clothing
brand"))
```

```
head(yt_fashion)

### Basic Analytics on YouTube Data

#### Most Frequent Words in Video Titles

titles <- yt_fashion$title
titles_clean <- tolower(titles) %>%
  stri_replace_all_regex("[[:punct:]]", "") %>%
  str_split(" ") %>%
  unlist()

# Word frequency table
word_freq <- table(titles_clean)
word_freq_df <- as.data.frame(word_freq, stringsAsFactors =
FALSE)
colnames(word_freq_df) <- c("word", "freq")

# Word cloud
word_freq_df <- word_freq_df %>% filter(!word %in%
tm::stopwords("en"))
set.seed(123)
wordcloud(words = word_freq_df$word, freq = word_freq_df$freq,
max.words = 50)


### Plot Video Publish Dates
yt_sm <- yt_fashion %>%
  mutate(publish_date = as.Date(publishedAt)) %>%
  count(publish_date)

# Plot the frequency of videos published over time
ggplot(yt_sm, aes(x = publish_date, y = n)) +
  geom_line(color = "blue") +
  labs(title = "Videos Published Over Time", x = "Date", y =
"Number of Videos") +
  theme_bw()

### Top Channels
top_channels <- yt_fashion %>%
  count(channelTitle, sort = TRUE) %>%
  top_n(10)

ggplot(top_channels, aes(x = reorder(channelTitle, n), y = n)) +
  geom_bar(stat = "identity", fill = "red") +
  coord_flip() +
```

```
  labs(title = "Top Channels on 'Fashion Brand'", x = "Channel",
y = "Number of Videos")
```

Appendix L: Ad Data from TikTok

id	first_shown_date	last_shown_date	days_shown	unique_users_seen	status
1796056037612545	4/12/2024	5/28/2024	46	10M-20M	active
1796659558673442	5/1/2024	6/30/2024	60	10M-20M	active
1799433634551842	5/21/2024	6/30/2024	40	10M-20M	active
1795927341595666	4/10/2024	6/26/2024	77	10M-20M	active
1796659558679554	5/1/2024	6/30/2024	60	10M-20M	active
1797321927951361	4/29/2024	6/20/2024	52	10M-20M	active
1796045164863506	4/17/2024	5/21/2024	34	10M-20M	active
1800233149129729	5/29/2024	5/31/2024	2	10M-20M	active
1800231314446386	5/30/2024	5/31/2024	1	10M-20M	active
1795926720803889	4/10/2024	6/9/2024	60	10M-20M	active

id	cover_image_url	url	business_id	business_name
1796056037612545	https://p19-vod-sign	https://v16m.tiktokc	687647096594	PROCTER & GAMBLE LIMITED
1796659558673442	https://p16-sign-sg.t	https://v16m.tiktokc	687647096594	PROCTER & GAMBLE LIMITED
1799433634551842	https://p16-sign-sg.t	https://v16m.tiktokc	698515029500	DPLAY ENTERTAINMENT LIMITED
1795927341595666	https://p16-sign-sg.t	https://v16m.tiktokc	687644461867	DOT INTERACTIVE (BEIJING) TECHNOLOGY CO., LTD.
1796659558679554	https://p16-sign-sg.t	https://v16m.tiktokc	687647096594	PROCTER & GAMBLE LIMITED
1797321927951361	https://p19-vod-sign	https://v16m.tiktokc	691464257303	KENTUCKY FRIED CHICKEN LIMITED
1796045164863506	https://p16-sign-sg.t	https://v16m.tiktokc	713878511663	MARS PET SERVICES UK LIMITED
1800233149129729	https://p16-sign-sg.t	https://v16m.tiktokc	687644887253	Supercell Oy.
1800231314446386	https://p16-sign-sg.t	https://v16m.tiktokc	687644887253	Supercell Oy.
1795926720803889	https://p16-sign-sg.t	https://v16m.tiktokc	687644461867	DOT INTERACTIVE (BEIJING) TECHNOLOGY CO., LTD.

Appendix N: TikTok Commercial Content API Code

```
##generate access token, saves it as 'access' for authorization

library(foreign)
library(httr)
library(stringr)
library(tidyr)
library(tidyverse)


headers = c(
  'Content-Type' = 'application/x-www-form-urlencoded',
  'Cache-Control' = 'no-cache'
)

body = list(
  'client_key' = 'aw6jhhp0d9b7yfpc',
  'client_secret' = 'Fu8Sz0ly0HtLucBBi24fn1pG4LQ6Uzv8',
  'grant_type' = 'client_credentials'
)

res <- POST(url = "https://open.tiktokapis.com/v2/oauth/token/",
body = body, add_headers(headers), encode = 'form')
```

```
info <- (content(res))
access <- info$access_token
access <- paste("Bearer",access, sep = " ")

#ad query:
  #fields to return: ad.id, ad.first_shown_date,
ad.last_shown_date
  #ad.status, ad.status_statement, ad.videos, ad.image_urls,
ad.reach
  #advertiser.business_id, advertiser.business_name,
advertiser.paid_for_by

  #filters: search_term, search_type (exact_phrase,
fuzzy_phrase)
  #max_count (def 10, max 50), ad_published_date_range,
country_code,
  #advertiser_business_ids, unique_users_seen_size_range

  #unnesting and unlisting will differ based on fields

headers = c(
  'authorization' = access,
  'Content-Type' = 'application/x-www-form-urlencoded'
)

body = list(
  'filters' = '{"ad_published_date_range": {"min":
"20240401","max": "20240601"}},"search_term": "pants",
"search_type" = "exact_phrase", "country_code" = "US"}'
)

#getting response and selecting ad data
response <- POST(url =
"https://open.tiktokapis.com/v2/research/adlib/ad/query/?fields=
ad.id,ad.reach,ad.status,ad.videos,advertiser.business_name,adve
rtiser.business_id,ad.first_shown_date,ad.last_shown_date", body
= body, add_headers(headers), encode = 'form')
ads_list <- (content(response))
repeatid <- ads_list$data$search_id
ads_list <- ads_list$data$ads

#data formatting and converting to csv with ad vectors as rows

ads_df <- tibble(data = ads_list)
ads_df <- ads_df |> unnest_wider(data) |>
  unnest_wider(ad) |> unnest_wider(advertiser) |>
```

```
  unnest_longer(videos, keep_empty = TRUE) |>
unnest_wider(videos) |>
  unnest_wider(reach)
ads_df$last_shown_date <- as.Date(ads_df$last_shown_date,
"%Y%m%d")
ads_df$first_shown_date <- as.Date(ads_df$first_shown_date,
"%Y%m%d")
ads_df$days_shown <- difftime(ads_df$last_shown_date,
ads_df$first_shown_date, units = c("days"))

write.csv(ads_df, file =
"C:/Users/nggal/OneDrive/Documents/R/projects/epps6302 -
web/tiktokdata/ad_info.csv")

#advertiser query

  #fields to return: business_name, business_id, country_code
  #filters: search_term, max_count


headers = c(
  'Authorization' = access,
  'Content-Type' = 'application/json'
)

body = '{
  "search_term": "clothing",
  "max_count": 25
}';

res <- POST(url =
"https://open.tiktokapis.com/v2/research/adlib/advertiser/query/
?fields=business_id,business_name,country_code", body = body,
add_headers(headers))

advertiser_list <- (content(res))
repeatid <- advertiser_list$data$search_id
advertiser_df <- tibble(data = advertiser_list$data$advertisers)
advertiser_df <- advertiser_df |> unnest_wider(data)
write.csv(advertiser_df, file =
"C:/Users/nggal/OneDrive/Documents/R/projects/epps6302 -
web/tiktokdata/advertisers.csv")
```

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