

# Shrinking Attention Spans

## Analyzing the Impact of Technology & Media Consumption on The Human Attention Span



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### Research Question

*Has technology & media consumption impacted the human attention span?*

## Introduction

Have you ever heard the phrase, “the attention span of a goldfish”? It seems increasingly relevant today as human attention spans shrink, partly due to the influence of digital technology. Attention span can be defined by three components: direction, depth, and duration.

### Direction

Have you ever found yourself going down a rabbit hole after encountering just one post? You start with a single video, then transition to articles, and before you know it, you end up on an e-commerce site. This process illustrates the flow of tasks and subjects we encounter online.

One of Microsoft’s Adoption and Change Specialists offers an analogy: think of our attention as a flashlight. It shines a beam on different topics and tasks at various moments. Now, consider the challenge of trying to point your flashlight in multiple directions at once. Is that an effective way to search for something or to stay on course?

This leads to the question of whether attention switching or multitasking is productive, especially in terms of work and our overall attention span. Digital media plays a significant role in this discussion; it encourages multitasking through constant notifications and pop-up ads that divert our focus between apps, messages, and tasks.

### Depth

Depth relates to how engaged we are in a task—essentially, how immersed we feel. This is about making a connection with what we are doing. Have you ever been so engrossed in what you're doing that you lose track of time until the day is over? Technology, our phones as a big example, interrupts the ability to connect deeply and really focus on tasks at hand. How many times have you pulled out your phone, even to just look at the time on the lock screen, during a meeting or during class? In today’s media landscape, constant disruptions through notifications, social media and multi-app interactions disrupt the immersive state and our “flow”.

### Duration

Duration involves how frequently we switch our attention and how long we can focus on a subject or task. Based on personal experience and observations of peers and social media users across all age groups, there has been a noticeable shift in our fast-paced environment, particularly in the digital landscape. This is where social media comes into play. By exploring how media consumption has shifted toward shorter formats, we can better understand how these changes impact human attention spans.

## Objective

With the advent of smarter phones, faster internet, and new social media platforms, we find ourselves constantly online. There have been previous extensive studies that have shown that online engagement has different negative effects such as mental health. *Has technology & media consumption impacted the human attention span?*

Exploring the relationship between these changes and how it has impacted our attention spans will give those interested in expanding their focus may find that understanding these trends encourages more mindful digital consumption, creating opportunities to counteract the effects of a fast-paced media environment. Individuals can then take the steps to manage their online presence in a healthier way.

## Dataset Overview

### Direction & Depth

Exploring a Lancaster University dataset on typical smartphone usage (typical\_smartphone). It shows participants' smartphone usage over a 13-day period. This includes the number of times a device was checked. Checks are defined as any period of usage lasting less than 15 seconds. The data consists of 26 participants. Checks can consist of notification popups where you raise to wake, phone taps to check the time on your lock screen, or unlocks for the sake of habit. The ages of participants are from 18 to 35.

The Mobile Phone Problematic Use Scale (MPPUS) is a questionnaire measuring the extent of problematic phone usage by looking at certain behaviors, similar to addiction, including dependence and withdrawal (Determining Typical Smartphone Usage - Research Portal | Lancaster University).

Disruptions through phone checks can show that just less than 15 seconds can shift your attention away from a task and potentially lead you down that “rabbit hole” of other distractions. With such a second-nature behavior, it can result in disrupting our attention quite often.

Kaggle's sp\_behavior dataset consists of over 1000 mobile users and contains data about phone usage and behavioral patterns. This includes information on demographics and app usage statistics. It focuses app usage on social media, productivity, and gaming apps, along with overall screen time.

Social media will consist of apps like Facebook and Instagram, a way to interact with other users. Productivity apps will be defined as apps used to increase the user's productivity. Gaming apps will be defined as entertainment applications involving gameplay.



## Duration

Using Kaggle’s Spotify Top 2000s Mega Dataset, we can analyze song durations, observing if music has truly gotten shorter. Also taken from Kaggle are YouTube’s trending videos and TikTok analytics data set that will show how video lengths and engagement metrics have evolved. Below are details of what the data sets are comprised of:

### Spotify

Audio statistics of the top 2000 tracks on Spotify, a music-sharing and playing application. There are 14 columns describing the track and its qualities. This contains songs made from 1956 to 2019. Analyzing changes in song duration with popularity metrics, highlighting trends in media adapted to shorter attention spans.

### Youtube

YouTube is a well-established video-sharing platform known for its wide range of content, with traditionally longer videos. The dataset is made up of 15 columns and almost 41K rows taken from Youtube's API and uploaded to Kaggle. This shows trending videos on YouTube from 2008 to 2017. The dataset is made up of various data types. Each row represents a different published YouTube video.

### TikTok

A newer video-sharing platform emerged recently called TikTok. TikTok's platform is uniquely optimized for short, engaging videos, typically under a minute, which has attracted a massive user base. Although YouTube has introduced its own short-form content format, known as YouTube Shorts, the platform remains primarily associated with longer video content. This dataset is made up of 19k rows and 12 columns uploaded on Kaggle. Each row represents a different published TikTok video in which a claim/opinion has been made.

Leveraging data from YouTube's trending videos and TikTok to analyze how video length and engagement metrics have changed over time, reflecting broader trends in media consumption that are influenced by shifting attention spans. By examining these platforms, that cater to different video length formats, insights are provided on how the prevalence of shorter and more engaging video formats may be responding to and shaping viewer's attention spans. This helps us understand whether current technological trends prefer bite-sized content.

## Methods

### Direction & Depth

Data preparation includes the following steps to clean the data for usage:

#### Changing Data Types

In the Spotify and YouTube datasets, I changed the Duration column from an object to an integer by removing the string ‘seconds’ and dividing the duration by 60. I converted the publish\_time column in the YouTube dataset to a date-time data type and extracted month and year.

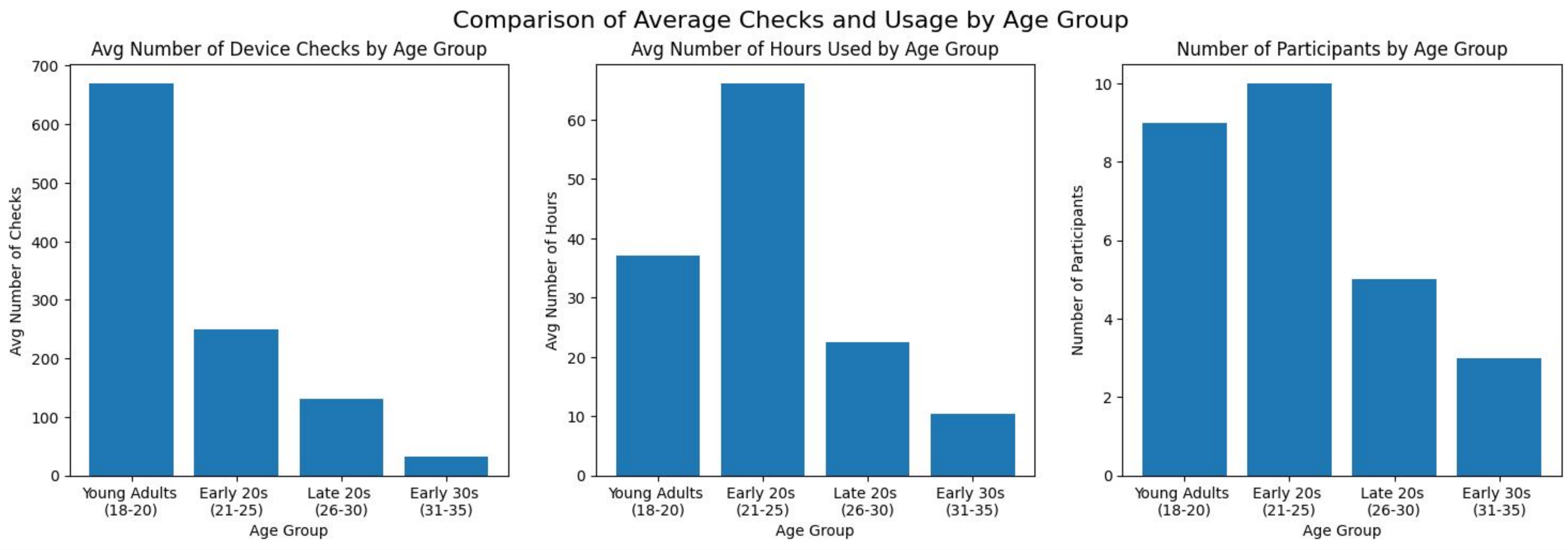
#### Drop Row & Columns

In YouTube's dataset, I excluded rows where comments and ratings were disabled, as well as those that had been removed or contained errors. I also removed videos that were under one minute in length since they account for a small percentage of the dataset. The goal was to compare the differences between long videos in the YouTube dataset and short videos in TikTok's dataset.

### Add Columns

I added age group cohorts to the typical smartphone dataset. These cohorts are labeled as follows: 18-20 for young adults, 21-25 for those in their mid-20s, 26-30 for late 20s, and 31-35 for early 30s. This categorization highlights the differences in maturity and life stages among these groups. Young adults, aged 18-20, are often transitioning from high school to college and have more leisure time compared to individuals in their early 30s, who are likely to have full-time jobs and may be starting families.

## Visualisation and Analysis



#### Young Adults (18-20) Group Behavior:

High Frequency, Low Duration: This group seems to have a high frequency of device checks but a lower duration of use compared to the Early 20s. This behavior may suggest they are frequently checking their devices for quick updates, like social media notifications or messages, but not engaging for long periods.

#### Early 20s (21-25) Group Behavior:

Moderate Frequency, High Duration: The Early 20s group has a lower average number of checks but the highest average usage hours, suggesting they might be engaging in longer sessions, such as watching videos or playing games. This age group may also have more responsibilities (e.g., school or work) that lead to more prolonged but fewer sessions.

#### Late 20s (26-30) and Early 30s (31-35):

These groups show lower average device checks and hours. This could be due to increased responsibilities, such as careers or family life, reducing the time available for frequent or prolonged device use.

#### Average Checks vs. Hours:

The contrast between average checks and average hours used across the age groups suggests that younger participants (18-25) are much more engaged overall, but the nature of engagement differs between those who are 18-20 and those in their early 20s. The 18-20 group checks their device frequently but uses it for shorter durations, while the 21-25 group checks less often but uses it for longer sessions.

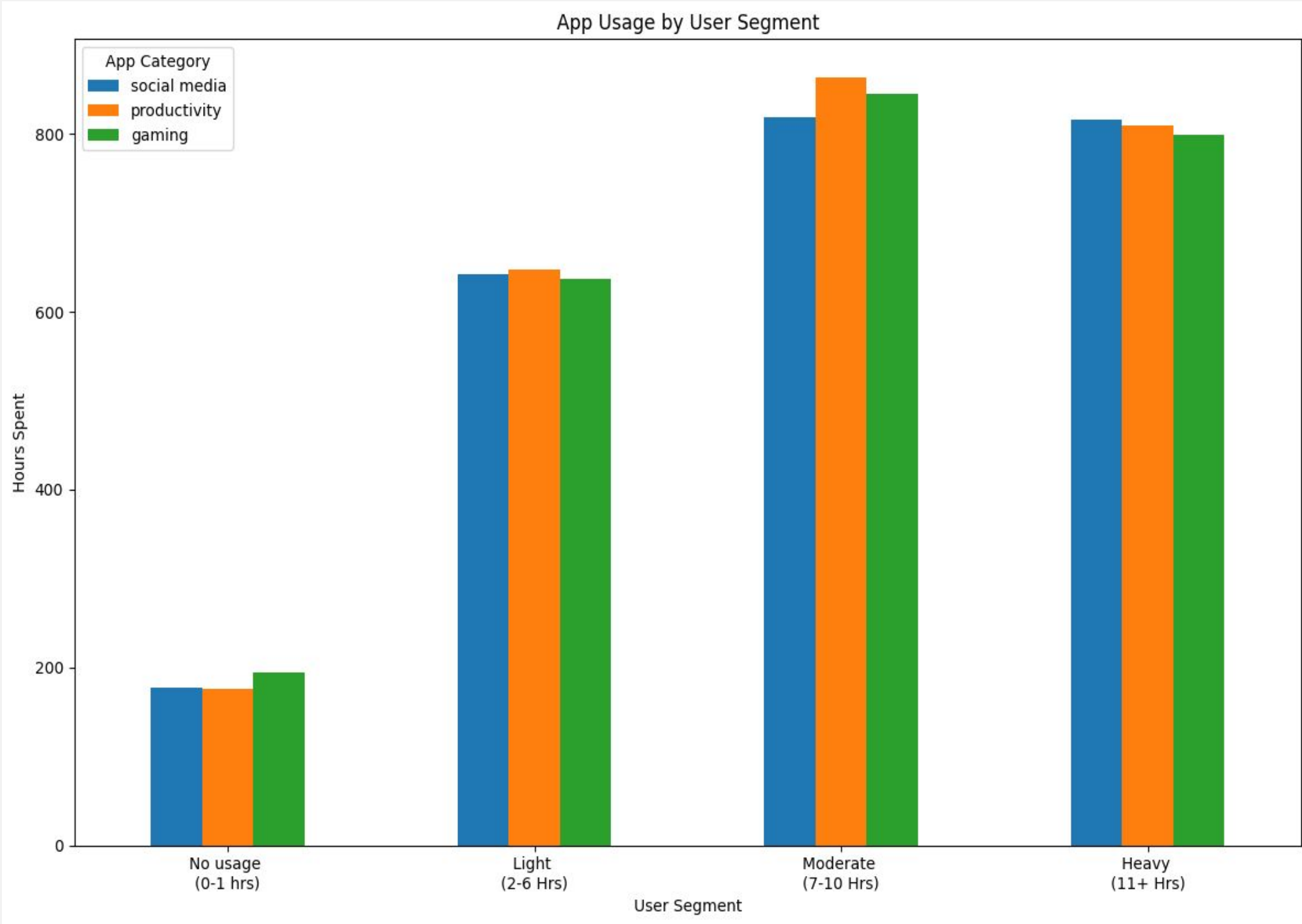
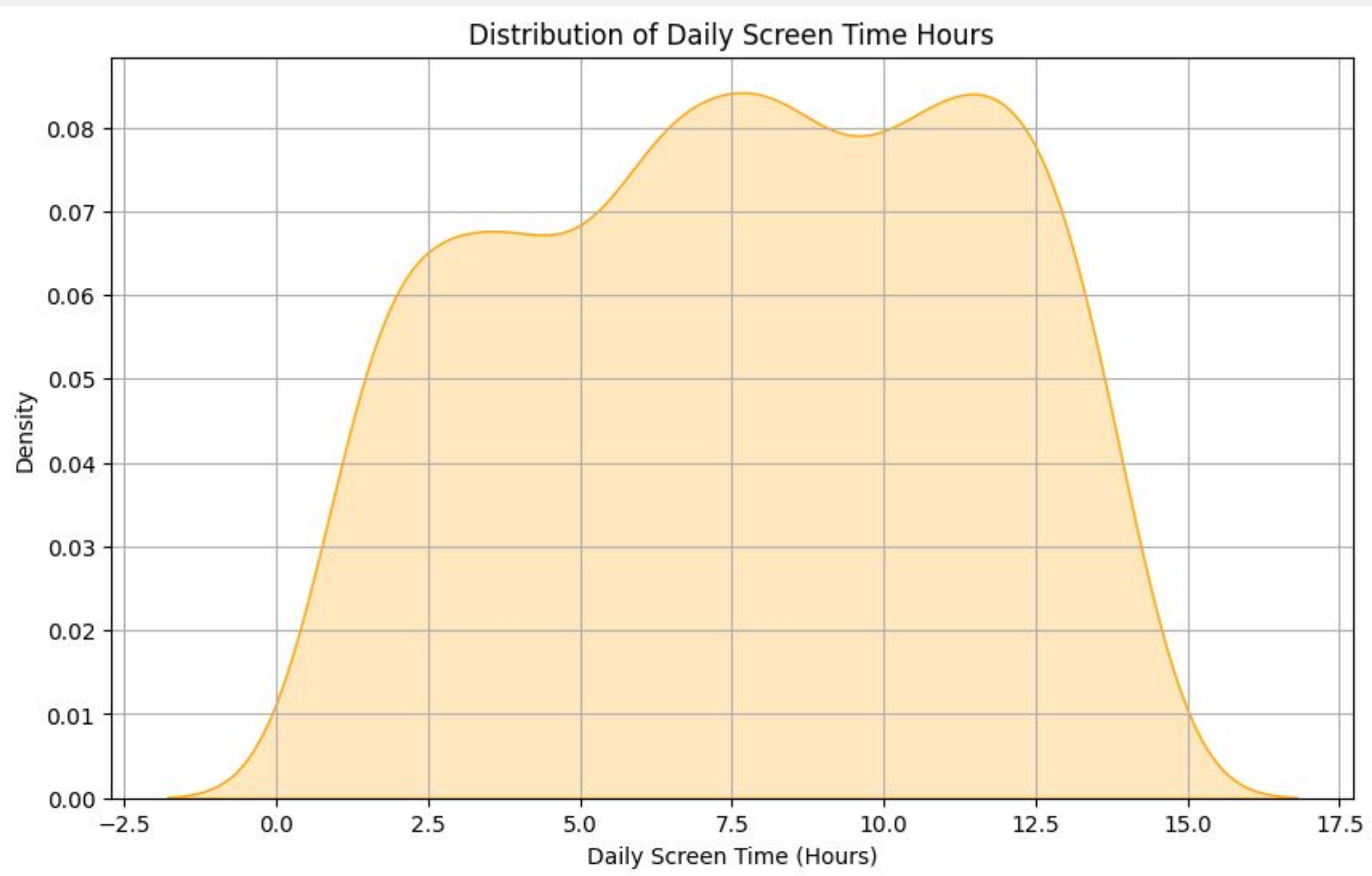


# Shrinking Attention Spans

## Analyzing the Impact of Technology on Technological-Focused Trends

Valentina Nguyen

### Visualisation and Analysis

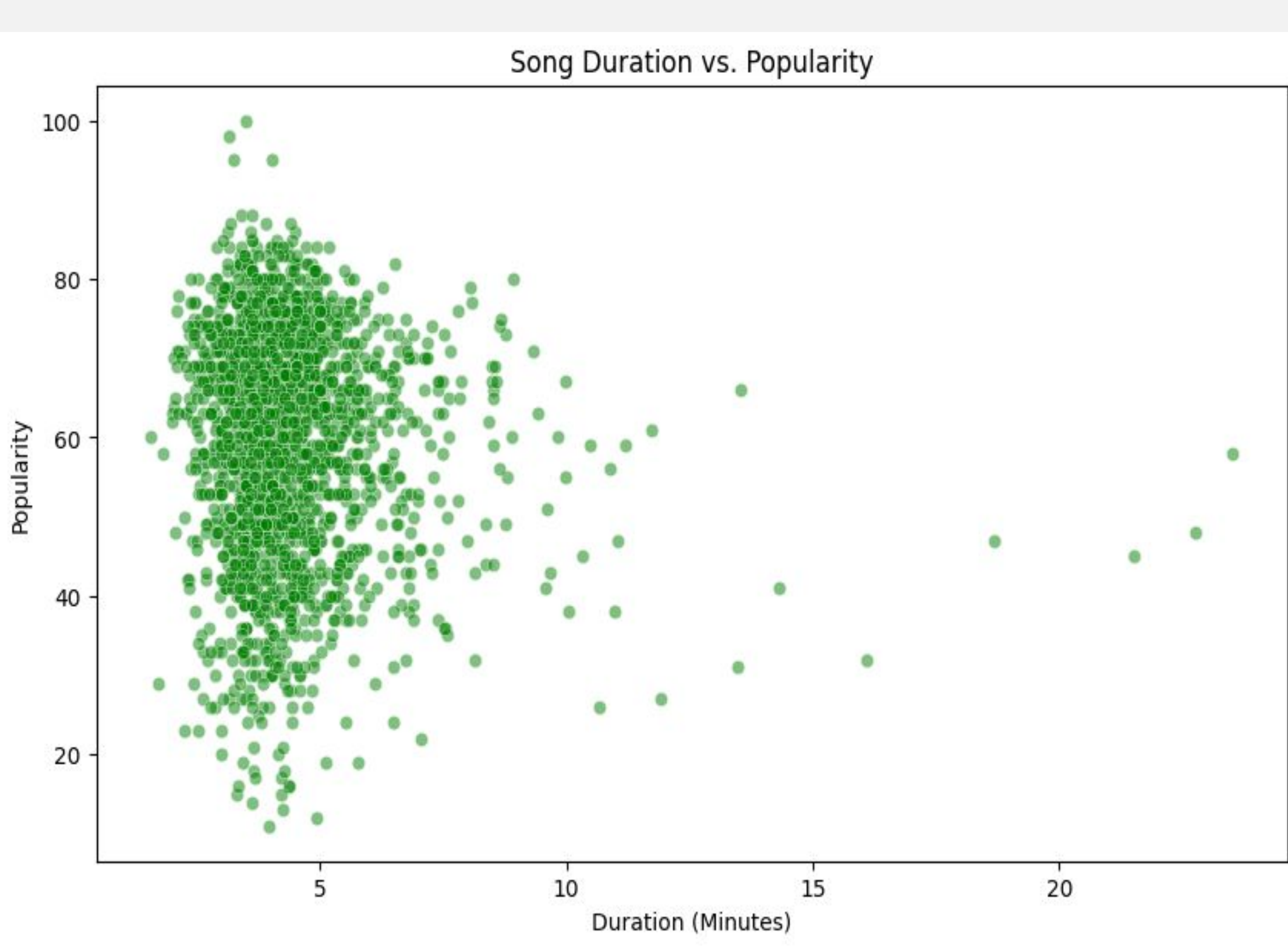
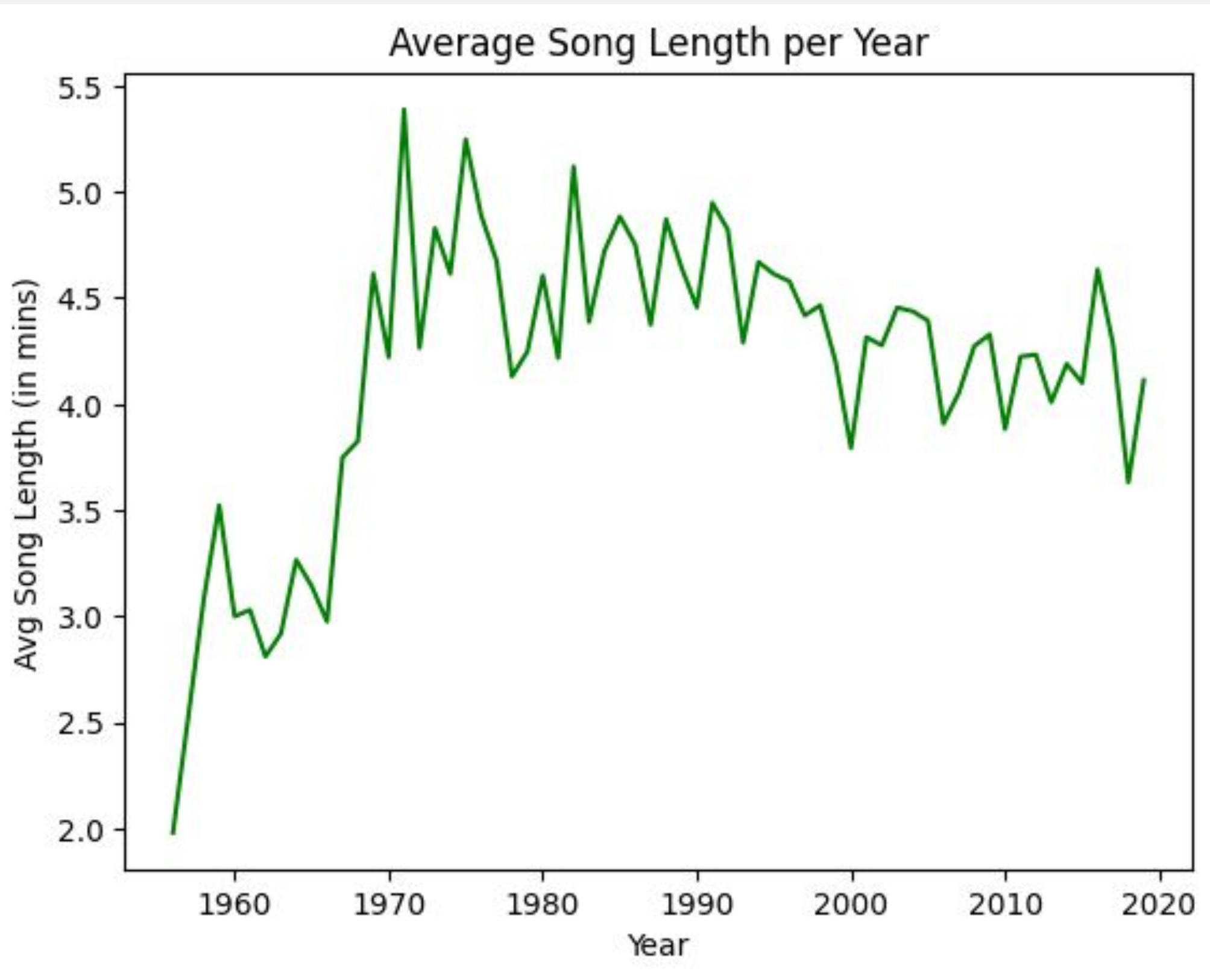


There is a Trimodal Distribution:

- First Peak: Around 2-3 hours
- Second Peak: Around 7-8 hours
- Third Peak: Around 11-12 hours

This can represent three different user types: light, moderate, and heavy users:

- Light Users: Around 2-3 hours of screentime. These users could be utilizing their phones for productivity and messaging. They would likely use apps like messenger, email, or quick browsing.
- Moderate Users: Around 7-8 hours. These users would potentially be using their phones throughout the day for work and leisure, there is a balance in usage activity, from productivity apps to social media and gaming.
- Heavy Users: Around 11-12 hours. These users are likely to be deeply engaged in activities like social media, gaming, or prolonged video consumption. They could represent those whose lifestyle or occupation involves constant mobile engagement, such as social media influencers, gamers, or those working primarily via mobile apps.

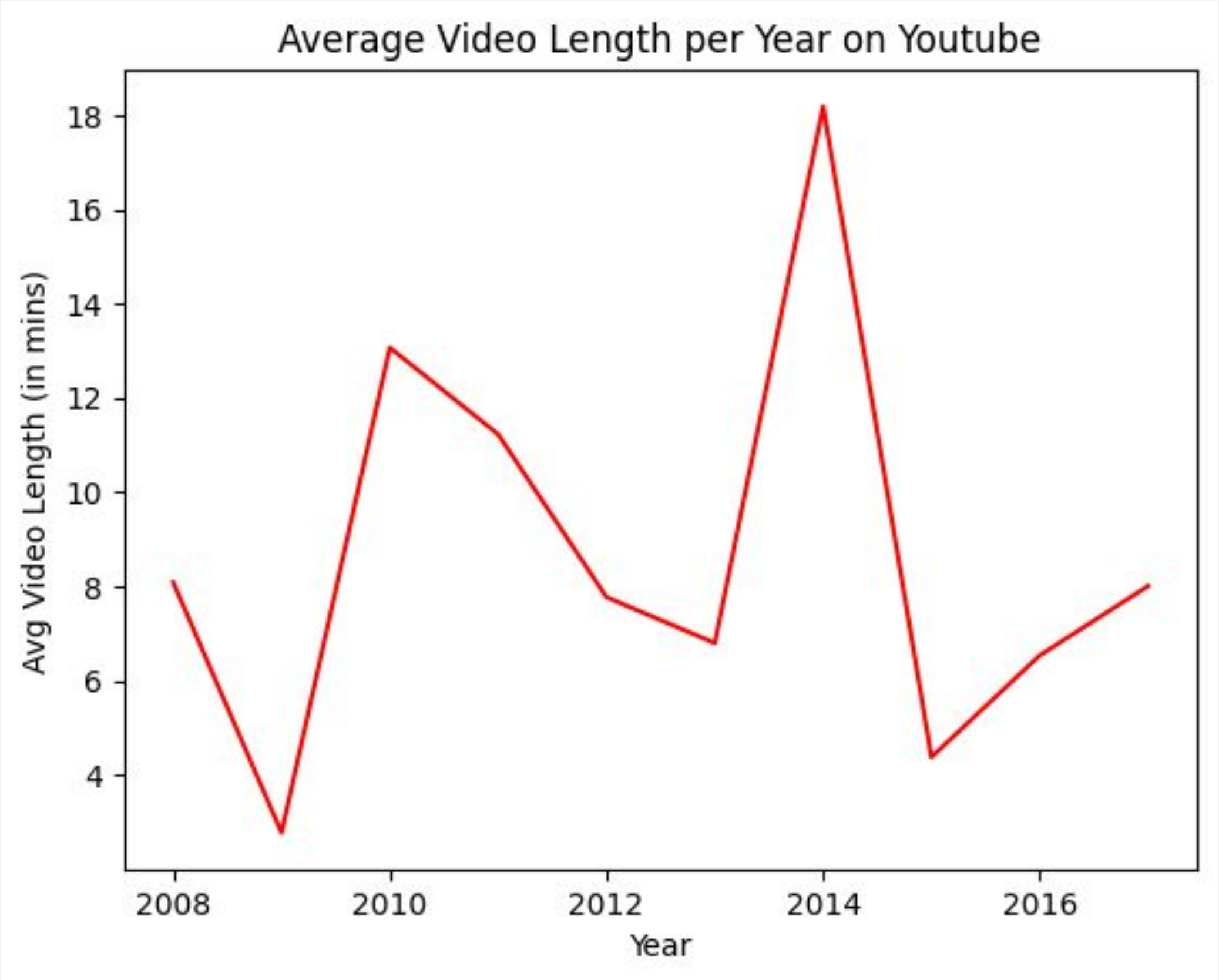


This analysis explores trends in song duration and popularity from the 1960s to the present, highlighting shifts in music production, listener preferences, and cultural influences:

1. **\*\*1960s-1970s: Rising Song Lengths\*\***
  - From the early 1960s to the 1970s, the average song length increased from around 2 to over 5 minutes.
  - This trend reflects a shift toward genres like rock and progressive music, which emphasized extended compositions with instrumental solos.
2. **\*\*1970s-2000s: Fluctuating Durations\*\***
  - Average song lengths oscillated between 4 and 5 minutes during this period, without a clear trend.
  - Genre diversity contributed to these fluctuations, with shorter pop songs coexisting with longer rock and jazz tracks.
3. **\*\*2000s-Present: Shorter Songs and Stabilization\*\***
  - Around the early 2000s, song lengths declined to near or below 4 minutes and stabilized during the 2010s.
  - This reflects the impact of the digital age, with streaming platforms and social media encouraging shorter, catchier songs to cater to shorter attention spans and playlist dynamics.
4. **\*\*Popularity and Duration Correlation\*\***
  - Songs with high popularity scores (above 70) are mostly between 2 to 5 minutes, aligning with audience preferences for concise content.
  - Popularity decreases significantly for songs over 5 minutes, with very few long tracks exceeding a popularity score of 60.
5. **\*\*Cultural Influences on Trends\*\***
  - The preference for shorter songs aligns with the rise of short-form content on platforms like TikTok, where instant gratification and quick engagement are paramount.
  - These trends underscore how evolving consumption habits shape music production and popularity dynamics.

In summary, the analysis reveals a clear evolution in song lengths, driven by shifts in music genres, technological advancements, and audience behavior, with shorter songs dominating modern popularity metrics.



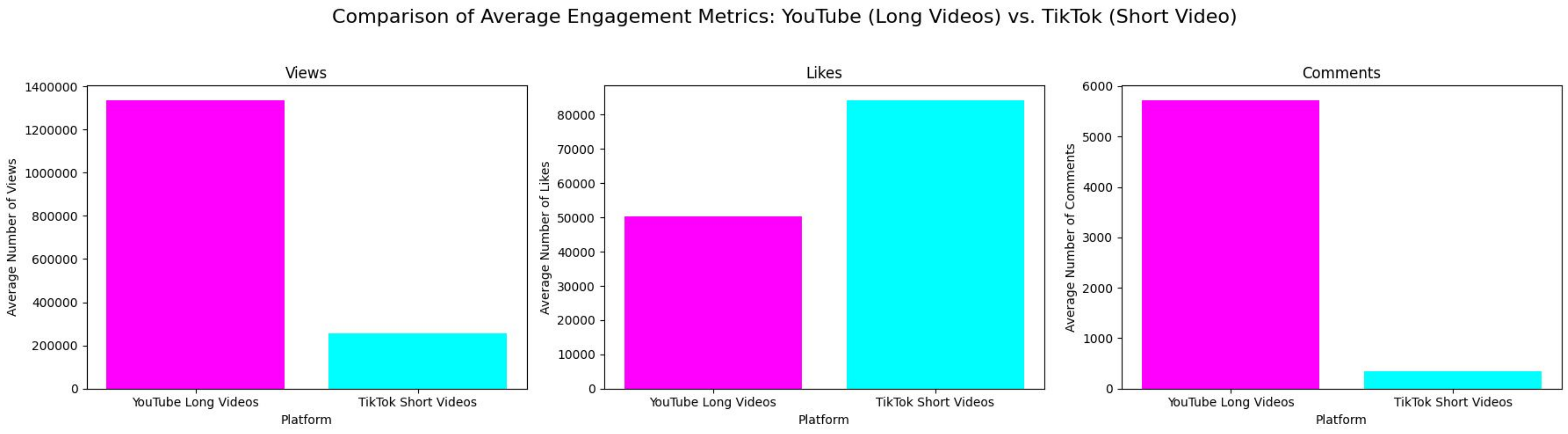


Video Length Trends: Use the duration to track changes in video length over time, checking if shorter videos have become more frequent on the trending list.

Though YouTube is primarily known for its longer video content, it is quickly shifting in the opposite direction with the introduction of YouTube Shorts and a declining average video duration in minutes.

Observations include intense fluctuations in average video length from year to year, with a notable peak in 2014, where the average length reached over 18 minutes. The lowest dips in average video length occurred in 2009 and 2015. There is no consistency in the increase or decrease of average video length over time; rather, we see periodic shifts. This variation may be influenced by content trends at the time and changes in the platform's algorithm.

Looking at YouTube's platform alone, there are no implications for technology's impact on attention spans. The graph suggests no strong trend towards shorter or longer videos. We must take into consideration the content of this video-sharing platform as it caters to a diverse audience and preferences.



For the purpose of this analysis "short" videos are defined as videos with a duration of a minute or under. We must note that short videos in our YouTube (YT) dataset make up only 2.36% of the data set. We will disregard the short videos in the YT set and compare the "long" videos with our TikTok dataset, which is strictly made up of "short" videos.

Since there is a larger number of entries for YT's dataset than TikTok, we will normalize our metrics and take the average of our engagement metrics. Engagement metrics are based on Views, Likes, and Comments.

Views

YouTube videos had a higher average number of views, unlike TikTok. This suggests that YouTube attracts overall attention, likely due to its established platform as well as more searchable content. In this case, searchable content refers to discoverability through relevance, metadata, and appeal.

Likes

TikTok has a significantly higher number of average likes, showing an engagement preference for its fast-paced content with a quick action that follows the same trend. TikTok's emphasis on high-energy, bite-sized videos seems to resonate with audiences who are more likely to quickly "like" content as part of the platform's design. After all it is just a double tap compared to writing a comment. This highlights TikTok's role in driving immediate engagement.

Comments

YouTube has higher average comments indicating there's room for discussion on the platform. Though TikTok seems to be going on the same trend, YouTube is not only a platform for entertainment, but also for educational purposes. When you look up tutorials on how to put something together or how to do something, YouTube is what pops up in regard to video content on that subject. So, YouTube fosters deeper engagement because of the type of content they provide but also a community-driven nature while Tiktok prioritizes quick reactions over in-depth discussions.

Content length impacted engagement considerably. TikTok encourages rapid interactions like likes but struggles to generate sustained attention or discussions such as views and comments. Their focus on likes also reflects the modern shift toward shorter attention spans and immediate gratification. Although this is true, it seems that YouTube demonstrates that engagement depends on the content and platform we consume.

Conclusion

The findings underline the growing dominance of short-form, high-energy content tailored for rapid consumption and immediate gratification. This shift poses challenges for sustained attention and deep engagement, emphasizing the need for mindful digital consumption. Recognizing these trends empowers individuals to develop healthier media habits, balancing efficiency with meaningful engagement to counteract the effects of a fast-paced digital landscape.

Resources

1. Determining Typical Smartphone Usage - Research Portal | Lancaster University. 2016, [www.research.lancs.ac.uk/portal/en/publications/determining-typical-smartphone-usage\(c13fd709-d781-4c49-a334-790d51dea2e1\).html](http://www.research.lancs.ac.uk/portal/en/publications/determining-typical-smartphone-usage(c13fd709-d781-4c49-a334-790d51dea2e1).html).
2. Smartphone Usage and Behavioral Dataset. 23 Oct. 2024, [www.kaggle.com/datasets/bhadramohit/smartphone-usage-and-behavioral-dataset](https://www.kaggle.com/datasets/bhadramohit/smartphone-usage-and-behavioral-dataset).
3. Spotify - All Time Top 2000s Mega Dataset. 4 Feb. 2020, [www.kaggle.com/datasets/iamsumat/spotify-top-2000s-mega-dataset](https://www.kaggle.com/datasets/iamsumat/spotify-top-2000s-mega-dataset).
4. TikTok User Engagement Data. 18 Oct. 2023, [www.kaggle.com/datasets/yakhyojon/tiktok](https://www.kaggle.com/datasets/yakhyojon/tiktok).
5. Trending YouTube Video Statistics. 3 June 2019, [www.kaggle.com/datasets/datasnaek/youtube-new?select=USvideos.csv](https://www.kaggle.com/datasets/datasnaek/youtube-new?select=USvideos.csv).
6. Typical Smartphone Usage Dataset - Research Portal | Lancaster University. 2016, [www.research.lancs.ac.uk/portal/en/datasets/typical-smartphone-usage-dataset\(24cc8151-a0fc-4753-8fd9-efb0313a8651\).html](http://www.research.lancs.ac.uk/portal/en/datasets/typical-smartphone-usage-dataset(24cc8151-a0fc-4753-8fd9-efb0313a8651).html).