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An in-depth investigation of social media content and engagement: the case of TikTok videos.

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Abstract

This thesis explores video content categories on TikTok's trending page and their impact on user engagement metrics, utilizing a mixed methods research design. Employing open/flexible coding, the study identifies 12 distinct video categories, shedding light on the diverse content landscape of the platform. The research further analyzes video attributes' influence on user engagement metrics, revealing preferences for certain attributes such as 'duet' videos for more likes and videos without text for higher overall engagement.

The findings hold practical implications for content creators, enabling them to optimize strategies and enhance user interaction. Aligning content with user preferences fosters a more engaging environment on TikTok, promoting a sense of community.

However, limitations include sole researcher coding and limited video representation in certain categories. Future research should involve multiple coders and larger, more diverse video samples.

In conclusion, this thesis provides valuable insights into video content and user engagement on TikTok. It offers practical guidance for content creators and enriches our understanding of engagement patterns on the platform. Future research could explore cross-platform applicability, delve into user perceptions through qualitative interviews and investigate the significance of video attributes within different video categories.

Introduction

The use of social media has witnessed significant growth in recent years, with a large number of people engaging with it daily. Consequently, social media marketing has become a vital strategy for companies to promote their products, attract new customers and convey brand values. Brands and businesses have recognized the potential of social media platforms as alternative means of enhancing their online presence and connecting with potential customers (De Cornière & Sarvary, 2022). Research has demonstrated that customers form stronger connections with brands when they interact with them on social media, leading to increased purchase likelihood and greater word-of-mouth advertising (Lee et al., 2018). Despite many companies utilizing social media for marketing, the absence of a clear social media strategy and uncertainty about their goals often hampers their ability to fully leverage its potential (Quesenberry, 2018). Additionally, existing research on content marketing and advertising content has primarily been confined to laboratory settings, underscoring the necessity for real-world investigations to better understand the practical implications of these marketing strategies (Lee et al., 2018).

With the continually growing platforms and emerging ones, there are many new possibilities and many companies do not know what all the possibilities are. One such relatively new and rapidly growing platform is ByteDance's TikTok, which allows users to record and share short videos. TikTok has approximatly 1 billion monthly active users (Brian Dean, 2023). Every user can record and share videos, which can be interacted with in various ways, such as liking or commenting on them, as well as saving or sharing them. A unique feature of the platform is the TikTok algorithm, which influences how many users see a particular video. The algorithm's intention is to give users the most personalized 'ForYou' page. This means that if the algorithm thinks that a user will like a certain video, it will show it on the user's ForYou page. This is a unique component that makes social media marketing on TikTok very interesting. Another interesting aspect of the algorithm is that videos can have an enormous number of views, with the average TikTok video having 9.6 million views and the most viewed video having 2.2 billion views (Smith, 2023). Companies can benefit greatly from using the algorithm and the large reach of TikTok, but it is still not being utilized to its full potential. Therefore, this paper studies the types of content on TikTok that generate the most engagement. The goal is to help companies, brands and/or influencers respond to this underutilization and maximize the benefits of their social media strategy.

Existing research on content categories and user engagement has predominantly focused on popular social media platforms like Facebook, Twitter, or Instagram. However, there remains a need to explore whether these findings hold true across other social media platforms. Notably, a substantial number of studies have primarily concentrated on platforms that mainly feature texts or photos-based content (e.g., Huang et al., 2019; Lee et al., 2018; Li & Xie, 2019; Roccapriore & Pollock, 2022; Shahbaznezhad et al., 2021; Yew et al., 2018). The biggest difference between TikTok and other platforms stems from its distinctive focus on short-form video content, dedication to inspiring creativity through a diverse array of sounds and filters, and its unique recommendation algorithm that ensures content reaches users who are likely to engage with it (Feldkamp, 2021).

A significant blind spot in social media content research is the lack of extensive investigation into platforms that exclusively host short videos, such as TikTok. Currently, there is limited research in this area. While some studies have analyzed longer and more in-depth videos, focusing on content such as group communications (Huber, 2020), movies (Li et al., 2006) and surgical procedures (Loukas, 2017), there is a dearth of theoretical frameworks tailored to analyze short videos created purely for amusement.

This study contributes to existing research on short video content and engagement by creating a comprehensive dataset of video-based social media content. Through systematic coding, the dataset will capture various video and content categories, along with key video attributes. The research seeks to unravel the relationship between different attribute values and content categories, specifically investigating their impact on engagement metrics within the TikTok platform. By analyzing these associations, this study aims to provide deeper insights into the characteristics of videos that drive maximum interaction and engagement, enhancing our understanding of effective content strategies on TikTok.

Literature review

To optimally understand the subject of this study the following sections will discuss the importance of user engagement, what has been found in previous research on social media content and engagement and what previous research on tiktok has resulted in.

The importance of engagement

Marketers recognize social media engagement is a vital objective that companies must achieve through their social media efforts. It serves as a key metric to evaluate the success of their social media strategy (Trunfio & Rossi, 2021). Customer engagement has been proven to strongly predict user satisfaction (Masrek et al., 2018) and reflects how customers interact with a brand beyond transactions, influencing and being influenced by other market stakeholders (Van Doorn et al., 2010). For companies, customer engagement directly impacts essential aspects, including firm performance, behavioral intention and word-of-mouth (De Oliveira Santini et al., 2020).

Behavioral dimensions of engagement, such as liking, commenting, sharing and viewing, are among the most measurable metrics on social media platforms (Trunfio & Rossi, 2021). Muntinga et al. (2011) categorized brand-related social media usage into three types: consuming (lower level, e.g., viewing), contributing (higher level, e.g., liking, commenting and sharing) and creating (the highest level of engagement) (Schivinski et al., 2016). This categorization contributes to a deeper understanding of how users interact with brands on social media and a meaningful perspective on the varying degrees of engagement. This can help businesses customize their social media efforts to better connect with their target audience.

Contrary to initial beliefs that high engagement relied on the number of followers or the desire to build relationships, research indicates that content is the primary driver of engagement (Lee et al., 2018). Shahbaznezhad et al. (2021) found that the format and platform of social media content significantly impact users' engagement behavior. Their results show that the effectiveness of social media content on users' engagement is moderated by the content context.

What other social media studies have found on content categories and engagement

In exploring content categories and engagement, previous studies by Hu et al. (2014) have identified eight distinct categories, encompassing Friends, Food, Gadget, Captioned Photo, Pet, Activity, Selfie, and Fashion, using a clustering method to classify five user types based on their content preferences. However, our focus in this subsection lies predominantly on the user perspective of social media and their interactions with various content types.

Lee et al. (2018) discovered that brand personality-related content leads to higher engagement by establishing human characteristics associated with the brand, attracting like-minded consumers and enhancing the brand's functional benefits. In contrast, directly informative content tends to yield lower engagement levels, possibly due to its perceived lack of interest and compatibility with users' motives, leading to cognitive elaboration and reduced liking and trust in the brand.

Roccapriore and Pollock (2022) investigated the relationship between cues and engagement metrics on social media. They found that image-based cues were positively associated with lower-level engagement, such as following, while word-based cues did not show a significant relationship in that context. However, in terms of higher-level engagement, like positive interactions, word-based cues exhibited a significantly stronger association compared to image-based cues. Moreover, they observed that competence cues, which are the signals that an influencer or a brand sends to their followers or customers to demonstrate their ability, skill, intelligence, or efficacy in their domain, had a stronger positive relationship with following, while warmth cues demonstrated a positive and significant relationship with positive interactions. However, competence cues did not show a similar association with positive interactions.

Related work - TikTok studies

Several studies have been conducted on various topics related to TikTok, exploring different aspects of user engagement and video content. Li et al. (2021) conducted a content analysis of COVID-19-related videos on TikTok, finding that subtitles positively influenced the number of shares and dance videos received the most shares. Another study by Ling et al. (2022) looked into video virality and found that close-up or medium-shot videos, with a second point of view, were more common among viral videos. Close-up or medium-shot videos involved the creator being relatively close to the camera, while videos with a second point of view featured the creator engaging with the viewer directly in front of the camera.

Bash et al. (2022) examined videos tagged with #mentalhealth on TikTok, revealing that almost half of them addressed mental distress symptoms, with general mental health and personal experience being the most prevalent content categories. Klug et al. (2021) investigated user assumptions about the TikTok algorithm, identifying video engagement and posting time as important factors, while disproving the assumption that by including trending and algorithm-related hashtags and using a large number of hashtags, a video's likelihood of being recognized by the algorithm and reaching the trending section or 'for you' pages would increase.

Ling et al. (2022) explored factors contributing to the virality of short videos on TikTok, identifying the number of followers, video scale and point of view, video lifespan, presence of text and video style as primary predictors. Serrano et al. (2020) conducted a pioneering analysis of political communication on TikTok, highlighting its interactive nature and use of communication trees for political discourse.

Additionally, Alley and Hanshew (2022) conducted a content analysis of videos from academic libraries on TikTok, finding that humanizing and fun content types garnered the highest user engagement.

TikTok stands out from other social media platforms due to its emphasis on short-form video content, dedication to inspiring creativity and its unique recommendation algorithm (Feldkamp, 2021). Consequently, researching TikTok necessitates a distinct approach compared to other platforms. Despite existing research on TikTok, there remains a notable gap in understanding the relationship between general content categories and their impact on engagement metrics.

To address this gap, this thesis will delve into the content categories of TikTok videos and their relevance to engagement metrics, with a specific focus on the trending page. By investigating these high-engagement videos, we aim to uncover valuable insights that will benefit creators in optimizing their content strategies to achieve greater engagement with their audience.

Methods

The study uses a mixed methods research design. Mixed methods research refers to a comprehensive approach where the researcher gathers and examines data, seamlessly integrates the outcomes and draws conclusions by combining both qualitative and quantitative methodologies within a single study (Tashakkori & Creswell, 2007). This research first investigates types of video content on Tiktok via a qualitative content analysis, aiming to identify categories within the data. To accomplish this, an inductive content analysis approach was utilized, involving key steps such as data preparation, which includes data coding, organization and reporting, as outlined by Elo and Kyngäs (2008) and Elo et al. (2014). Once the content/video categories were established, they were further analyzed using various quantitative engagement metrics to gain insights into the level of engagement within each category. Second, this thesis uses several statistical tests, such as Kruskal-Wallis, Dunn's test and Cliff's delta's effect size, to examine potential differences in engagement across the categories and attributes identified in the qualitative content analysis.

Data collection

In order to gather the necessary data on TikTok videos for this thesis research, we employed the Apify TikTok scraper, a powerful tool designed specifically for automated extraction of information from websites. The process of scraping involves automatically retrieving data that was originally intended for human consumption (Glez-Peña et al., 2013). By utilising the Apify TikTok Scraper, we were able to efficiently collect videos from the trending page, ensuring that we obtained videos with the highest engagement metrics.

In order to obtain desirable results, we chose to scrape videos using the hashtag "#fyp," which stands for "For You Page" and is the most viewed hashtag on TikTok worldwide, accumulating almost 35 trillion views. A total of 942 videos were successfully scraped using this approach. The collected data for each video encompassed various variables, as depicted in Table 1.

Table 1: Description of Variables for TikTok Video Dataset	
Variable	**Definition**
id	The video ID
diggCount	Number of likes on the video
commentCount	Number of comments on the video
shareCount	Number of shares on the video
playCount	Number of view on the video
createTime	The time and date the video has been uploaded
webUrl	The url of the video
engagementRate	The overall engagement compared to the number of views

In order to provide a comprehensive assessment of video engagement, we introduced an additional variable to our analysis. This new attribute aimed to capture the overall engagement rate, which represents the quantity of engagement relative to the number of views. To calculate the engagement rate for a certain video we employed a simple formula, see Equation 1.

$$ER = (l + c + s)/v \tag{1}$$

Here variable l describes the number of likes, variable c describes the number of comments, variable s describes the number of shares and variable v describes the number of views.

To ensure the validity of our findings, we implemented specific criteria for video selection. Firstly, we required that the videos had accumulated at least one million views, indicating a considerable level of popularity. Secondly, the videos needed to have been posted for a minimum of one month at the time of scraping, allowing sufficient time for engagement and interaction to occur. These criteria were set to ensure that the selected videos had garnered the engagement they "deserved" based on their exposure and longevity. After implementing these criteria, we were left with a total of 930 videos that met the aforementioned conditions.

Video coding

To guide our coding process, we used flexible coding (Deterding and Waters 2018). According to this approach qualitative sources, including videos, can be analysed following three basic steps. These steps are first, indexing and memos; second, analytical coding; and third, exploring coding validity. Although the article primarily focuses on in-depth interviews, we recognized its potential applicability to coding short videos such as TikToks. Given the nascent nature of (short) video coding in research, limited literature exists on the subject and a definitive best practice has yet to emerge. There are studies that analyse videos using content analysis (e.g. Huber (2020), Li et al. (2006) and Loukas (2017)), but a theoretical framework for analyzing short videos that are made purely for amusement has not yet been developed.

Following Deterding and Waters' (2018) approach, we commenced with Stage 1, known as "The Big Picture: Indexing and Memos." During this stage, we watched each video once, exclusively focusing on coding the video attributes. Attributes can be defined as "*the salient personal characteristics of the interviewees that played a role in the study design*" (Deterding & Waters, 2018). In the case of analysing videos, we are not interested in an interviewee's characteristics, but those of a video. In this study, we coded for the following attributes: video type, usage of text, originality of the sound, number of main actors and gender of the main actor. The potential variables for each attribute are outlined in Table 2.

Table 2: Description of Attributes and Possible Variables for TikTok Video Categorization

Attribute	**Possible variables**
Video type	General, stitch video, reply video, duet video
Text usage	True, Flase
Original sound	True, False
Number of main actors	0, 1, multiple
Gender of main actors	Male, female, mixed, none

Some of these terms require some additional explanation. The video types include Stitch videos, Reply videos, Duet videos and General videos.

Firstly, a Stitch video involves incorporating a snippet of one video, referred to as "video 1," before showcasing the main content of another video, termed "video 2." Usually, the content of video 2 is based on or serves as a reaction to video 1. The caption of video 2 contains a link to the complete video 1, allowing viewers to access it fully by clicking on the provided link.

Secondly, a Reply video revolves around a video, denoted as "video 1," serving as a response to a specific comment made on another video, referred to as "video 2." In the opening of video 1, the original comment that inspired the response is displayed. Additionally, the caption of video 1 provides a link to the commented video 2, offering viewers the chance to navigate to it for context.

Thirdly, a Duet video showcases two videos simultaneously, with "video 1" being the original post. In this case, "video 2" acts as an interactive component, likely related to or engaging with video 1. Both videos' sounds are played simultaneously, merging to form a unified experience as represented by video 2.

Lastly, a General video stands as an independent creation, existing solely as an individual video without any direct linkage to other videos or creators.

The determination of sound originality in the videos was made through careful observation while watching each video. The process involved identifying whether the accompanying sound was inherent to the video itself or that an existing sound from the so-called TikTok library was used. If an existing sound was used, the originality of the sound was coded ‘False’ and if the sound was inherent to the video the originality was coded ‘True’. It's important to note that the assessment of sound originality extended beyond merely considering the sound stated beneath the TikTok. We focused on what could be audibly perceived in the video. For instance, a video might incorporate an existing sound as background music while someone speaks over it. In such cases, the sound heard in the video is inherent to the content, as the primary purpose of the sound is to enable the audience to hear the speech.

For the purpose of this research we will define the main actor as “the individual(s) or entity that actively engages in or performs the central action or focus of the video. It represents the primary subject or character that drives the narrative or content of the video." The main actor of the video was either a human or an animal. The attribute gender of the main actor could only be coded if the main actor was an adult human being. This means if the main actors were a female and her dog the attribute gender of the main actor would be female. For videos with only animals the gender of the main actor would be none, in addition if the main actor was a baby/child whose gender was not clear the code would also be none. Lastly, if the main actors of the video were both male and female, or represented as non binary the code 'mixed' was assigned.

Proceeding to Stage 2 according to Detering and Waters (2018), we coded the videos analytically. Our coding approach aimed to capture the broader ideas, themes and thoughts conveyed in the videos, rather than meticulously documenting specific details of the content. This strategy facilitated subsequent analysis, as we focused on identifying overarching categories. A category, within the context of content analysis, refers to a concept or classification that emerges as a result of the analysis process (Elo & Kyngäs, 2008). A category contains videos with similar goals, actions, themes or characteristics.

Ultimately on to Stage 3: Exploring Coding Validity, Testing and Refining Theory (Detering and Waters., 2018). Following the initial round of coding, which encompassed 200 videos, we proceeded with the identification of underlying categories within the coded data. To ensure comprehensive coverage of relevant themes, we continued to add more videos to our research until the point of saturation was reached. Ultimately, our dataset consisted of a total of 295 videos, which were classified into 12 categories which will be defined in the Results section. This approach was employed to ensure the theory's thorough testing and refinement, aiming to strengthen its validity and applicability.

To ensure the reliability of our coding process, we implemented the following requirements. Firstly, each video was meticulously watched a minimum of three times. This approach aimed to minimise any potential oversight or omission of relevant information during the coding process. Secondly, after assigning each video to a specific category, it was re-watched to confirm the accuracy of the assigned category. This step further enhanced the reliability of our coding results.

Furthermore, we diligently updated coding memos whenever decisions were made regarding the selection of analytic code words. This practice ensured that any changes or clarifications in our coding approach were thoroughly documented, promoting consistency and transparency in our analysis.

By adhering to these stringent requirements, we aimed to enhance the reliability and validity of our coding process, thereby bolstering the credibility of our research findings..

Quantitative tests

To assess the significance of video categories and attributes on engagement metrics, we utilized the Kruskal-Wallis test (Kruskal & Wallis, 1952), chosen for its suitability in comparing categorical variables with multiple numerical variables. The data exhibited non-normal distribution, confirmed by the Shapiro-Wilk test (p-value>0.05)(Shapiro & Wilk, 1965), likely attributed to the high scores of videos on the trending page. Thus, the non-parametric nature of the Kruskal-Wallis test was well-suited for our analysis. Nonparametric tests, such as the Kruskal-Wallis test, do not depend on assumptions about the distribution or parameters of a statistical population (Harris et al., 2008). Moreover, this test accommodates independent groups, including video categories and established attributes.

As a post hoc analysis, we utilized Dunn's test (Dunn, 1964). This choice was motivated by its non-parametric nature, allowing for robust analysis in the absence of normal distribution assumptions. Dunn's test facilitated pairwise comparisons between groups, providing insights into specific group differences. Moreover, the test proved to be robust and capable of handling unequal sample sizes, which was advantageous for our dataset.

In addition to significance testing, Cliff Delta's effect size (Cliff, 1993) was calculated. By quantifying the magnitude of an effect, Cliff Delta's effect size offers insights into the practical significance of observed relationships. Its interpretability and range of values between -1 and +1 make it easier to compare results across different studies and variables. Another advantage is that Cliff's delta is robust to variations in sample size, making it useful even with smaller sample sizes.

Results

Category analysis

After carefully analysing the flexible coded videos, these are the categories were defined: Animal videos, baby videos, captured memories, educational videos, fails and falls, multi channel segments, personal imitation videos, reaction videos, relatable videos, serenity videos, talent videos and user stimuli. The definitions can be found in Table 3. Some categories are self-explanatory, while others require further explanation. In the next paragraph, we will provide additional details about the categories and their criteria. It is crucial to bear in mind that, for the purpose of this research, each video was restricted to having only one primary category, based on the most suitable fit. Consequently, some videos could potentially fall under multiple categories or be subject to different interpretations. However, during the coding process, careful consideration was given to the video's objective and its core content to assign the best fitting category.

Animal videos: Almost all videos featuring animals as the main focus were placed in this category. These videos often showcase amusing or cute animal behaviour without much depth. However, there were some videos with an animal as the main actor, yet they were placed in another category that was a better fit. For example: a video of a man getting a puppy from his family. The puppy is one of the main actors in the video, but because the purpose of the video was to show the man's reaction, this video was assigned the reaction video category.

Baby videos: The main focus of videos labelled under this category are babies. In these types of videos, babies exhibited amusing or cute behaviour. The videos did not have much depth.

Captured memories: This category was created for videos that primarily aim to document significant events or experiences.

Educational videos: These videos are self-explanatory, as their purpose is to share knowledge, provide educational content, spread awareness and/or show how to do something.

Fails and falls: While they might seem similar to reaction videos, these videos often end before the main actor has a chance to react. They feature unexpected mishaps or funny incidents. An important aspect of these videos is that they were not intended to be recorded as originally planned. The creators had the intention of capturing something on camera, but their initial idea failed.

Table 3: Description of Video Categories, Examples and Frequency of Occurrence (N=295) in TikTok Video Dataset			
Category	**Definition**	**Example**	**n**
Animal videos	A video featuring an animal as the or one of the main actors.	https://www.tiktok.com/@chipmunksoftiktok/video/7068793156183035182	69
Baby videos	A video featuring a baby as the or one of the main actors	https://www.tiktok.com/@briannagawne/video/7157833669854432513	5
Captured memories	Videos that focus on capturing a memory or specific event.	https://www.tiktok.com/@kerryhirz/video/6810000404328369414	4
Educational videos	Videos created with the purpose of educating the viewer or creating awareness on a certain subject.	https://www.tiktok.com/@onlyjayus/video/6947042507532406022	17
Fails & falls	Videos that show how one of the main actors falls or fails to do something.	https://www.tiktok.com/@kisonkee/video/6753718966637677830	8
Multichannel segments	These are videos that show (short) clips from another channel.	https://www.tiktok.com/@jhengkdrama/video/7009630016992480513	7
Personal imitation videos	Videos in which the main actor shows their version of a video that has been done before.	https://www.tiktok.com/@bellapoarch/video/6862153058223197445	45
Reaction videos	Videos that show the reaction of one of the main actors to something that happens in that video itself or as reaction to another video.	https://www.tiktok.com/@samuelgrubbs/video/6869149203290000645	46
Relatable videos	Videos with relatable topics. These videos can either be acted or real, they often bring up a sensitive topic in a funny way. The goal is to let the user know they are not alone	https://www.tiktok.com/@joerauth_/video/6996704727069101317	27
Serenity videos	These videos bring a feeling of serenity with them.	https://www.tiktok.com/@juleko_o/video/7212984121407048965	31
Talent videos	Videos showing a talent or the result of a talent.	https://www.tiktok.com/@maytree_music/video/7011467408380677378	25
User stimuli videos	Videos that are made especially to elicit a reaction from the user/viewer.	https://www.tiktok.com/@gianni_palumbo/video/7170057413243047214	11

Multichannel segments: these are videos that gather short clips from different channels. They include a mix of content like TV show snippets, movie scenes, animations, celebrity interviews and more. The main aim is to present these engaging clips from various sources, offering viewers a quick and exciting viewing experience.

Personal imitation: Personal imitation videos require some familiarity with TikTok. When a video appears to be a typical animal video or a video that showcases a talent, it sometimes signifies an imitation of an original video. Hence, all videos classified under this category are either based on or inspired by another video.

Reaction videos: As the name suggests, these videos capture peoples' reactions to specific actions performed in the video itself. Alternatively, the video acts as a reaction to another video.

Relatable videos: Although certain videos within this category may initially seem fitting for another category, they share a common underlying concept: relatability. Whether these videos portray stereotypes, highlight cultural differences, or provoke unexpressed thoughts, viewers find elements of recognition.

Serenity videos: This category primarily consists of satisfying videos and nature videos, which initially appear unrelated. However, they do belong together because their overall goal is to provide satisfaction or create a sense of calm. These videos often do have a person that performs the action of the video, though they are not a main actor because they themselves do not add to the content of the video.

Talent videos: In this category, TikTok users showcase their specific talents or the results of their talents. These videos often highlight a diverse range of skills and abilities. The focus of talent videos is to captivate viewers with displays of remarkable abilities and creativity.

User stimuli: User stimuli videos represent a rare category that requires individual classification. These videos are intentionally crafted to elicit specific reactions from viewers. For instance, one such video may build tension by showcasing multiple clips of intimidating figures in hiding, culminating in one of the figures abruptly appearing on the screen to startle the viewer. These videos are carefully staged and may incorporate special effects.

A representation and some examples of possible subcategories that could be recognised from the data can be seen in Figure 1.

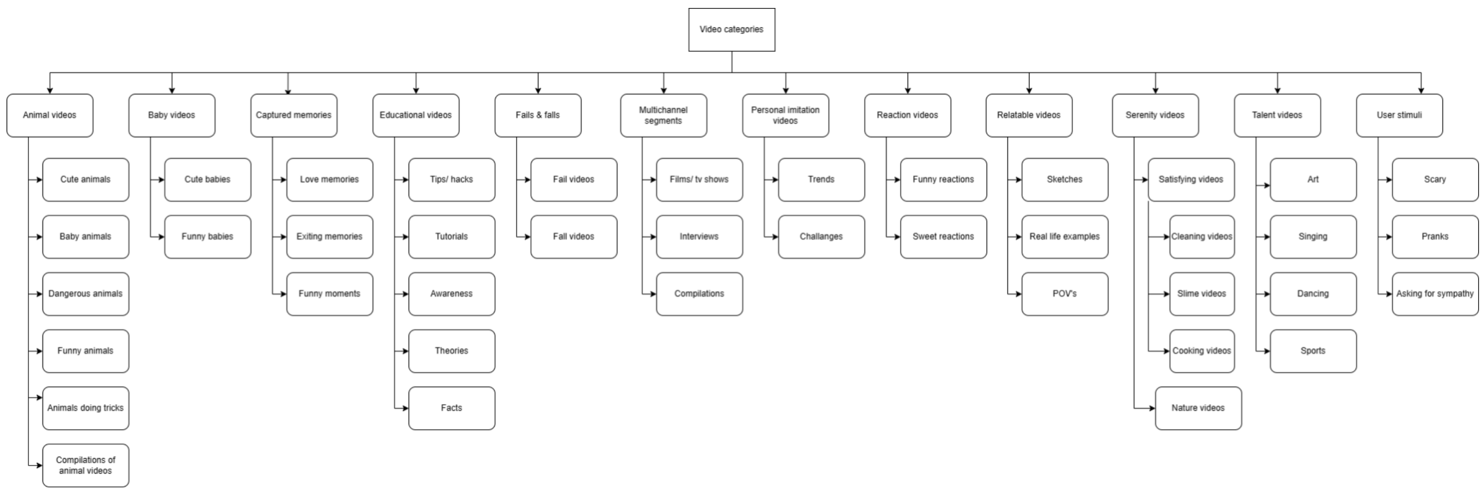


Figure 1: The defined categories and possible subcategories.

Exploration analysis

The 295 videos together received a total of 4,903,200,000 likes, 47,104,700 comments, 162,585,700 shares and 39,348,800,000 views. The videos had a mean number of likes of 16,621,016.95 (SD=5,754,261.86), mean number comments of 159,676.95 (SD=178,268.82), mean number of shares of 551,137.97 (SD=2,474,004.15), mean number of views of 133,385,762.71 (SD=82,410,860.94) and mean engagement rate of 0.15 (SD=0.05). The number of videos per category can be seen in Table 3.

Table 4 presents the category-wise analysis of key engagement metrics. Among the categories, Personal Imitation attained the highest mean number of likes (18.60 million), closely followed by Fails and Falls (18.29 million) and Talent Videos (18.19 million). On the other hand, Baby Videos (12.78 million) and Relatable Videos (14.76 million) obtained the lowest mean likes. In terms of mean number of comments, Fails and Falls ranked the highest (0.38 million), followed by User Stimuli (0.24 million) and Personal Imitation (0.21 million). Conversely, Multichannel Segments (0.05 million) recorded the fewest mean comments, followed by Reaction Videos (0.12 million).

Regarding mean number of shares, Personal Imitation claimed the top spot (1.31 million), followed by Fails and Falls (0.88 million), while Multichannel Segments (0.07 million) and Talent Videos (0.23 million) registered the lowest mean shares.

Table 4: Mean Metrics for Each Video Category on TikTok (N=295)
Note: SD denotes Standard Deviation.

Category	**Likes Mean (SD)**	**Comments Mean (SD)**	**Shares Mean (SD)**	**Views Mean (SD)**	**Engagement Rate Mean (SD)**
Animal videos	17,592,753.62 (6,357,471.72)	180,681.16 (114,804.68)	636,591.30 (433,336.63)	139,726,086.96 (86,918,664.91)	0.16 (0.05)
Baby videos	12,780,000.00 (383,405.79)	141,480.00 (75,726.13)	537,740.00 (326,344.79)	137,680,000.00 (64,589,410.90)	0.12 (0.05)
Captured memories	15,650,000.00 (4,091,047.14)	157,100.00 (38,692.81)	537,740.00 (224,332.65)	114,500,000.00 (89,644,483.01)	0.18 (0.07)
Educational videos	15,917,647.06 (5,501,390.20)	138,594.12 (153,447.77)	330,541.18 (242,619.16)	114,552,941.18 (93,231,131.59)	0.17 (0.05)
Fails and falls	18,287,500.00 (7,344,470.71)	381,537.50 (419,674.78)	875,387.50 (862,365.31)	143,475,000.00 (103,183,300.84)	0.16 (0.05)
Multi channel segments	15,214,285.71 (2,207,886.30)	51,671.43 (17,168.65)	76,314.29 (29,364.57)	116,385,714.29 (32,840,037.99)	0.14 (0.03)
Personal imitation	18,595,555.56 (8,030,169.12)	211,133.33 (319,429.66)	1,308,624.44 (6273,229.64)	155,228,888.89 (111,753,388.44)	0.14 (0.04)
Reaction videos	14,963,043.48 (2,712,715.63)	106,902.17 (77,176.13)	254,560.87 (224,758.06)	120,065,217.39 (62,280,192.03)	0.15 (0.06)
Relatable videos	14,755,555.56 (2,491,421.18)	126,374.07 (60,921.35)	371,459.26 (229,406.01)	88,259,259.26 (24,948,119.39)	0.18 (0.04)
Serenity videos	15,832,258.06 (3,827,130.09)	116,029.03 (71,312.37)	257,051.61 (267,456.55)	154,232,258.06 (84,334,929.05)	0.12 (0.05)
Talent videos	18,192,000.00 (8,059,358.95)	138,120.00 (163,544.43)	226,396.00 (218,064.07)	134,116,000.00 (67,026,354.77)	0.15 (0.05)
User stimuli	15,481,818.18 (1,952,853.39)	241,027.27 (149,605.18)	648,263.64 (380,275.79)	147,818,181.82 (68,656,912.52)	0.14 (0.07)

When it comes to mean number of views, Personal Imitation (155.23 million), Serenity Videos (154.23 million) and User Stimuli (147.82 million) achieved the highest figures. On the other hand, Relatable Videos (88.26 million) garnered the lowest mean views.

Examining the mean engagement rate across categories, Relatable Videos (0.18), Captured Memories (0.18) and Educational Videos (0.17) exhibited the highest levels of engagement. In contrast, Serenity Videos (0.12) and Baby Videos (0.12) had the lowest mean engagement rates. These findings shed light on the varying levels of engagement observed within different categories.

The distribution of videos across different attributes is summarized as follows: 91.53% of the videos (270) were classified as general, while stitch videos accounted for 5.76% (17), reply videos for 1.69% (5) and duets for 1.01% (3) of the total. Regarding the use of text, a majority of the videos 69.83% (206) did not incorporate text, whereas 30.17% (89) of the videos did include text.
In terms of sound usage, 57.97% (171) of the videos utilized an original sound, while 42.03% (124) did not.. The majority of videos featured one main actor (45.76%, 135), followed by videos with multiple main actors (39.6%, 117) and a smaller portion of videos that did not have a main actor (14.58%, 43).When considering the gender of the main actor, 37.29% (110) of the videos had an unknown or unspecified gender, 29% (86) featured male main actors, 17.63% (52) had main actors of mixed genders and 15.93% (47) featured female main actors.For detailed information on the mean engagement metrics and Standard Deviations for these attributes, please refer to Table 5

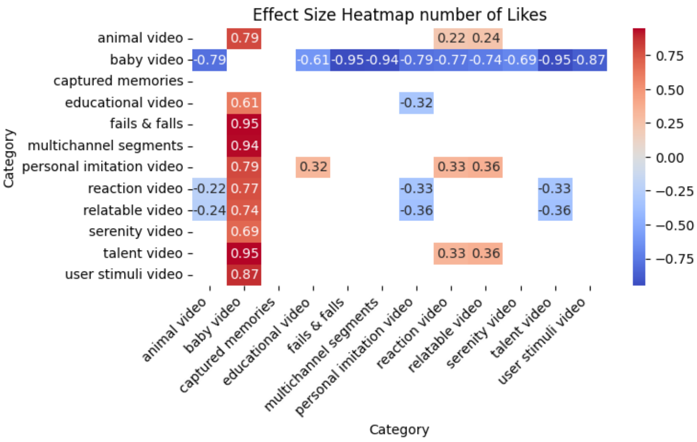
Substantial analysis

The Kruskal-Wallis tests were conducted to examine the influence of specific factors on the engagement metrics. The results revealed significant differences in the engagement metrics between different groups. Dunn's test helped with pairwise comparisons and Cliff delta's effect size helped to determine which group was dominating. In the following section the results of these tests are listed. When referring to the term value groups, we mean the group of videos that is coded as a specific value for one of the attributes. For example, for the attribute text usage, the value groups are True and False, the value group 'True' contains all videos that are coded True for text usage.

First, we examined if user engagement differed for the categories. The test showed that the number of likes (Statistic: 4.35, P-value=0.01<0.05), number of comments (statistic: 55.85, P-value= 0.00<0.05), number of shares (statistic: 75.23, P-value= 0.00<0.05), number of views (Statistic: 26.01, P-value=0.01<0.05) and engagement rate (31.03, P-value= 0.00<0.05) differed between the

Table 5: Mean Metrics for Attribute Values on TikTok (N=295) Note: SD denotes Standard Deviation."						
Attribute	**Value**	**Likes Mean (SD)**	**Comments Mean (SD)**	**Shares Mean (SD)**	**Views Mean (SD)**	**Engage-ment rate Mean (SD)**
Video Type	General	16,620,000.00 (5,890,598.65)	157,177.41 (182,840.58)	570,318.89 (2,584,163.50)	134,812,962.96 (84,805,0877.71)	0.15 (0.05)
	Stitch	17,529,411.76 (4,436,181.45)	192,505.88 (124,565.87)	362,411.76 (322,154.75)	130,082,352.94 (49,088,214.41)	0.15 (0.05)
	Reply	15,400,000.00 (2,782,085.55)	187,080.00 (107,122.00)	337,340.00 (230,382.96)	99,360,000.00 (40,929,610.31)	0.17 (0.03)
	Duet	13,600,000.00 (1,734,935.16)	152,933.33 (127,150.40)	250,633.33 (161,676.85)	80,366,666.67 (30,373,398.45)	0.18 (0.040
Text usage	Yes	16,207,865.17 (5,399,289.19)	138,268.54 (103,152.64)	357,003.37 (308,043.99)	103,974,157.30 (56,376,684.67)	0.18 (0.050
	No	16,799,514.56 (5,904,785.14)	168,926.21 (201,802.59)	635,011.65 (2,951,916.24)	146,092,718.45 (88,531,975.18)	0.14 (0.05)
Original sound	Yes	16,494,736.84 (4,694,781.37)	151,474.85 (97,710.88)	409,590.64 (358,980.05)	125,801,754.39 (72,214,822.88)	0.16 (0.05)
	No	16,795,161.29 (6,973,432.22)	170,987.90 (250,086.55)	746,336.29 (3,792,833.06)	143,844,354.84 (93,997,498.93)	0.14 (0.05)
Number of main actors	0	15,797,674.42 (3,478,881.07)	113,888.37 (66,451.88)	252,132.56 (248,539.32)	147,627,906.98 (79,085,996.97)	0.13 (0.05)
	1	17,622,222.22 (7,225,944.82)	198,487.41 (236,449.12)	793,191.85 (363,0271.02)	135,477,037.04 (95,760,527.61)	0.16 (0.05)
	Multiple	15,768,376.07 (4,131,703.53)	131,723.93 (105,093.24)	381,735.90 (369,184.85)	125,738,461.54 (64,932,152.72)	0.15 (0.05)
Gender of main actors	Male	16,622,093.02 (5,358,191.12)	164,332.56 (123,142.51)	385,165.12 (340,161.15)	122,340,697.67 (56,485,374.22)	0.16 (0.05)
	Female	18,027,659.57 (8,757,324.94)	230,402.13 (364,540.19)	1,343,374.47 (6,136,158.94)	134,693,617.02 (116,959,196.53)	0.16 (0.050
	Mixed	15,365,384.62 (3,611,576.41)	100,250.00 (88,675.34)	239,384.62 (225,950.46)	127,823,076.92 (74,620,311.11)	0.15 (0.06)
	None	16,612,727.27 (5,181,514.59)	153,910.91 (101,190.11)	489,771.82 (402,936.58)	144,091,818.18 (84,998,287.23)	0.14 (0.05)

categories. The significant pairs and their effect sizes can be seen in Figure 2 for the number of likes, Figure 3 for the number of comments, Figure 4 for the number of shares, Figure 5 for the number of views and Figure 6 for the overall engagement rate.



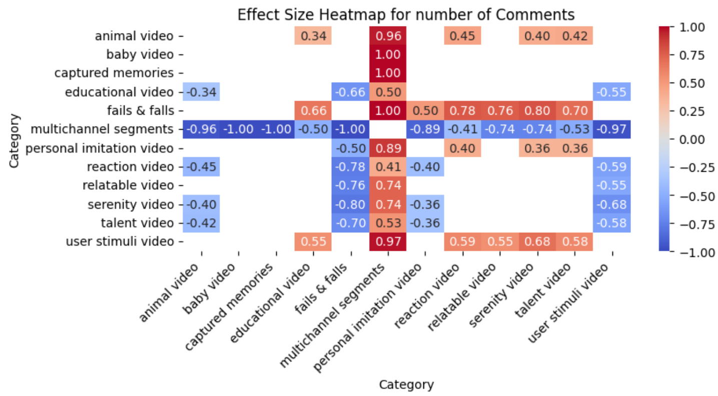
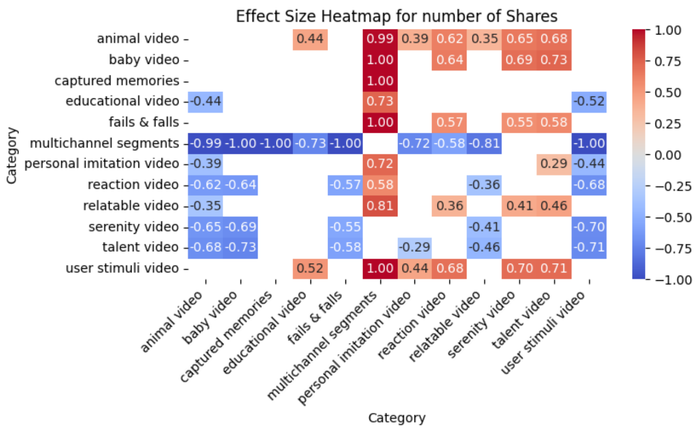


Figure 2: Effect size heatmap for the number of likes.

Figure 3: Effect size heatmap for number of comments.



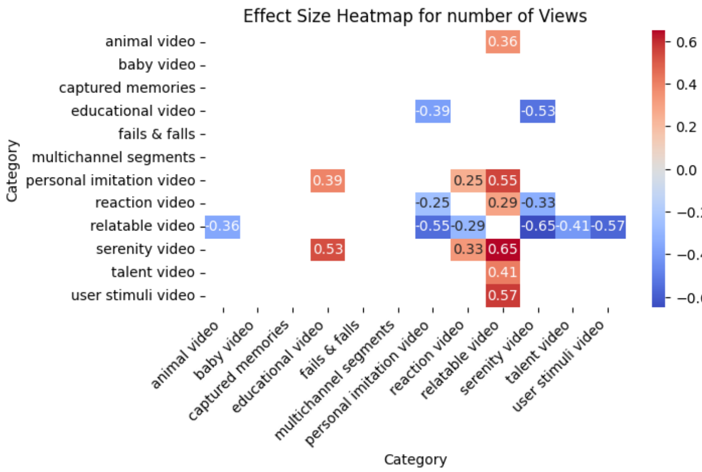


Figure 4: Effect size heatmap for the number of shares.

Figure 5: Effect size heatmap for number of views.

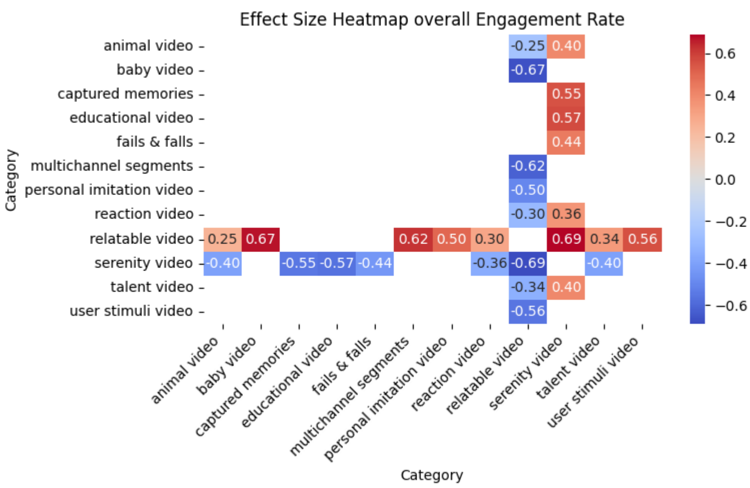


Figure 6: Effect size heatmap for overall engagement rate.

In Figures 2-6, we present the effect sizes represented by Cliff's Delta values. These effect sizes range from -1 to +1, signifying the degree of distinction between the video categories in our analysis. A value near 0 indicates substantial overlap between the categories, whereas a value close to |1| suggests a significant absence of overlap, indicating a more pronounced difference between the categories. To facilitate understanding, we provide context for interpreting the effect sizes as follows:

- Effect sizes ≤ |0.147| are considered negligible.
- Effect sizes > |0.147| and ≤ |0.33| are categorized as small effects.
- Effect sizes > |0.33| and ≤ |0.474| are considered medium effects.
- Effect sizes > |0.474| and ≤ 1.000| indicate large effects (Abbott et al., 2022).

A positive effect size in the figures implies that the video category on the y-axis tends to have higher values for the respective engagement metric than the video category on the x-axis. Conversely, a negative effect size indicates that the video category on the x-axis tends to exhibit higher values compared to the video category on the y-axis.

The analysis of video attributes revealed varying results. While the Kruskal-Wallis test did not always indicate a significant difference between all value groups for some attributes, Dunn's test showed significant differences between certain value group pairs. Specifically, when the Kruskal-Wallis test did indicate a significant difference between all value groups, only the p-value obtained from this test was reported. On the other hand, in cases where the Kruskal-Wallis test did not indicate a significant difference between all value groups, but Dunn's test showed significant differences between a value group pair, both p-values were reported. This approach allowed for a comprehensive examination of the relationships between video attributes and engagement metrics, providing valuable insights into the impact of specific attributes on user engagement on TikTok's trending page.

There were no significant differences observed between the video type value groups (general, stitch, duet, reply) for number of likes (statistic: 5.03, p-value: 0.17). There were for the value group pairs ‘stitch’ and ‘duet’. The ‘duet’ group tends to have a higher number of likes compared to the ‘stitch’ group, with a large effect size (p-value:0.04<0.05, effect size: 0.73). For the other engagement metrics, there are no significant differences between the value groups or value group pairs.

Regarding text usage value groups (True, False), significant differences have been found for views (Statistic: 24.03, p-value: 0.00<0.05) and for overall engagement rate (Statistic: 30.16, p-value: 0.00<0.05). For the other engagement metrics, there are no significant differences between the value groups. The ‘True’ group tends to have higher views compared to the ‘False’ group with a medium effect size (0.36). For the overall engagement rate, the ‘False’ group tends to have a higher rate compared to the ‘True’ group with a medium effect size (0.40).

There is a significant difference between the original sound value groups (True, False) for the overall engagement rate (Statistic: 5.29, p-value: 0.02<0.05). No significant differences have been found for the other engagement metrics. The overall engagement rate tends to be higher for the ‘False ‘ group than the ‘True’ group with a small effect size (0.16).

Regarding the number of main actors value groups (0, 1, multiple) significant differences have been found for number of comments (Statistic: 18.62, p-value:0.00<0.05), number of shares (Statistic:18.31, p-value:0.00<0.05) and overall engagement rate (Statistic:13.63, p-value:0.00<0.05). The number of likes had no significant differences between the value groups. The ‘0’ group tends to have a higher number of comments compared to the ‘1’ group with a medium effect size (0.34) and the ‘multiple’ group tends to have a higher number compared to the ‘1’ group with a small effect size (0.27). For the number of shares the ‘0’ group tends to be higher compared to both the ‘1’ group, with a medium effect size (0.41) and the ‘multiple’ group, with a small effect size (0.23). The ‘multiple’ group tends to be higher compared to the ‘1’ group with a small effect size (0.18). For the overall engagement rate the ‘0’ group tends to be higher than both the ‘1’ group, with a medium effect size (0.37) and the ‘multiple’ group, with a small effect size (0.30). Additionally, while no significant differences have been found for the number of views (Statistic:4.79, p-value:0.09), there were significant differences for the value group pairs 0, 1 and multiple. For the number of views both the ‘1’ group and the ‘multiple’ group tend to be higher compared to the ‘0’ group with a small effect size (p-value:0.04<0.05, effect size:0.21 & p-value:0.04<0.05, effect size:0.21).

Significant differences were observed between the gender of main actor groups (male, female, mixed and none) for number of comments (Statistic: 22.08, p-value: 0.00<0.05) and number of shares (Statistic: 18.57, p-value: 0.00<0.05). For the number of views, there was no significant difference between the value groups. For number of comments, the ‘mixed’ group tends to be higher compared to the ‘male’ group with a medium effect size (0.41), the ‘female’ group with a medium effect size (0.42) and also to the ‘none’ group, with a medium effect size (0.41). For the number of shares the ‘mixed’ group tends to be higher compared to the ‘male’ group with a small effect size (0.29), the ‘female’ group with a medium effect size (0.37) and also to the ‘none’ group, with a medium effect size (0.40). Additionally, there were no significant differences between all value groups for number of likes (Statistic: 5.40, p-value: 0.14) and overall engagement rate (Statistic: 5.49, p-value: 0.14). Though there were significant differences for number of likes and overall engagement rate for some specific value group pairs. For number of likes the ‘mixed’ group tends to be higher compared to both the ‘male’ group, with a small effect size (p-value:0.05<0.05, effect size:0.21) and the ‘female’ group, with a small effect size (p-value:0.04<0.05, effect size:0.24). For the overall engagement rate, the ‘none’ group tends to be higher compared to the ‘female’ group with a small effect size (p-value:0.04<0.05, effect size:0.22).

Discussion

This study explored the different content categories on TikToks trending page and a number of different video attributes. Additionally, it studied how those categories and attributes were related to the engagement metrics. This study mostly examined: likes, comments, shares, views and overall engagement rate.

Tiktok is a growing platform on which not many studies have been done yet. This study provides insights into the significant differences between the categories and attributes on engagement metrics. The results can help social media content creators to make an informed choice on what category of videos they should make and what attributes to use. The following section discusses the study’s main findings in relation to:

1. General video categories
2. Video attributes and engagement metrics
3. Video categories and engagement metrics

In addition, the discussion section outlines the practical implications and limitations of this study.

Video categories on TikTok's trending page

The present study contributes to the study of video categories on social media by employing flexible coding to identify different video categories in the context of TikTok. By analyzing and coding 295 TikTok videos, this research identified 12 distinct video categories: animal videos (n=69), baby videos (n=5), captured memories (n=4), educational videos (n=17), fails & falls (n=8), multichannel segments (n=7), personal imitation videos (n=45), reaction videos (n=46), relatable videos (n=27), serenity videos (n=31), talent videos (n=25) and user stimuli (n=11). These categories were established based on careful consideration of each video's objective and core content, providing a comprehensive framework for analyzing and understanding video content on TikTok.

Through the identification of these 12 video categories, this study expands our knowledge of the content landscape on TikTok. Prior to this study, the literature offered limited insights into the specific video topics prevalent on the platform. Previous research has focused on various aspects, such as COVID-19 related videos (Li et al., 2021), political communication (Serrano et al., 2020) and academic library accounts (Alley & Hanshew, 2022). However, a comprehensive investigation into the trending video categories on TikTok's platform remained unexplored until this research. By employing flexible coding, this study goes beyond predefined categories and allows for the emergence of previously unrecognized content types. This new knowledge enables researchers and practitioners to have a more comprehensive understanding of the diverse video content on TikTok, capturing both popular and niche categories that contribute to the richness of the platform.

Video attributes and engagement metrics

When considering the medium and large effect sizes, several noteworthy trends emerge regarding video attributes and their impact on user engagement metrics on TikTok.

To generate the most likes, the video type 'duet' appears to be preferred over 'stitch.' This preference could be attributed to the perception of joint creativity and interaction, whereas stitch videos might be perceived as more one-sided responses. This is in line with Kaye(2022), who argues that Duet enables distributed creativity and collaborative emergence among creators and suggests that Duet videos generate much engagement because they are spontaneous, fun, unpredictable and invite participation from other users.

For generating the most comments and shares, videos featuring 0 main actors seem to outperform those with 1 main actor. Additionally, videos with a 'mixed' group of main actors are preferred over those with 'male,' 'female,' or 'none.' This preference for 'mixed' actors might stem from the appeal of diversity and inclusivity. Videos that feature actors from different genders can resonate with a broader audience, as they encompass a wider range of experiences and perspectives. This inclusivity likely fosters a stronger connection between viewers and the content, leading to increased engagement in the form of comments and shares.The appeal of diversity and inclusivity, leading to higher engagement for videos with 'mixed' group actors, is in line with the research on the impact of brand personality-related content and cues on user engagement metrics (Roccapriore and Pollock, 2022).

Moreover, in terms of overall engagement, it appears that videos without any text usage are favored over videos with text. This could be due to the impact of visual storytelling. Content without text may rely more on compelling visual elements, making it easier for viewers to interpret and engage with the video's message or story. Text, in contrast, might be perceived as distracting or less visually appealing, potentially resulting in slightly lower overall engagement as viewers may focus more on the text than on the video's content. This observation echoes the notion that visual storytelling plays a significant role in engaging audiences (Shahbaznezhad et al., 2021). This suggests that content creators should prioritize compelling visual elements to enhance user interaction and interpretation of the video's message or story.

The preference for videos with 0 main actors in generating more comments, shares and overall engagement could be attributed to users feeling a greater sense of ease and comfort when interacting with such content. In videos where no main actors are directly involved, viewers may feel less inhibited and more at ease to engage with the content freely. The perceived anonymity or distance from main actors may encourage users to comment, share and interact with the video more actively, as they do not feel a direct interaction with someone on screen. This increased level of user comfort may contribute to higher engagement metrics for videos featuring 0 main actors.

Video categories and engagement metrics

The analysis of the video categories in relation to engagement metrics, including likes, comments, shares, views and overall engagement rate, revealed significant effects. The video categories demonstrated a statistically significant influence on all of the engagement metrics studied. To focus the discussion, we will only consider the significant results of category pairs with a medium or high effect size. Within this scope, our attention will be on the videos that either outperformed or underperformed at least half (6/11) of the other categories.

One interesting finding was that 'baby videos' received fewer likes compared to 10 other categories. This might be because these videos are mainly intended for parents, caregivers and people interested in babies. As a result, the smaller audience size in comparison to broader categories leads to fewer viewers engaging with and liking these videos. The videos' focus on parenthood and caregiving might also limit their appeal to a wider audience without a personal connection to the subject matter.

When it comes to comments, the category 'multichannel segments' received fewer comments than all the other categories. This unique result highlights the distinct nature of multichannel segments. One possible explanation is that users perceive the main actors in these videos as not being the ones who posted the content. Consequently, the comment sections of these videos become more about user interactions rather than direct engagement with the content creator. On the other hand, both user stimuli videos and fails and falls received significantly higher numbers of comments compared to more than half of the videos (6 other categories for user stimuli videos and 7 other categories for fails & falls). This suggests that users might feel compelled or invited to comment on user stimuli videos due to the personalized targeting of the content.

In terms of shares, the category 'relatable videos' outperformed 7 other categories. This could be because users feel an emotional connection to these videos. When viewers can relate to the content, they are more motivated to share it with others, believing it could evoke similar emotions or create a sense of camaraderie among their friends. Even if the viewer does not personally relate, they might think of a friend who would, which encourages them to share it. The finding that 'relatable videos' outperform other categories in terms of shares resonates with the research on brand personality-related content, which establishes a human connection with the audience and enhances functional benefits

(Lee et al., 2018). The higher engagement rate for 'relatable videos' could be attributed to the emotional connection people often feel with such content, as indicated in previous literature (Shahbaznezhad et al., 2021).Similarly, the category 'user stimuli videos' surpassed 6 of the other categories in terms of shares. Users might want to share these videos to elicit a relatable response from their friends. For example, if the video involves a prank targeting the user, they might share it to enjoy the laughter with a friend. These findings are consistent with Shawky et al. (2020), who found that customers are more likely to engage with posts when they perceive potential benefits for others in their networks. This observation reflects the notion that social media communities function as support networks.

The video category 'multichannel segments' received fewer shares than 9 of the other categories. This might be because these videos are relevant to specific shows or events, making them less engaging to users who are not familiar with the original content. Additionally, these segments might lack a strong emotional connection, which hampers their potential for widespread sharing. The category 'talent videos' also received fewer shares than 6 of the other categories. Users might like these videos, but they might not feel as emotionally connected, leading to less inclination to share them with others. Regarding views, no category showed significant differences compared to more than half of the other categories.

Lastly, the overall engagement rate for the category 'relatable videos' was higher than 8 other categories. This might be due to the emotional connection people often feel with such videos. Additionally, these videos often appear on a user's personalized ForYou page, which contributes to their higher engagement rate, as viewers find content tailored to their interests. This encourages them to engage further with the video. Conversely, 'serenity videos' received a lower engagement rate than 7 of the other categories. This might be because viewers prefer to enjoy these videos alone, finding a sense of serenity or peace without the need for further engagement.Moreover, the relatively lower engagement rate for 'serenity videos' compared to other categories aligns with the previous notion that certain content types, like directly informative content, might yield lower engagement due to perceived lack of interest and compatibility with users' motives (Lee et al., 2018). The appeal of 'serenity videos' to viewers who prefer solitary enjoyment without the need for further engagement is consistent with their potential for lower overall engagement.

Practical Implications

The findings regarding video categories and their impact on engagement metrics have practical implications for content creators on TikTok. By understanding which video categories are associated with higher engagement, creators can make informed choices about the type of content they produce. This knowledge can guide content creation strategies, allowing creators to focus on content that resonates with their target audience and maximizes user interaction.

Understanding the influence of video attributes on engagement metrics also provides opportunities for content optimization. Creators can utilize the insights related to video attributes, such as text usage, original sound and the number of main actors, to enhance user engagement. For instance, considering the impact of text usage, creators can experiment with incorporating or excluding text in their videos based on their goals for views and overall engagement rate. Similarly, leveraging the presence of an original sound or optimizing the number of main actors can help creators maximize comments, shares and overall engagement.

The knowledge gained from this study can enhance the user experience on TikTok. By optimizing video attributes based on their impact on engagement metrics, creators can produce content that resonates with users, leading to increased satisfaction and enjoyment. Additionally, aligning content with user preferences and engagement patterns can create a more engaging and interactive environment for users, fostering a sense of community and encouraging continued user participation.

By incorporating these practical implications, content creators and users can benefit from the findings of this study, leading to more enjoyable content experiences on TikTok. This understanding can inform content creation strategies, allowing creators to prioritize content that resonates with their target audience and maximizes user interaction. Utilizing the insights into video attributes, such as text usage, original sound and the number of main actors, can help creators optimize their content for increased user engagement. Furthermore, aligning content with user preferences and engagement patterns can create a more interactive environment on TikTok, fostering a sense of community and encouraging continued user participation.

Limitations

There are several limitations to this study, which should inform future research on TikTok content and engagement.

Methodological Challenges: One limitation was the scarcity of research specifically focused on coding methods for short videos. While we intended to use coding methods to define video categories, most existing articles on coding were centered around interviews. To overcome this challenge, we adapted and applied the available coding methods to the analysis of short videos, documenting every decision and step taken to ensure the research's reproducibility.

Additionally, the absence of an existing theory that could inform video categorization necessitated the use of flexible coding. While this approach allowed for flexibility, it posed challenges in initiating and maintaining consistent coding practices. To mitigate this, thorough documentation of coding decisions was performed in memos (available in the appendices) to ensure transparency and provide insights into the coding process.

Sole Researcher and Coding Accuracy: A limitation of this research was that only one researcher coded the videos, without a mechanism to assess coding accuracy. To address this limitation, future studies are recommended to involve at least two coders to obtain a more comprehensive perspective on the videos. Involving multiple coders facilitates a more inclusive and thorough analysis, allowing for different perspectives and reducing the likelihood of overlooking important aspects of the coding process.

Limited Number of Videos in Some Categories: Another limitation lies in the distribution of videos across specific categories. Notably, the categories 'baby videos' and 'captured memories' were found to have a relatively small number of videos, comprising only 5 and 4 videos, respectively. Consequently, any conclusions drawn from these categories should be interpreted with caution due to the limited sample size. The restricted representation of 'baby videos' and 'captured memories' may constrain the generalizability and statistical power of the findings concerning these specific content types. Future studies with larger and more diverse samples within these categories would be beneficial to gain a more comprehensive understanding of the dynamics and patterns associated with 'baby videos' and 'captured memories' on the TikTok platform

Limitations of Video Scraping: The scraping of TikTok videos from the trending page required the use of a hashtag as a filtering mechanism. Due to limitations in the Apify tool, it was not possible to scrape videos without using at least one filter. In this study, the "#fyp" hashtag was chosen as it was the most viewed at the time of the research. However, for future investigations, it is recommended to explore alternative methods that allow video scraping without relying on a specific filter, ensuring a more diverse and representative sample of videos

Limited Focus on User Engagement: This research primarily examined user engagement through the platform's predefined engagement metrics and the calculation of an overall engagement rate. However, other forms of engagement beyond the platform were not considered. Future research should incorporate surveys or qualitative methods to explore additional ways in which users engage with videos, both within and outside the platform. Understanding user engagement in a more comprehensive manner can provide deeper insights into the impact of video categories and attributes.

Conclusion and Outlook

In conclusion, this research provides valuable insights into video categories, attributes and their impact on user engagement metrics on TikTok's trending page. Through flexible coding, we identified 12 distinct video categories, highlighting the platform's diverse content landscape. Our analysis revealed significant relationships between video attributes and engagement metrics, as well as differences between video categories and engagement metrics.

This study contributes to understanding video content and user engagement on social media platforms, particularly short videos. We have demonstrated the importance of video categories and attributes in influencing user engagement metrics, providing valuable insights into content consumption patterns and user preferences on TikTok.

The findings offer practical guidance to content creators in optimizing their strategies and enhancing user interaction and satisfaction. Overall, this research has enriched our understanding of how video categories and attributes influence user engagement on TikTok.

At the same time, there are still areas that warrant further investigation to expand our understanding.

To begin with, exploring cross-platform applicability would be intriguing. Investigating whether the identified video categories are applicable to short videos on other social media platforms could offer a broader understanding of video content trends across different platforms. This research could reveal similarities or differences in category prevalence, shedding light on video content preferences beyond TikTok.

Conducting qualitative research to explore user perceptions and preferences regarding video attributes is another important avenue for future research. Uncovering the motivations and emotional responses of users could provide a deeper understanding of why specific video attributes drive engagement. This qualitative investigation could offer valuable context to optimize content creation and enhance user interactions.To gain deeper insights into user engagement motivations, qualitative interviews can be conducted to explore user perceptions and emotional responses to video attributes. Subsequently, a large-scale survey can be deployed to capture a broader perspective from the general public, enriching the understanding of factors influencing engagement on TikTok.

Finally, researchers should explore the presence and significance of video attributes within different video categories. Investigating whether specific combinations of attributes within certain categories generate significantly higher engagement could reveal new opportunities for content optimization.

Additionally, future work could focus on refining and expanding the existing categories to encompass a broader range of content. This could involve exploring emerging video trends and user-generated content to ensure the framework remains relevant and up-to-date.

Appendices

Thorough documentation of coding decisions was performed in memos to ensure transparency and provide insights into the coding process.

Coding Memo 1: Main Actor Objective/Purpose: To code the main actor(s) featured in the video, including humans (coded by gender), animals (including species), and the number of main actors. Definition of Code: Codes will identify the main actors in the video, distinguishing between human actors (coded by gender: "male," "female," "mixed") and animals (specific species when identifiable, otherwise general "animal"). Additionally, a "group of people" code will be used to represent multiple human main actors. Examples: - "male" code will be applied for videos featuring male individuals as the main actor. - "2 females" code will be used for videos with two female main actors. - "dog" code will represent videos with dogs as the main actor. - "group of people" code will identify videos with multiple human main actors. Relationship with Other Codes: These codes serve to identify who performs the action or constitutes the main content of the video. Rationale for the Code: Understanding the main actors in the videos is crucial for analyzing the content and identifying potential patterns or trends related to different actor categories. Revisions and Modifications: The code was divided into two attributes: "Number of Main Actors" and "Gender of Main Actors," providing insights into who made the video and who performed the main content.
Coding Memo 2: Text Usage Objective/Purpose: To code whether text was used in the video itself, excluding official subtitles from TikTok itself or captions, and to explore the purpose/meaning of the text. Definition of Code: Codes will identify the presence ("True" or "False") of text in the video and include descriptions of the text's purpose or content and/or the meaning of the text. Examples: - "True" code will indicate that text is present in the video. - "Asking for engagement" code will represent videos with text encouraging viewer engagement. - "Translation" code will identify videos with text used for translation purposes. Rationale for the Code: Understanding whether the video uses text and the context of the text is crucial to analyze its influence on engagement metrics. Revisions and Modifications: The code was transformed into an attribute: "Text Usage," with the options "True" or "False," simplifying the categorization process.
Coding Memo 3: Sound Objective/Purpose: To code the type of sound and characteristics of the audio in the video, including whether it is original sound. Definition of Code: Codes will describe the sound elements in the video, such as "talking sound," "instructing audio," "trending sound," "regular song," and "original sound." Examples: - "Talking sound" code will be used for videos with spoken dialogue in the audio. - "Original sound" code will represent videos with unique or authentic audio created specifically for the video. Rationale for the Code: Understanding the type of sound and audio characteristics will provide insights into the video's purpose and potential influence on engagement metrics. Revisions and Modifications: A part of this code was turned into the attribute "Original Sound," which can be coded as "True" or "False" to indicate whether the video includes original sound.
Coding Memo 4: Emotion in Videos

Objective/Purpose: To add an emotion code to videos to identify emotions expressed by the main actors or intended to evoke in viewers. Definition of Code: Codes will describe the emotions portrayed in the video, such as "funny," "cute," "amusing," and "surprising." Examples: - "Funny" code will be applied to videos that aim to be humorous or provoke laughter .- "Cute" code will represent videos with endearing or adorable content. Rationale for the Code: Emotion codes help to understand the video's intended impact on viewers and contribute to the analysis of content and engagement. These codes are subjective and are not directly used for creating categories. Instead, they provide insights into comparisons between videos based on their emotional content.
Coding Memo 5: Video Type Objective/Purpose: To code whether a video follows a specific format, and if so, to identify the type of format used. Definition of Code: Codes will represent different video formats, such as "stitch video," "duet video," and "reply video." Examples: - "Stitch video" code will be used for videos that include short clips from another video. - "Duet video" code will represent videos where the creator collaborates with another video by displaying them side by side. Rationale for the Code: Understanding the video format helps to analyze its potential influence on engagement metrics. Revisions and Modifications: This code was transformed into an attribute: "Video Type," which can be categorized as "stitch," "duet," "reply," or "general."
Coding Memo 6: Realness of the Video Objective/Purpose: To code whether a video was taken in real-life or created using special effects, and to differentiate between acted/staged and real videos. Definition of Code: Codes will describe the realness of the video, such as "edited," "special effects," "acting," "staged," and "real." Examples: - "Edited" code will be used for videos that have undergone post-production editing. - "Staged" code will represent videos that were intentionally acted out or performed. Rationale for the Code: Identifying the realness of the video provides insights into the authenticity and potential influence on viewer engagement. This code helps in understanding the nature of the video, which is vital for creating categories and analyzing content.
Coding Memo 7: Action in the Video Objective/Purpose To code the main action or activity portrayed in the video. Definition of Code: Codes will describe the primary actions or activities captured in the video, such as "dance," "cooking," "drawing," "eating," "prank," "falling," etc. Examples: - "Dance" code will be applied to videos where the main action involves dancing. - "Eating" code will represent videos featuring the action of eating food. Rationale for the Code: Understanding the main action in the video helps to grasp the primary content and purpose of the video, contributing to the creation of categories. This code aids in identifying the main content and focus of the video, which is valuable for analyzing and categorizing the videos effectively.

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