



Department of Business and Management

Bachelor's Degree in Management and Computer Science

Chair of Business & Marketing Analytics

**The Power of #TikTokMadeMeBuyIt &
the Impact of Social Medias on Purchasing Behavior**

Thesis supervisor

Prof. Francisco Villaroel Ordenes

Candidate

Rachele Cecere

Academic Year 2021/2022

Table of Contents

INTRODUCTION	4
PHENOMENON	4
MANAGERIAL RELEVANCE & PROBLEMS	5
PREVIOUS RESEARCH & RESEARCH GAPS	5
APPROACH OF THE THESIS TO STUDY THE RESEARCH GAPS	6
EXPECTED CONTRIBUTIONS	7
CONCEPTUAL FRAMEWORK	7
LITERATURE REVIEW	8
HYPOTHESES	12
SENTIMENT ANALYSIS & CALL TO ACTION	12
SPONTANEOUS NATURE	12
VIDEO DURATION	13
METHOD	14
DATA DESCRIPTION	14
MEASUREMENT DEVELOPMENT	15
BINOMIAL REGRESSION MODEL	17
RESULTS	18
DISCUSSION	24
CONTRIBUTIONS	24
MANAGERIAL IMPLICATIONS	25
FURTHER RESEARCH DIRECTIONS	25
ACADEMIC PAPERS	27
BUSINESS MAGAZINES	28

Acknowledgments

I would like to thank my professor and supervisor Francisco Villaroel Ordenes for the opportunities he made sure to create during my last year of bachelor's and for his invaluable support throughout the realization of my thesis.

I would also like to thank Niccoló Barbetti for his fundamental editing suggestions, late-night feedback sessions, and moral support.

INTRODUCTION

Phenomenon

It is no surprise that companies all around the world are constantly looking for new and better ways to reach consumers. Not so long ago, television and print advertising stood at the basis of marketing strategies. In the current era, these traditional marketing streams are only a small fragment of the varied approaches used to market and brand products and will likely be long forgotten in a few decades. The rising focus on social media shifted the way companies interact and connect with their target, creating the need of finding new ways to advertise. For instance, recent research states that 82% of shoppers have discovered a product on social media and purchased it directly on their phones. Consequently, companies now place considerable value on how social media can be used to shape consumer brand perception and influence their buying intention, crucial to creating and maintaining a competitive advantage. Many factors can influence consumers' purchase intention, such as cultural, social, personal, and psychological factors. For this reason, companies need to understand how consumers think, feel, and choose from different options, but it is safe to state that consumers can be affected by what they hear from others (WOM). In fact, 90% of people are much more likely to trust a recommended brand (even from strangers), and, out of the top five popular ways to recommend a business, word-of-mouth comes first, followed by Facebook, Google, and Twitter. On top of that, the emergence of web 2.0 and social networking sites increased the influence groups and individuals have in shaping others' purchasing intentions online, leading to the advent of eWOM and influencer marketing to name a few. Consumers are now encouraged to interact with brands, share information with different consumers and create content that mirrors their brand preferences. The more consumers are engaged in this process, the more likely they are to encourage others to explore specific brands (Christodoulides, 2009).

Managerial Relevance & Problems

In this scenario, TikTok, the \$75 billion worth platform, has become one of the most important marketing tools that brands have at their disposal. In particular, the hashtag #TikTokMadeMeBuyIt currently has 17.6 billion views (01/08/2022). Intuitively from the name, the hashtag is used by users to showcase the latest products they purchased through the platform, and, if the video goes viral, the product quickly sells out. This trend perfectly embraces the concept of eWOM, but it's not so common for eWOM to be this successful. Most of the time, when we surf the web and encounter one of the many product recommendations, we tend to doubt the integrity of such recommendations, reconding it to influencer marketing or even scam. Instead, according to the New York Times, TikTok's competitive advantage is that even when strangers are trying to sell you something, their messages seem off-the-cuff, like trustworthy recommendations rather than a sponsored shilling. In fact, 71% of users agree that TikTok inspired them to shop even when they weren't looking for that product, encouraged by the platform's joyful and spontaneous nature. #TikTokMadeMeBuyIt has the power to make any type of product go viral, from a fluffy headband to a Bluetooth keyboard or a rechargeable candle lighter. However, it is still unclear how this happens. The common framework of videos using the aforementioned hashtag is the following: the user makes a short introduction of the product, they show its usage and utility, then they highlight the positive impact the product can have on everyone's everyday life, stressing how you *really* cannot live without it. Because of the spontaneous and persuasive nature of the content, this may lead you to desire a brand-new cat litter without even owning a cat.

Previous Research & Research Gaps

Although there is vast research on how social media can impact consumer purchasing behavior, there is still little research on the phenomenon of #TikTokMadeMeBuyIt and TikTok in general. As is the case for most social media platforms, TikTok does not offer an official API to

extract data at scale, making it trickier for researchers to scrape information. In addition, the recent nature of this platform is probably another reason why the topic is still ambiguous. According to previous research, brand communities are made up of individuals who choose to participate and demonstrate a relationship to content or materials that are being shared in the community. This can include commentary on products, responses to new products, and methods to create a social connection that has emotional or socially driven experiential elements, including creating a sense of belonging (Laroche, Habibi, & Richard, 2013). On top of that, online comments on digital social platforms have an impact on the purchase intention for that product: in particular, negative comments generate a steeper decline in brand trust, while positive ones do not increase it significantly (Saavedra et al, 2015). Moreover, a recent study has been conducted on the skincare and beauty company Somenthic and their digital presence on TikTok. The study confirms that there is a positive influence between eWOM on TikTok on the purchase intention of Somethinc skincare products (Hasena et al, 2021). Lastly, TikTok has impacted Generation Z purchasing behavior and has influenced users to consume products, as they felt recommendations and reviews were done by genuine people (Martina Ngangom, 2020).

Approach of the Thesis to study the Research Gaps

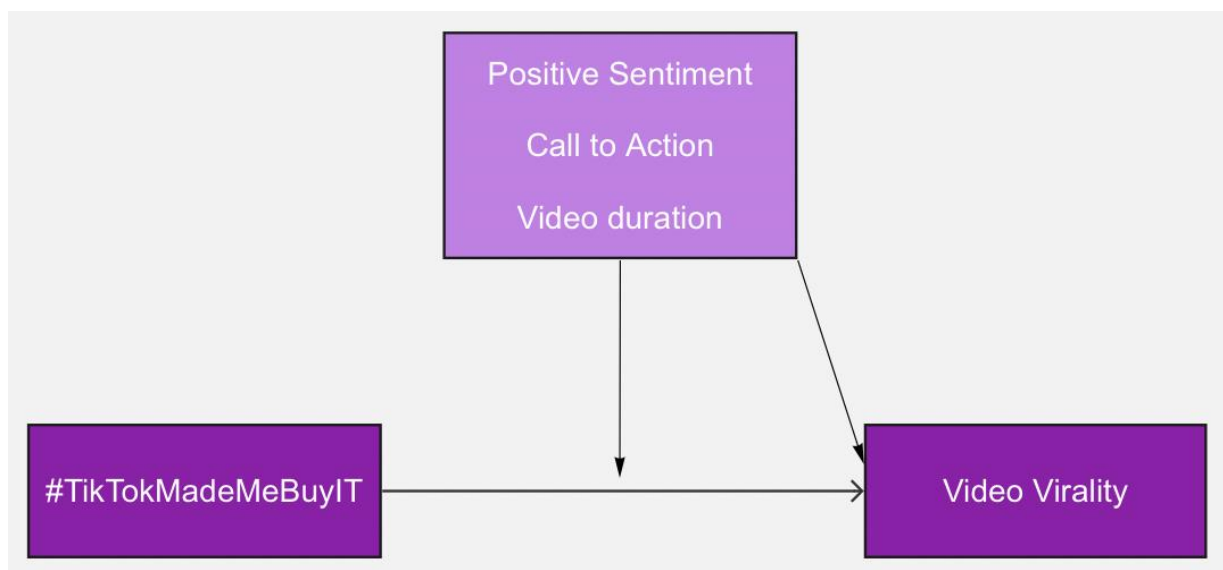
My research aims to study the phenomenon of #TikTokMadeMeBuyIt, as I strongly believe it is an immensely powerful tool not just for brands but also for content creators. With the help of Apify, I used a TikTok scraper and extracted relevant information from the 1000 most liked TikTok videos that contained the hashtag #TikTokMadeMeBuyIt. After creating the dataset, I used the Knime Analytics platform to preprocess the data and perform an exploratory and explanatory analysis. Moreover, I performed text mining on the video captions.

Expected Contributions

Since the subject of my research is quite recent and unexplored, I was left with ample room to develop its various nuances. Therefore, I aim to make three main contributions. First, by focusing on the spontaneous TikTok nature and proving that most viral videos under the hashtag #TikTokMadeMeBuyIt have been made by common people and not influencers or brand ambassadors. Second, by performing sentiment analysis and studying the impact of Positive Sentiment or Call to Action terms on the overall engagement of the post. Third, by considering the video durations and establishing a recommended video duration range for this particular TikTok trend.

Conceptual Framework

I developed a proposition-based conceptual framework that has been tested with empirical data (Lindgreen et al, 20200). The candidate dependent variable was the presence of the hashtag #TikTokMadeMeBuyIt in TikTok videos. The candidate independent variable was the video virality and the consequent potential product purchase. The candidate moderators were the presence of Positive Tone terms, Call to Action terms, and video duration.



LITERATURE REVIEW

Social Media

The development of digitalization has made changes to people's lifestyles that were originally the completion of manual activities into an instant solution (Christiani & Ikasari, 2020). The growing use of social media is proof that social media is very popular with the public today because it is easy to use (Zebua & Nadilla, 2021). According to Kotler and Keller (2016), social media is a tool or intermediary that consumers use to share text, audio, images and video, and information with each other either with companies or vice versa. The selection of media for advertising is also important. According to Kotler (Kotler, 2008), during media selection it is important to find the most cost-effective solution to deliver the desired amount and type of exposure to the target consumer.

Purchase Intention

The advent of the Internet has increased the consumer's ability to shop in any location, at any time, and acquire any number of things with ease by comparing features, value, and pricing before making in-store purchases. Online purchase intention plays a vital role in online consumer behavior. As per, Raza et al. (2014), purchase intention means, a condition between the customer and the seller when the customer is ready to make a deal with the seller. Purchase intention process starts with the product evaluation. To do the evaluation individuals use their current knowledge, experience, and external information (Bukhari et al. 2013). Hence, external factors also play a major role in the purchase intention process by influencing consumers' attitudes.

A more complete summary of relevant literature on the use of eWOM and Sentiment Analysis on TikTok can be found on the following pages.

Authors & Year	Context	Purpose	Theoretical Framework & Methodology	Results	Conclusions
Ming Zhan 2018	Sentiment Analysis on Instagram captions with hashtag #read and #reading.	This study serves as an example of how public libraries could employ UGC with Big Data attributes and create value through data analysis.	Opinion polarity classification and emotion classification. Polarity classification allows each collected caption to be grouped into negative, neutral, or positive categories. Emotion classification entails assigning the caption an emotion. The two results were then combined.	Negative posts merely account for 4.9% of the total, while positive posts account for 50.5%. Captions with positive emotions account for 78.8% of the positive posts. However, captions with negative emotions account for 68.6% of the negative posts.	Findings show that people express themselves when reading on social media. Therefore, it would appear necessary for public libraries to use social media. The opinion polarities and emotions expressed concerning these topics could be used by public libraries to guide their future strategies. Providing reading materials that pleasantly surprise readers, highlighting the benefits of reading, and enticing people to include reading in their daily lives are a few examples of such tactics.
Martina Ngangom; 2020	TikTok's influence on the user buying behavior and relationship with brands.	Explore the new phenomenon of TikTok and how using this application has impacted Generation Z as consumers.	This study design deploys a mono-method, exclusively using qualitative data collection techniques via interviews with active TikTok users between the age of 18 - 23 years.	The individuals interviewed agree that on TikTok they make informed choices mostly based on authentic reviews not made by brands.	In addition to being entertaining, Generation Z values transparency and authenticity in the material. The platform's creators have the power to affect users' purchasing decisions, yet most users prefer to watch frank product reviews made by 'regular' users rather than influencers or famous people.
Camelia Hasena;	eWOM on TikTok and Increased	Study whether consumer buying	Use of a quantitative approach focused on	The respondents subject of this study stated that they strongly	There is an influence between e-WOM in TikTok on purchase intention of

Eko Sakapurnama 2021	Consumer Purchase Intention.	interest and brand image on Somethinc skincare products were influenced by eWOM on TikTok.	measurement and sampling design problems. Primary data is obtained via a Google form questionnaire. The target was 100 TikTok users over 18 years old who knew but had never bought Somethinc skincare products. The researcher used a non-probability sampling technique with a purposive/judgmental type of sampling. The data collected was tested for validity and reliability, then analyzed using a linear regression model and a t-test was performed. The Sobel test was used to test strength of the indirect effect of the independent variable on the dependent variable through the mediating variable.	agreed they got information about positive reviews of Somethinc skin care consumers through TikTok because of the high desire of consumers to share their consumption experiences. Somethinc brand image significantly mediates the effect of eWOM on TikTok on the purchase intention of Somethinc skincare products.	Somethinc skincare products, influence between e-WOM on TikTok on Somethinc brand image, influence between Somethinc brand image on purchase intention of Somethinc skincare product, and influence between Electronic word of mouth on TikTok towards purchase intention of Somethinc skincare products through brand image.
Felipe Uribe-Saavedra; Rialp Josep; Joan Llonch 2015	Online Consumer Reviews & Brand Awareness	Analyze the effect of online brand reviews in OSNs (positive and negative) on purchase intention and brand trust and the moderating role of consumer brand awareness and product	H1 - The type of online comments about a product (positive or negative) will affect purchase intention for this product. H4 - Consumer brand awareness moderates the relationship between the type of online reviews about a product and brand trust.	To test the hypotheses, data were analyzed using MANOVA because this technique permits analyzing multiple independent variables on two or more dependent ones.	When compared to the control group, negative comments considerably alter purchase intentions, whereas positive ones barely influence them at all. Positive evaluations have a greater impact on boosting the purchase intent of less well-known products than they do for more well-known ones since their importance is

type within
the
relationships.

Experimental
Design with 3x3x2
factorial treatments

Seven-point Likert
scale

Pilot Research
performed among
40 students

inversely correlated
with brand
recognition levels.
However, negative
feedback has a higher
impact on
consumers'
intentions to buy
products from well-
known brands than it
does on less well-
known firms,
creating an inverted-
U phenomenon.

HYPOTHESES

Sentiment Analysis & Call to Action

One common task in text processing is sentiment analysis. This involves taking a piece of text and automatically determining whether the overall sentiment expressed is positive, negative, or neutral. Sentiment analysis can be useful for a variety of applications, such as automatically flagging reviews that are excessively negative or identifying social media posts that are spreading false information. Moreover, I will take into consideration another crucial tool in Marketing, known as Call to Action. A CTA is an instruction to the audience to provoke an immediate response, usually in the form of a purchase or sign-up. A CTA can be as simple as an instruction to “click here” or “call now,” or it can be more complex, like an offer to “get a free consultation.” In my study, I aim to investigate whether the presence of Positive Sentiment and CTA terms can positively influence the overall engagement of the post.

H1.1: The presence of one or more Positive Sentiment term on video captions result in overall higher engagement in the #TikTokMadeMeBuyIt trend.

H1.2: The presence of one or more Call to Action term on video captions result in overall higher engagement in the #TikTokMadeMeBuyIt trend.

Spontaneous Nature

There's something about TikTok that just feels so spontaneous. Maybe it's the fact that most videos are only a few seconds long, or maybe it's the fact that so many people are just filming themselves in the moment. Whatever the reason, with TikTok, you never know what you're going to see. One minute you could be watching a hilarious skit and the next you could be watching someone's heartfelt tribute to a lost loved one. It's this unpredictability that keeps people coming back for more. On top of that, anyone can blow up on TikTok. Whether they have 2 followers or 200k, the app's

algorithm provides an equal opportunity to all users to go viral and build an audience over time. As mentioned before, TikTok's competitive advantage is that even when strangers are trying to sell you something, it feels like a trustworthy recommendation rather than a scam. For the aforementioned reasons, I expect the majority of viral videos containing the hashtag of study to have been posted by users who are not verified on TikTok. Therefore, I state my hypothesis as follows.

H2: Being a verified user is not positively correlated with the virality of the video in the #TikTokMadeMeBuyIt trend.

Video Duration

TikTok videos typically last between 15 and 60 seconds. However, video length on social media platforms is vertical-specific. For example, while the average length of top-performing TikTok videos about TV shows was 47 seconds, between January – August 2021, the average length for the 10 best-performing video posts for Consumer-Packaged Goods Food on TikTok was 13 seconds long. In the same period, the top 10 CPG Food posts averaged 1:42 minutes on YouTube, 0:34 seconds on Facebook, and 0:29 seconds on Twitter. The data just highlights how critical it is to benchmark your performance against brands in your own vertical to determine the most effective video length for your brand content. Moreover, according to a survey conducted by Real Research Media on TikTok users' preferred video lengths, 47.93% stated that they happen to enjoy videos of less than 15 seconds, 21.68% of 15-30 seconds, 13.03% of 30 seconds -1 minute, and 10.13% of 1-2 minutes. For these reasons, I hypothesize that videos containing the hashtag #TikTokMadeMeBuyIt result in lower engagement if they are of long length.

H3: Longer durations of videos containing the hashtag #TikTokMadeMeBuyIt result in lower overall engagement of the post.

METHOD

Data Description

Due to the novelty of the subject, it was not easy to retrieve data exclusively on videos with the hashtag #TikTokMadeMeBuyIt. However, thanks to a web scraping platform named Apify, I was able to retrieve a dataset containing information about the most liked 1000 videos that included the hashtag of study. The raw dataset contained 126 variables but only the ones shown in the table below were functional to my analysis.

Variable Name	Variable Type	Description
<i>row_id</i>	independent	value that uniquely identifies a row in a table.
<i>author_name</i>	independent	the account name of the user.
<i>author_fans</i>	independent	the number of followers of the user. It has a lower bound of 0 and an upper bound of 11,900,000.
<i>author_verified</i>	independent	indicates if the user has been verified or not by TikTok. It can either take the value “true” or “false”.
<i>#_comments</i>	independent	the number of comments the video received. It has a lower bound of 0 and an upper bound of 3444.
<i>#_likes</i>	independent	the number of likes the video received. It has a lower bound of 124 and an upper bound of 954,300.
<i>#_plays</i>	independent	the number of times the videos have been played. It has a lower bound of 274 and an upper bound of 7,600,000.

<i>#_shares</i>	independent	the number of times the videos have been shared. It has a lower bound of 0 and an upper bound of 11,900.
<i>time</i>	control	indicates the time of video upload. The time span of the analyzed videos goes from 5/03/2020 to 11/08/2022.
<i>video_caption</i>	independent	indicates the text included in the description of the video.
<i>video_duration</i>	dependent	indicates the video length in seconds. It has a lower bound of 4 and an upper bound of 181.
<i>Count (Positive)</i>	independent	Indicates the number of terms in <i>video_caption</i> tagged Positive by the LIWC dictionary.
<i>Count (CTA)</i>	independent	Indicates the number of terms in <i>video_caption</i> tagged Positive by the CTA dictionary.

Measurement Development

My analysis has been carried out in its entirety on the Knime Analytics platform and, in the following sections, I will explain the measurement process of the three main constructs.

Sentiment Analysis

The analysis has four main stages: Preprocessing, Enrichment, Bag of Words, and Variable Creation or Operationalization. Preprocessing is an important step in sentiment analysis as it can help improve the accuracy of the results. This step involves tasks such as removing stop words [Stop Word Filter node], lemmatizing [Kuhlen Stemmer node], and converting all text to lowercase [Case Converter node]. Moreover, I filtered out the variables that were not relevant to my intent and renamed the remaining variables for future use. Then, to perform text mining on *video_caption*, I converted the specified strings to documents [Strings to Document node], meaning that for each row a document is created containing all the information in a single cell. Next, during the enrichment

stage, I inserted the nodes “Pos Tagger”, “Dictionary Tagger”, and “Wildcard Tagger” to tag words using external dictionaries. In my case, I used two different dictionaries. On the one hand, I measured the Positive Sentiment of the video captions via the Linguistic Inquiry and Word Count dictionary (LIWC). On the other hand, I manually created a CTA dictionary and positively tagged the words in the video caption that fell under the “CTA” category. Now that caption terms have been tagged if they contain a Positive Sentiment or CTA term, we move on with the bag of words. The bag of words technique consists in tokenizing the text, which means splitting it into individual words and assigning them a unique integer ID. Finally, I created two new variables, one for the presence of Positive Sentiment and the other one for the presence of CTA. To do so, I split the dataset depending on whether the terms contained either the tag “Positive” for Sentiment or for CTA. Subsequently, I concatenated the two datasets to obtain a sub-dataset with just the video captions with either a term belonging to the CTA or LIWC dictionaries. The sub-dataset had 409 rows, roughly 41% of the initial dataset. Finally, I calculated the average views, average comments, and average likes of the posts in this sub-dataset to spot differences with the rest of the dataset.

Spontaneous Nature

Considering that my dataset contained the variable *author_verified*, which can take the value “true” if the user has been verified by TikTok and “false” if it hasn’t, I simply visualized that column variable in a pie chart to observe its relevance.

Video Duration

To identify an optimal video duration for this specific TikTok trend, I separated the videos into three different length intervals and assigned each of them to a different category. More specifically, I consider a video “short” if its length is between 1 and 20 seconds, “medium” if its length is between 21 and 45 seconds, and “long” if its length is over 45 seconds. After creating the three categories, I assigned a constant value of “0” to the *short* category, “1” to the *medium* category, and “2” to the *long* category. Then, for each category, I calculated the average reviews, the average

likes, and the average comments. Finally, to test the different length intervals, I normalized my data and fed it to a binomial regression model.

Binomial Regression Model

A binomial regression model is often used in explanatory analytics to identify the factors that influence the probability of an event occurring. Moreover, the model can be used to identify which factors are most important in predicting the probability of an event occurring and to quantify the relationship between the factors and the probability of the event occurring. In this case, I wanted to identify the factors that influence the *video_duration* and constructed the model as follows.

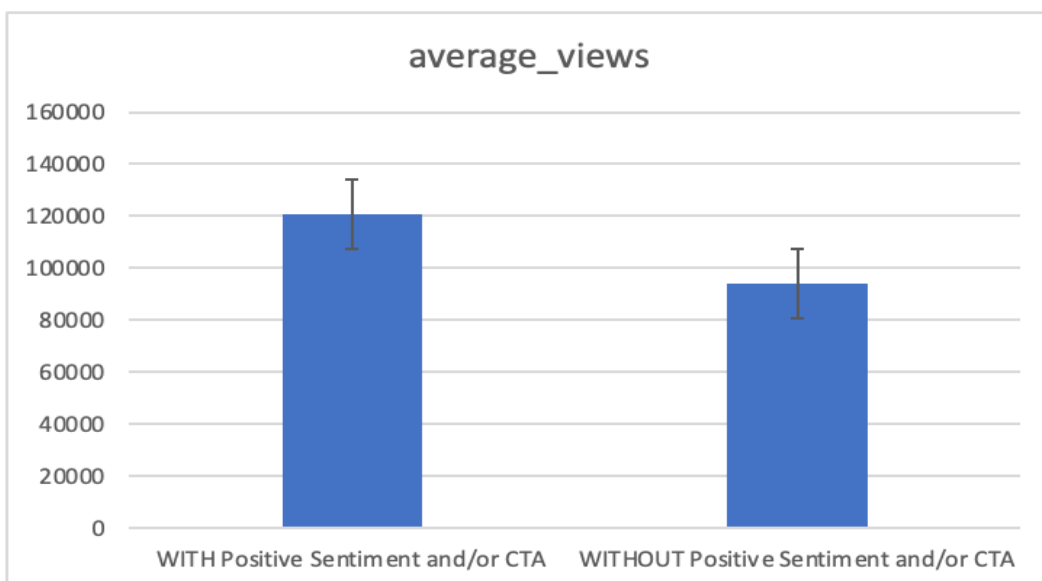
$$\begin{aligned} \mathbf{Video_duration} = & \alpha + \beta_1 * \#_comments + \beta_2 * \#_views + \beta_3 * \#_likes + \beta_4 * \#_shares \\ & + \beta_5 * \mathbf{Positive} \end{aligned}$$

Table 2



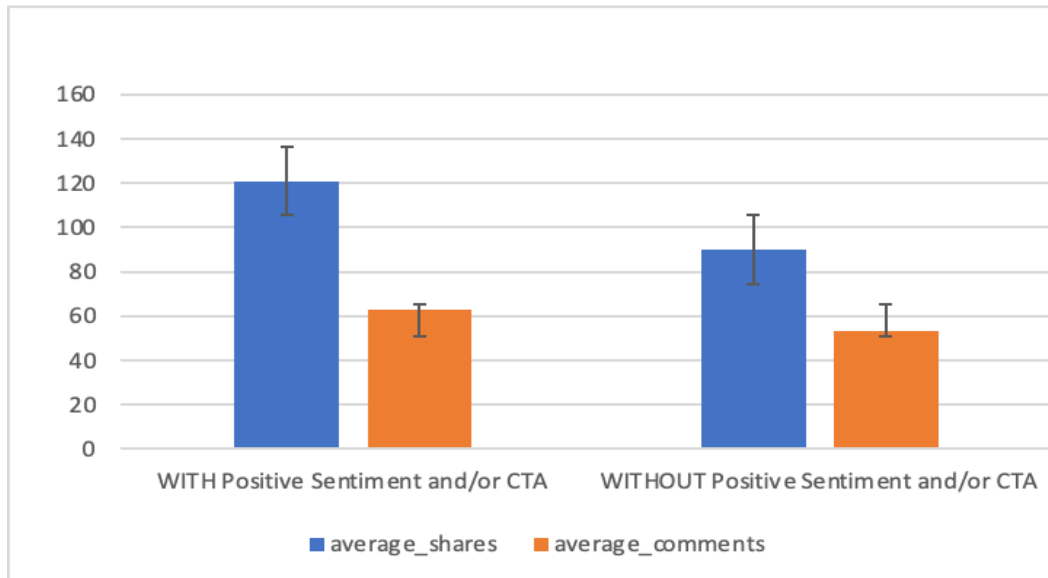
In table 3, I plotted the average views for the posts with Positive Sentiment or CTA terms against the posts without Positive Sentiment or CTA terms. From the graph, the average views are higher if the video contained at least one of the two elements.

Table 3



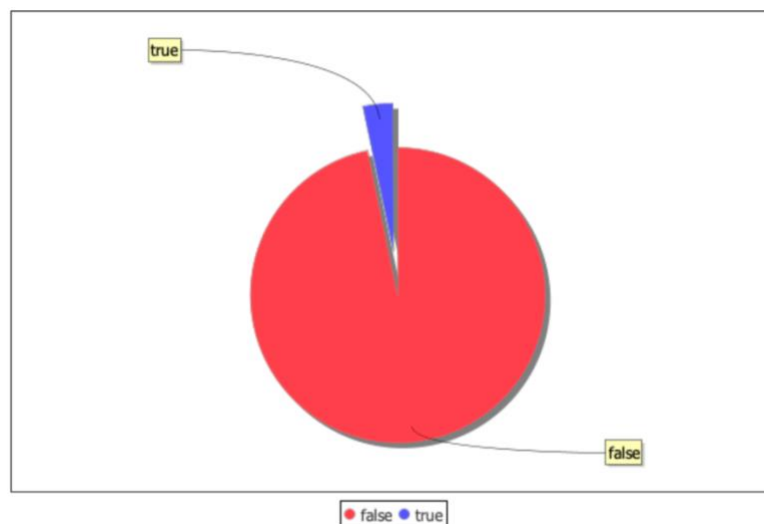
In table 4, I take into account the other variables related to engagement (average_shares, average_comments, average duration). The results in Table 3 and Table 4 are in line with hypotheses H1 and H1.2, as the overall engagement is higher if the video contained at least one of the two elements for this particular TikTok trend.

Table 4



Spontaneous Nature

Table 5



As shown in the pie chart above, out of the 1000 videos in the dataset, only around 3.5% of users are verified on the platform. The result is in line with H2, as it means that being verified is not a necessary feature for users to get viral in the #TikTokMadeMeBuyIt trend.

Video Duration

Model 1

<i>video_duration</i>	<i>Coefficients</i>	<i>Standard Errors</i>	<i>p-values</i>
<i>#_comment</i>	0.48859	1.07118	0.666
<i>#_views</i>	-1.26925	2.00746	0.523
<i>#_likes</i>	2.18000	1.55697	0.159
<i>#_shares</i>	-0.18166	1.43141	0.888
<i>Positive</i>	0.09179	0.14819	0.536
<i>Intercept</i>	-1.34884	0.07233	<2e ⁻¹⁶

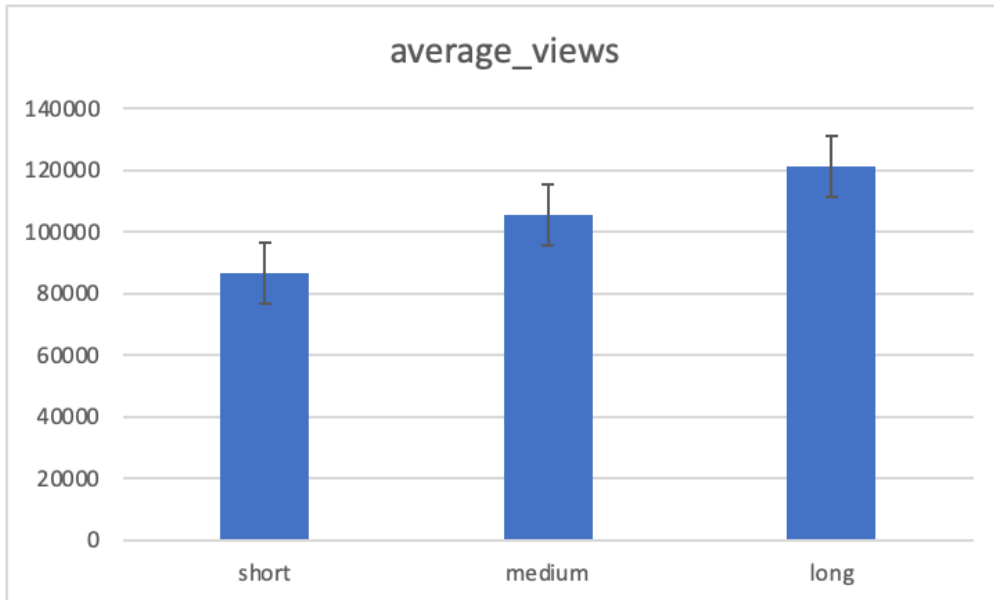
Model 2

<i>#_likes</i>	<i>Coefficients</i>	<i>Standard Errors</i>	<i>p-values</i>
<i>#_comment</i>	2.1016	1.7534	0.231
<i>video_duration</i>	0.7363	0.9961	0.460
<i>#_views</i>	5.3871 ***	1.3559	7.1e ⁻⁰⁵
<i>#_shares</i>	2.1535	2.0017	0.282
<i>Positive</i>	-0.2166	0.9569	0.821
<i>Intercept</i>	-5.9160	0.6754	< 2e ⁻¹⁶

The table above shows the coefficients of the binomial regression. In Model 1, there is no variable with a p-value < 0.05 suggesting that there is neither positive nor negative influence between *video_duration* and the predictor variables of the model. Instead, in Model 2, the p-value of *#_views* is 7.1e⁻⁰⁵, indicating that its coefficient is statistically significant (5.2878 ***) and there is a positive influence between *#_likes* and *#_views*. This result may not be particularly surprising, but it confirms the purpose of TikTok, which is to keep users attached to their screens as much as possible to gain views and likes.

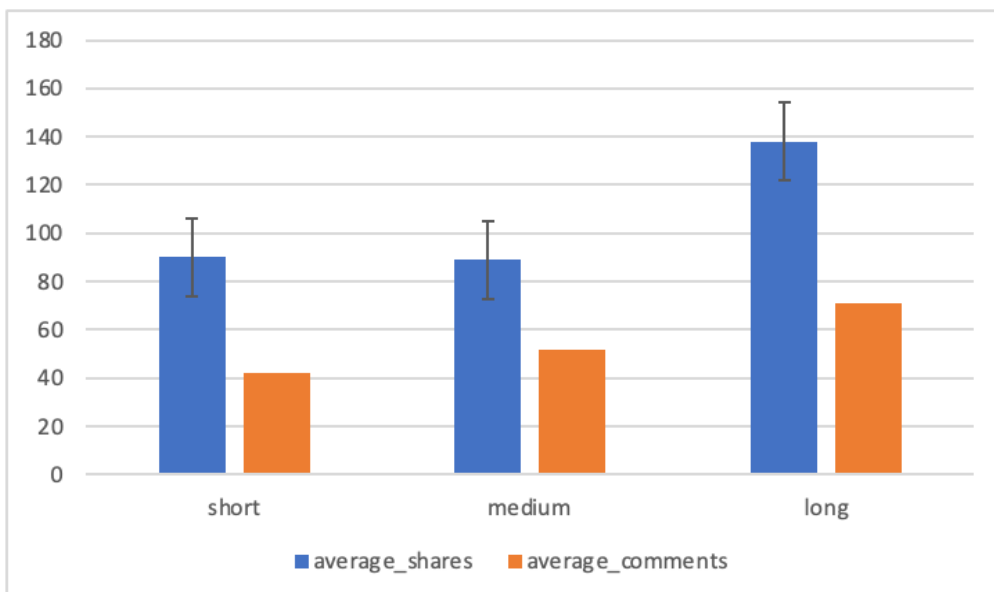
In Table 6 we can observe the three video categories plotted against the average views. Quite surprisingly, videos belonging to the “long” category reported higher average views.

Table 6



Instead, in Table 7, I plotted the three video categories against average shares and average comments. Again, contrary to what I had hypothesized, average shares and average comments result higher in longer videos for this TikTok trend.

Table 7



DISCUSSION

Contributions

My study focuses on the analysis of the TikTok trend of #TikTokMadeMeBuyIt and on how social media can influence consumer purchasing behavior. Particularly, the #TikTokMadeMeBuyIt trend is all about the power of genuine recommendations on social media. If a post containing the aforementioned hashtag gets viral, users are likely to go out and buy the product in question. My research focused on three main hypotheses and in the following paragraphs, I will consider each of them separately.

Firstly, H1.1 and H1.2 are consistent with the results. More specifically, by comparing the overall engagement of videos that didn't contain any Positive Sentiment or CTA terms in their captions with videos that instead did contain at least one of those two elements, we can conclude that the latter ones recorded a higher overall engagement for this trend on TikTok.

Secondly, H2 is consistent with the results. Keeping in mind that my dataset contained exclusively the 1000 most liked - and hence viral - videos that included the hashtag #TikTokMadeMeBuyIt, the analysis suggests that being a non-verified user is not a barrier to entry for this particular trend. Moreover, this is quite a unique feature of the platform, in which regular users interact mostly with other regular users and not necessarily influencers or brand ambassadors. If we take into consideration YouTube as an example, it is much more common for channels with a higher subscriber count to end up in the trending section of the platform. On TikTok, instead, it is safe to say that anyone can potentially participate in the #TikTokMadeMeBuyIt trend and go viral.

Thirdly, H3 is not consistent with the results. More specifically, the results of the binomial regression model suggest video duration does not influence the overall engagement of the post neither positively nor negatively. On top of that, by plotting the three length categories (short, medium, and long) against average views, average likes, and average comments, the graphs suggest users prefer

longer videos for this TikTok trend. This might be because longer videos mean longer exposure for the product and longer time for the authors to showcase its characteristics, utility, and value-added.

Managerial Implications

It is evident that TikTok is a powerful marketing tool that can be used to reach a wide variety of consumers. Businesses should consider using TikTok to connect with consumers, especially Gen Zers who are known for being highly engaged with the platform. When creating content for TikTok, businesses should consider what trends are popular among users and create content that is entertaining and engaging. However, businesses should keep in mind that users value genuine content. Therefore, they should engage with content creators or influencers that incarnate this spontaneous nature. Before advertising it on TikTok, content creators or influencers must have trust in the product in the first place. Besides, verified content creators or influencers should not be the first choice, as in most cases being verified does not imply a higher virality rate. In addition, including Positive Sentiment and CTA terms when formulating a video caption is important to increase the chance of the video going viral. Lastly, from my findings, it seems that videos longer than 45 seconds are preferred by users and potentially result in higher engagement.

Further Research Directions

As mentioned before, due to the novelty of the subject, there hasn't been much research on the trend of #TikTokMadeMeBuyIt and TikTok in general. Moreover, data scraping from TikTok for research purposes is still quite complicated. For these reasons, further research should focus on obtaining large datasets with a lower level of bias. Indeed, my dataset contained 1000 videos and only the ones that were already viral. Moreover, further analysis could include the application of video mining on TikTok videos. As TikTok is built around videos of short length, it is an ideal platform for video mining. Certainly, video mining can be an extremely valuable way to find out what content is

popular on TikTok and, by using hashtags, the Explore page, and analytics tools, businesses can extract crucial information in order to get an idea of who their potential customers might be.

REFERENCES

Academic Papers

Uribe-Saavedra, Felipe & Josep, Rialp & Llonch, Joan. (2015). The effect of online comments on purchase intention and brand trust: the moderating role of brand awareness and type of product. https://www.researchgate.net/publication/280087516_The_effect_of_online_comments_on_purchase_intention_and_brand_trust_the_moderating_role_of_brand_awareness_and_type_of_product

Lindgreen, A., Di Benedetto, C. A., Brodie, R. J., & Jaakkola, E. (2021). How to Develop Great Conceptual Frameworks for Business-to-Business Marketing. *Industrial Marketing Management*, 94, A2-A10. <https://doi.org/10.1016/j.indmarman.2020.04.005>

Pütter, Michael. (2017). The Impact of Social Media on Consumer Buying Intention. *Journal of International Business Research and Marketing*, 3, 7-13. https://www.researchgate.net/publication/335500761_The_Impact_of_Social_Media_on_Consumer_Buying_Intention

Tien, Duong & Amaya, Adriana & Liao, Ying-Kai. (2018). Examining the influence of customer-to-customer electronic word-of-mouth on purchase intention in social networking sites. *Asia Pacific Management Review*. https://www.researchgate.net/publication/326469837_Examining_the_influence_of_customer-to-customer_electronic_word-of-mouth_on_purchase_intention_in_social_networking_sites

Christodoulides, George. (2009). Branding in the post-internet era. *Marketing Theory - Mark Theory*, 9, 141-144. https://www.researchgate.net/publication/247757274_Branding_in_the_post-internet_era

Babić Rosario, Ana & Valck, Kristine & Sotgiu, Francesca. (2019). Conceptualizing the electronic word-of-mouth process: What we know and need to know about eWOM creation, exposure, and evaluation. *Journal of the Academy of Marketing Science*. https://www.researchgate.net/publication/336473966_Conceptualizing_the_electronic_word-of-mouth_process_What_we_know_and_need_to_know_about_eWOM_creation_exposure_and_evaluation

Laroche, Michel & Habibi, Mohammad Reza & Richard, Marie-Odile. (2013). To be or not to be in social media: How brand loyalty is affected by social media?. *International Journal of Information Management*, 33, 76–82. https://www.researchgate.net/publication/257103198_To_be_or_not_to_be_in_social_media_How_brand_loyalty_is_affected_by_social_media

Hasena, C., & Sakapurnama, E. (2021). Leveraging Electronic Word of Mouth on TikTok: Somethinc Skin Care Product Innovation to Increase Consumer Purchase Intention. *Hasanuddin Economics and Business Review*, 5(1), 19. <https://www.google.com/url?sa=t&rct=j&q=&esrc=s&source=web&cd=&ved=2ahUKEwjapp6d5JH6AhX9gP0HHVB5AHEQFnoECBIQAQ&url=http%3A%2F%2Fpasca.unhas.ac.id%2Ffojs%2Findex.php%2Fhebr%2Farticle%2Fdownload%2F2746%2F759&usg=AOvVaw0bQL2OqMQLG8CYeFcgmf4U>

Ngangom, M. (2020). How TikTok Has Impacted Generation Z's Buying Behaviour and Their Relationship With Brands?

https://esource.dbs.ie/bitstream/handle/10788/4116/msc_nganom_m_2020.pdf?sequence=1&isAllowed=y

Zhan, Ming & Tu, Ruibo & Yu, Qin. (2018). Understanding Readers: Conducting Sentiment Analysis of Instagram Captions. 33-40.

https://www.researchgate.net/publication/331421153_Understanding_Readers_Conducting_Sentiment_Analysis_of_Instagram_Captions

Nurjannah, A. (2022). The influence of Tiktok, Brand ambassador, and brand awareness on Shopee's purchase interest. *Interdisciplinary Social Studies*.

<https://iss.internationaljournalabs.com/index.php/iss/article/view/143/130>

Business Magazines

<https://www.businessofapps.com/news/82-of-shoppers-use-social-media-to-make-a-purchase/>

<https://www.semrush.com/blog/word-of-mouth-stats/>

<https://www.worldfinance.com/strategy/tiktok-made-me-buy-it>

<https://www.nytimes.com/2021/10/02/style/tiktok-shopping-viral-products.html>

<https://www.renolon.com/average-time-spent-on-tiktok/>

<https://realresearcher.com/media/over-47-said-tiktok-has-the-most-variety-of-short-form-videos/>

<https://www.listenfirstmedia.com/4-insights-you-need-to-know-about-video-length-on-social-media/>

/