REVERSE SYNTHESIS ACTIVITY **Name** ______________________________

for the week of 4/11/22 – 4/15/22

1. You will be provided 7 sources. Your fist task to is skim the sources and see what they have in common, how they complement AND how they contradict one another.

Commonalities	Differences	Gaps (See #3 below)

2. Secondly, you will create a prompt task statement from which writers could develop a position using these sources. Viewing a sample synthesis prompt page will help you here.

3. Identify gaps in the information provided (information that is NOT provided that would be needed to develop a position on your created prompt).

4. Find a documentary using YouTube that fills some of those gaps. Record the title, URL, and basic information from the documentary here:

SOURCE H (documentary)

5. Next, you will write an introductory context paragraph similar to those provided in the College Board synthesis prompts.

Source A

The Wall Street Journal

"TikTok Brain Explained: Why Some Kids Seem Hooked on Social Video Feeds"

The dopamine rush of endless short videos makes it hard for young viewers to switch their focus to slower-moving activities. 'We've made kids live in a candy store.'

By Julie Jargon
Follow
Apr. 2, 2022 9:00 am ET

Remember the good old days when kids just watched YouTube all day? Now that they binge on 15-second TikToks, those YouTube clips seem like PBS documentaries.

Many parents tell me their kids can't sit through feature-length films anymore because to them the movies feel painfully slow. Others have observed their kids struggling to focus on homework. And reading a book? Forget about it.

What is happening to kids' brains?

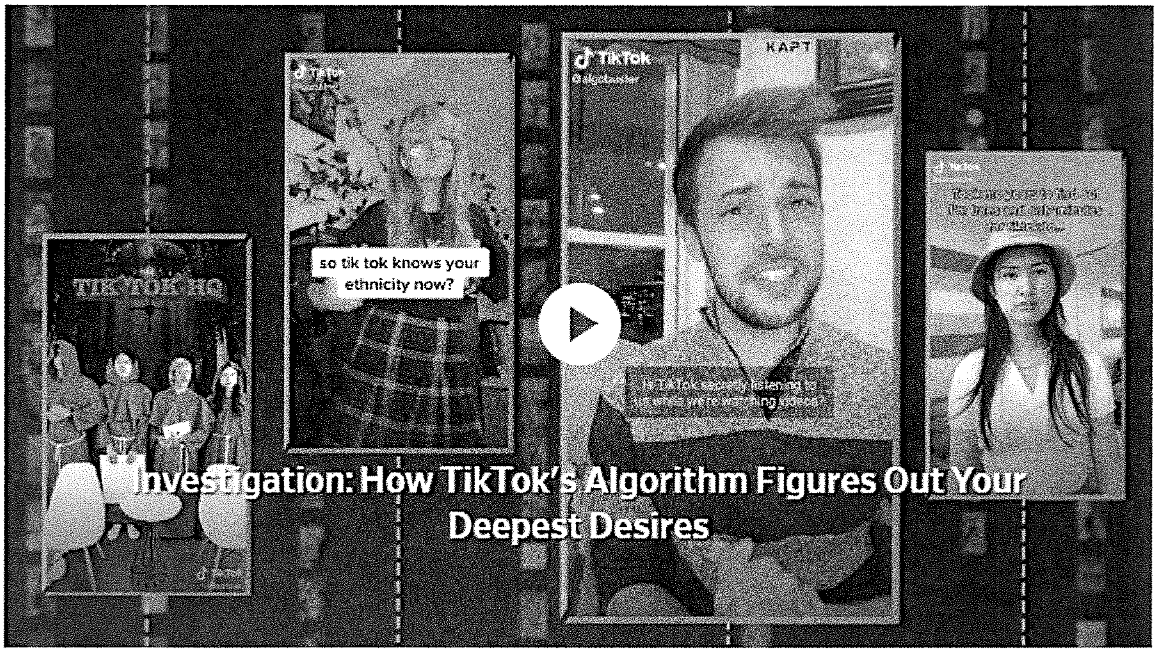
"It is hard to look at increasing trends in media consumption of all types, media multitasking and rates of ADHD in young people and not conclude that there is a decrease in their attention span," said Carl Marci, a psychiatrist at Massachusetts General Hospital in Boston.

Links between attention-deficit hyperactivity disorder diagnoses and screen time are subject to debate, since many factors could account for a steady rise in cases. Yet even parents whose children don't qualify for that medical diagnosis say their kids are more distracted. Emerging research suggests that watching short, fast-paced videos makes it harder for kids to sustain activities that don't offer instant—and constant—gratification.

One of the few studies specifically examining TikTok-related effects on the brain focused on Douyin, the TikTok equivalent in China, made by the same Chinese parent company, ByteDance Ltd. It found that the personalized videos the app's recommendation engine shows users activate the reward centers of the brain, as compared with the general-interest videos shown to new users.

Brain scans of Chinese college students showed that areas involved in addiction were highly activated in those who watched personalized videos. It also found some people have trouble controlling when to stop watching.

"We speculate that individuals with lower self-control ability have more difficulty shifting attention away from favorite video stimulation," the researchers at China's Zhejiang University wrote.



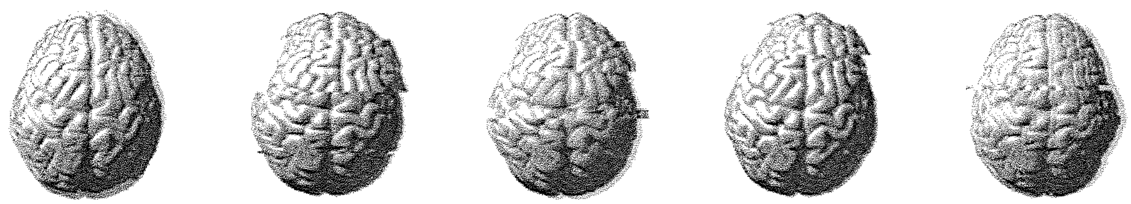
A Wall Street Journal investigation found that TikTok only needs one important piece of information to figure out what you want: the amount of time you linger over a piece of content. Every second you hesitate or rewatch, the app is tracking you. Photo illustration: Laura Kammermann/The Wall Street Journal

A Wall Street Journal investigation last year found that TikTok's algorithm figures out what users like based on the amount of time they watch each video, and then serves up more of the same. TikTok said it is now developing ways to diversify the videos its algorithm recommends to viewers.

A2

A TikTok spokeswoman said the company wants younger teens to develop positive digital habits early on, and that it recently made some changes aimed at curbing extensive app usage. For example, TikTok won't allow users ages 13 to 15 to receive push notifications after 9 p.m. TikTok also periodically reminds users to take a break to go outside or grab a snack.

Kids have a hard time pulling away from videos on YouTube, too, and Google has made several changes to help limit its use, including turning off autoplay by default on accounts of people under 18.



Brain science

When kids do things that require prolonged focus, such as reading or solving math problems, they're using directed attention. This function starts in the prefrontal cortex, the part of the brain responsible for decision making and impulse control.

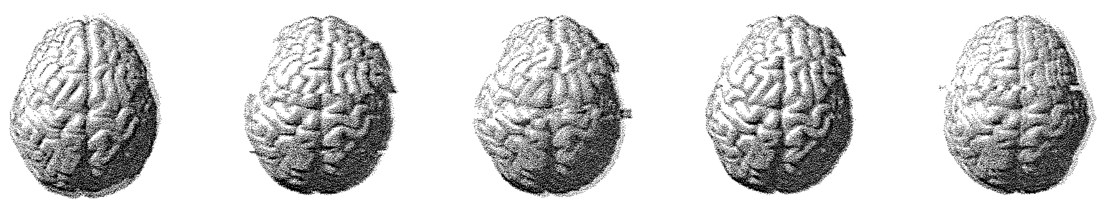
"Directed attention is the ability to inhibit distractions and sustain attention and to shift attention appropriately. It requires higher-order skills like planning and prioritizing," said Michael Manos, the clinical director of the Center for Attention and Learning at Cleveland Clinic Children's.

Kids generally have a harder time doing this—and putting down their videogame controllers—because the prefrontal cortex isn't fully developed until age 25.

Dr. Manos said the ever-changing environment of TikTok doesn't require sustained attention. "If kids' brains become accustomed to constant changes, the brain finds it difficult to adapt to a nondigital activity where things don't move quite as fast," he said.

TikTok is now allowing users to make videos as long as 10 minutes, up from the previous maximum of 3 minutes and from its initial 60-second maximum.

"In the short-form snackable world, you're getting quick hit after quick hit, and as soon as it's over, you have to make a choice," said Mass General's Dr. Marci, who wrote the new book "Rewired: Protecting Your Brain in the Digital Age." The more developed the prefrontal cortex, the better the choices.



The infinite candy store

Dopamine is a neurotransmitter that gets released in the brain when it's expecting a reward. A flood of dopamine reinforces cravings for something enjoyable, whether it's a tasty meal, a drug or a funny TikTok video.

"TikTok is a dopamine machine," said John Hutton, a pediatrician and director of the Reading & Literacy Discovery Center at Cincinnati Children's Hospital. "If you want kids to pay attention, they need to practice paying attention."

A4

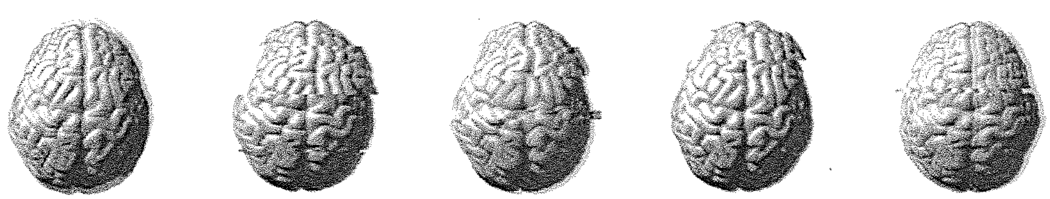
Researchers are just beginning to conduct long-term studies on digital media's effects on kids' brains. The National Institutes of Health is funding a study of nearly 12,000 adolescents as they grow into adulthood to examine the impact that many childhood experiences—from social media to smoking—have on cognitive development.

The study's investigators are focusing now on the impact specific apps have on children's brain development.

The results aren't in yet. Bonnie Nagel, one of the study's investigators and a professor of psychiatry and behavioral neuroscience at Oregon Health & Science University, said she predicts they will find that when brains repeatedly process rapid, rewarding content, their ability to process less-rapid, less-rewarding things "may change or be harmed."

As media gets faster and more stimulating, it's bumping up against the realities of the nondigital world, and parental expectations.

"It's like we've made kids live in a candy store and then we tell them to ignore all that candy and eat a plate of vegetables," said James Williams, a tech ethicist and author of "Stand Out of Our Light: Freedom and Resistance in the Attention Economy." "We have an endless flow of immediate pleasures that's unprecedented in human history."



What you can do

Parents and kids can take steps to boost attention, but it takes effort, the experts say.

Swap screen time for real time. Exercise and free play are among the best ways to build attention during childhood, says Johann Hari, author of "Stolen Focus: Why You Can't Pay Attention—and How to Think Deeply Again." Dedicating after-school and weekend time for sports, play dates, family hikes or trips to the park can help focus the brain.

"Depriving kids of tech doesn't work, but simultaneously reducing it and building up other things, like playing outside, does," Mr. Hari said.

Practice restraint. Your child's brain won't inherently want to set aside a device that's delivering entertainment, Dr. Nagel said. "When you practice stopping, it strengthens those connections in the brain to allow you to stop again next time."

SHARE YOUR THOUGHTS

Do you think online videos affect your child's attention span? Why or why not? Join the conversation below.

There are various ways to do that, such as scheduling regular times each day when tech isn't used—such as at the dinner table—and by setting time limits on screen sessions.

Use tech's own tools. TikTok has a screen-time management setting that allows users to cap their app usage. Parents can also establish screen-time limits for their kids with Family Pairing, which requires parents to create a TikTok account and link it to their teen's.

YouTube allows parents to set time limits for younger kids. For kids using the regular YouTube app, parents can create supervised accounts using Google Family Link to manage screen time, provide take-a-break reminders and choose age-appropriate content.

Parents can also set time limits on specific apps directly from Apple and Android devices.

Ensure good sleep. Teens are suffering from a sleep deficit. Proper sleep is essential for focus and attention, which is why phones and other devices should be kept out of the bedroom at night.

The New York Times https://www.nytimes.com/2021/12/05/business/media/tiktok-algorithm.html

THE MEDIA EQUATION

How TikTok Reads Your Mind

It's the most successful video app in the world. Our columnist has obtained an internal company document that offers a new level of detail about how the algorithm works.

By Ben Smith
Dec. 5, 2021

There are four main goals for TikTok's algorithm: 用户价值, 用户价值 (长期), 作者价值, and 平台价值, which the company translates as "user value," "long-term user value," "creator value," and "platform value."

That set of goals is drawn from a frank and revealing document for company employees that offers new details of how the most successful video app in the world has built such an entertaining — some would say addictive — product.

The document, headed "TikTok Algo 101," was produced by TikTok's engineering team in Beijing. A company spokeswoman, Hilary McQuaide, confirmed its authenticity, and said it was written to explain to nontechnical employees how the algorithm works. The document offers a new level of detail about the dominant video app, providing a revealing glimpse both of the app's mathematical core and insight into the company's understanding of human nature — our tendencies toward boredom, our sensitivity to cultural cues — that help explain why it's so hard to put down. The document also lifts the curtain on the company's seamless connection to its Chinese parent company, ByteDance, at a time when the U.S. Department of Commerce is preparing a report on whether TikTok poses a security risk to the United States.

If you're among the billion people (literally!) who spend time on TikTok every month, you're familiar with the app as 2021's central vehicle for youth culture and online culture generally. It displays an endless stream of videos and, unlike the social media apps it is increasingly displacing, serves more as entertainment than as a connection to friends.

It succeeded where other short videos apps failed in part because it makes creation so easy, giving users background music to dance to or memes to enact, rather than forcing them to fill dead air. And for many users, who consume without creating, the app is shockingly good at reading your preferences and steering you to one of its many "sides," whether you're interested in socialism or Excel tips or sex, conservative politics or a specific celebrity. It's astonishingly good at revealing people's desires even to themselves — "The TikTok Algorithm Knew My Sexuality Better Than I Did," reads one in a series of headlines about people marveling at the app's X-ray of their inner lives.

TikTok has publicly shared the broad outlines of its recommendation system, saying it takes into account factors including likes and comments as well as video information like captions, sounds and hashtags. Outside analysts have also sought to crack its code. A recent Wall Street Journal report demonstrated how TikTok relies heavily on how much time you spend watching each video to steer you toward more videos that will keep you scrolling, and that process can sometimes lead young viewers down dangerous rabbit holes, in particular toward content that promotes suicide or self-harm — problems that TikTok says it's working to stop by aggressively deleting content that violates its terms of service.

The new document was shared with The New York Times by a person who was authorized to read it, but not to share it, and who provided it on the condition of anonymity. The person was disturbed by the app's push toward "sad" content that could induce self-harm.

The document explains frankly that in the pursuit of the company's "ultimate goal" of adding daily active users, it has chosen to optimize for two closely related metrics in the stream of videos it serves: "retention" — that is, whether a user comes back — and "time spent." The app wants to keep you there as long as possible. The experience is sometimes described as an addiction, though it also recalls a frequent criticism of pop culture. The playwright David Mamet, writing scornfully in 1998 about "pseudoart," observed that "people are drawn to summer movies because they are *not* satisfying, and so they offer opportunities to repeat the compulsion."

To analysts who believe algorithmic recommendations pose a social threat, the TikTok document confirms their suspicions.

"This system means that watch time is key. The algorithm tries to get people addicted rather than giving them what they really want," said Guillaume Chaslot, the founder of Algo Transparency, a group based in Paris that has studied YouTube's recommendation system and takes a dark view of the effect of the product on children, in particular. Mr. Chaslot reviewed the TikTok document at my request.

"I think it's a crazy idea to let TikTok's algorithm steer the life of our kids," he said. "Each video a kid watches, TikTok gains a piece of information on him. In a few hours, the algorithm can detect his musical tastes, his physical attraction, if he's depressed, if he might be into drugs, and many other sensitive information. There's a high risk that some of this information will be used against him. It could potentially be used to micro-target him or make him more addicted to the platform."

The document says watch time isn't the only factor TikTok considers. The document offers a rough equation for how videos are scored, in which a prediction driven by machine learning and actual user behavior are summed up for each of three bits of data: likes, comments and playtime, as well as an indication that the video has been played:

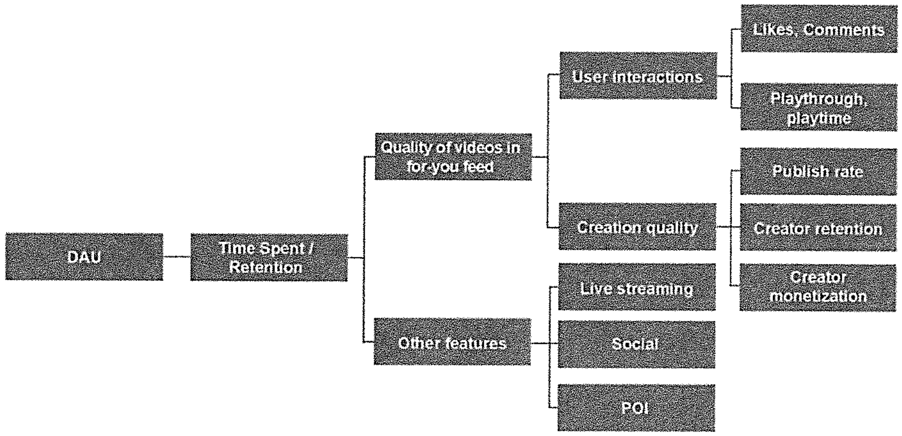
Plike X Vlike + Pcomment X Vcomment + Eplaytime X Vplaytime + Pplay X Vplay

"The recommender system gives scores to all the videos based on this equation, and returns to users videos with the highest scores," the document says. "For brevity, the equation shown in this doc is highly simplified. The actual equation in use is much more complicated, but the logic behind is the same."

The document illustrates in detail how the company tweaks its system to identify and suppress "like bait" — videos designed to game the algorithm by explicitly asking people to like them — and how the company thinks through more nuanced questions.

"Some authors might have some cultural references in their videos and users can only better understand those references by watching more of the author's videos. Therefore, the total value that a user watches all those videos is higher than the values of watching each single video added up," the document says. "Another example: if a user likes a certain kind of video, but the app continues to push the same kind to him, he would quickly get bored and close the app. In this case, the total value created by the user watching the same kind of videos is lower than that of watching each single video, because repetitiveness leads to boredom."

"There are two solutions to this issue," the document goes on. "Make some assumptions, and break down the value into the value equation. For instance, in terms of repeated exposure, we could add a value 'same_author_seen,' and for the boredom issue, we could also add a negative value 'same_tag_today.' Other solutions besides value equation may also work, such as forced recommendation in users' for u feed and dispersion etc. For example, the boredom issue can be solved through dispersion."



A chart illustrating the goals of TikTok's algorithm was part of the report. (Note: This image was reproduced by The New York Times from original documents.) The New York Times

Another chart in the document indicates that "creator monetization" is one of the company's goals, a suggestion that TikTok may favor videos in part if they are lucrative, not just entertaining.

Julian McAuley, a professor of computer science at the University of California San Diego, who also reviewed the document, said in an email that the paper was short on detail about how exactly TikTok does its predictions, but that the description of its recommendation engine is "totally reasonable, but traditional stuff." The company's edge, he said, comes from combining machine learning with "fantastic volumes of data, highly engaged users, and a setting where users are amenable to consuming algorithmically recommended content (think how few other settings have all of these characteristics!). Not some algorithmic magic."

Mr. McAuley added that he was a bit perplexed about why people were always asking him about TikTok.

"There seems to be some perception (by the media? or the public?) that they've cracked some magic code for recommendation, but most of what I've seen seems pretty normal," he wrote.

And indeed, the document does much to demystify the sort of recommendation system that tech companies often present as impossibly hard for critics and regulators to grasp, but that typically focus on features that any ordinary user can understand. The Journal's coverage of leaked Facebook documents, for instance, illustrated how Facebook's decision to give more weight to comments helped divisive content spread. While the models may be complex, there's nothing inherently sinister or incomprehensible about the TikTok recommendation algorithm outlined in the document.

But the document also makes clear that TikTok has done nothing to sever its ties with its Chinese parent, ByteDance, whose ownership became a spasmodic focus at the end of President Donald J. Trump's administration in 2020, when he attempted to force the sale of TikTok to an American company allied with his administration, Oracle.

The TikTok document refers questions to an engineering manager whose LinkedIn biography says he works on both TikTok and ByteDance's similar Chinese app, Douyin, offering a glimpse at the remaining global element of an increasingly divided tech industry, the engineering talent. According to LinkedIn, the engineering manager attended Peking University, received a master's degree in computer science at Columbia University and worked for Facebook for two years before coming to ByteDance in Beijing in 2017. The document is written in clear, but nonnative, English, and comes from the perspective of the Chinese tech industry. It makes no references, for instance, to rival American companies like Facebook and Google, but includes a discussion of "if Toutiao/Kuaishou/Weibo have done something similar, can we launch the same strategy as they have done?"

TikTok's development process, the document says, is closely intertwined with the process of Douyin's. The document at one point refers TikTok employees to the "Launch Process for Douyin Recommendation Strategy," and links to an internal company document that it says is the "same document for TikTok and Douyin."

TikTok employees are also deeply interwoven into ByteDance's ecosystem. They use a ByteDance product called Lark, a corporate internal communications system like Slack but with aggressive performance-management features aimed at forcing employees to use the system more. There is, for instance, a graphic that tells you whether you have performed actions — like opening messages — more or less than your co-workers, according to screenshots I was given.

Concern about Chinese consumer technology is bipartisan in the United States. President Trump's executive order attempting to ban the app in August 2020 warned that TikTok's "data collection threatens to allow the Chinese Communist Party access to Americans' personal and proprietary information." The Chinese government could "build dossiers of personal information for blackmail, and conduct corporate espionage," it said. That ban stalled in court and faded after the presidential election. President Biden rescinded the executive order, but his administration then announced its own investigation into security threats posed by TikTok, with an unnamed senior administration official telling reporters that China was "working to leverage digital technologies and American data in ways that present unacceptable national security risks."

In an emailed statement, Ms. McQuaide said that "while there's some commonality in the code, the TikTok and Douyin apps are run entirely separately, on separate servers, and neither code contains user data."

She also said, "TikTok has never provided user data to the Chinese government, nor would we if asked."

TikTok, whose chief executive lives in Singapore, hired a raft of well-connected American and European executives and security experts as political pressure intensified under Mr. Trump. It says it has no formal headquarters. It has sought to soothe American concerns by storing user data in the United States, with a backup in Singapore.

The American government's security concerns come in two forms. The first, as Mr. Trump suggested in his executive order, is whether the vast trove of data TikTok holds — about the private sexual desires of fans of the app who might end up becoming American public officials, for instance — should be viewed as a national security issue. There's no evidence the data has ever been used that way, and TikTok is hardly the only place Americans share details of their lives on social media. The second concern is whether TikTok censors politically sensitive posts.

A report this year by Citizen Lab, the cybersecurity watchdog organization in Toronto, suggested that both of these concerns are, at best, latent: It did not find any indication that TikTok was either censoring sensitive topics or transmitting data to China.

But TikTok's glimpses of people's inner lives are unusual. Another screenshot shared with me indicates that its content moderators have access not just to videos posted publicly, but also to content sent to friends or uploaded to the system but not shared, a difference from apps like WhatsApp and Signal that provide end-to-end encryption.

The second question is whether the Chinese government could use the platform to spread propaganda. After getting caught censoring a video condemning the mass detention of minority Muslims in China, TikTok has allowed criticism of the country's government. For instance, the hashtag #whereispengshuai, a reference to the Chinese tennis star who accused a top Chinese leader of sexual assault, autocompletes in the system, though TikTok videos with that hashtag have few views. There is no independent way of telling whether the company is suppressing the search, which has far more engagement on Twitter but similarly little on Instagram.

Some American analysts see TikTok as a profound threat; others view it as the kind of clueless panic that Americans now approaching middle age faced when their parents warned them that if they shared details of their lives on social media, they'd never get a job. Many, many other products, from social networks to banks and credit cards, collect more precise data on their users. If foreign security services wanted that data, they could probably find a way to buy it from the shadowy industry of data brokers.

"Freaking out about surveillance or censorship by TikTok is a distraction from the fact that these issues are so much bigger than any specific company or its Chinese ownership," said Samm Sacks, a cybersecurity policy fellow at the research organization New America. "Even if TikTok were American-owned, there is no law or regulation that prevents Beijing from buying its data on the open data broker market."

One thing that reporting this column has reminded me: The menace that TikTok poses to American national security appears to be entirely hypothetical, and depends on your analysis of both the U.S.-China relationship and the future of technology and culture. But the algorithm's grasp on what keeps me hooked — between trick tennis shots, Turkish food videos and all the other things it's figured out I like to watch — did pose a clear and present danger to my ability to finish this column.

Source C

An Empirical Investigation of Personalization Factors on TikTok

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ABSTRACT

TikTok currently is the fastest growing social media platform with over 1 billion active monthly users of which the majority is from generation Z. Arguably, its most important success driver is its recommendation system. Despite the importance of TikTok's algorithm to the platform's success and content distribution, little work has been done on the empirical analysis of the algorithm. Our work lays the foundation to fill this research gap. Using a sock-puppet audit methodology with a custom algorithm developed by us, we tested and analysed the effect of the language and location used to access TikTok, follow- and like-feature, as well as how the recommended content changes as a user watches certain posts longer than others. We provide evidence that all the tested factors influence the content recommended to TikTok users. Further, we identified that the follow-feature has the strongest influence, followed by the like-feature and video view rate. We also discuss the implications of our findings in the context of the formation of filter bubbles on TikTok and the proliferation of problematic content.

CCS CONCEPTS

• **Information systems → Personalization; Collaborative filtering; World Wide Web.**

KEYWORDS

TikTok, algorithm audit, recommender systems, personalization, social media

1 INTRODUCTION

In September 2016, ByteDance, a Chinese IT company, has launched a short video-sharing platform Douyin. While Douyin is only available in Mainland China, a similar application, called TikTok, was rolled out by ByteDance a year later in other countries [49]. TikTok users can upload short videos with a variety of settings and filters, search for videos based on hashtags, content or featured background sounds, or explore the videos on their "For You" page - a feed of videos recommended to users based on their activity. As of September 2021 TikTok welcomed 1 billion active users every month and was the most downloaded application of 2020 [11, 14, 26, 50] with more than 1 billion video views recorded daily in the same year [5, 37]. On average, people use TikTok's mobile application for 52 minutes and open it from 38 to 55 times a day [5, 26]. TikTok thus has by now become a major competitor for other social media and video platforms such as Instagram and YouTube, prompting them to attempt emulating TikTok's success by implementing similar features (e.g., Instagram Reels or YouTube Shorts - short videos with recommender system-based distribution).

TikTok is different from other major social media platforms such as Facebook or Instagram in one key aspect: its content distribution approach is purely algorithmic-driven, unlike other social media platforms where relationships between users play an important role in content distribution [3, 9, 15, 30]. Tiktok's success is largely attributed to its recommendation algorithm behind the selection of videos on the "For You" page [57]. The proliferation of folk theories about the innerworkings of TikTok's algorithm among its users[30], and the appearance of several media articles and blog posts attempting to describe how the algorithm works (e.g., [23, 47]) highlight public attention to TikTok's recommendation system (RS). In part, this is driven by the curiosity of users and the public and by the willingness of content creators to figure out how to achieve popularity on TikTok. Beyond that, interest in TikTok's algorithm is warranted by societal concerns such as the formation of filter bubbles and facilitation of addiction to the platform, especially among younger people as the majority of TikTok's users is between 10 and 29 years old [10, 26].

Despite TikTok's rapid growth in popularity and, consequently, its potentially high impact in political, social and cultural realms, both in part facilitated by its RS, the exact innerworkings of TikTok's RS remain a "black box" [22, 57]. Several studies have highlighted the importance of examining this algorithm [7, 22] through algorithm auditing - the investigation of functionality and impact of an algorithm [36]. While some research contributes to this goal [12, 30, 57] and there are several media articles discussing the algorithm [32, 47, 53], many gaps remain. This is especially the case with user-centric examination of TikTok's RS - i.e., the examination of how user actions affect recommendations of the algorithm. The only analysis going in this direction has been published by the Wall Street Journal [27], and despite yielding interesting results it was limited in scope and not strictly scientific. We aim to address the existing research gap with a user-centric audit of TikTok's algorithm.

We make two main contributions. First, we develop and describe a methodology for conducting user-centric algorithm auditing of TikTok's RS. Second, we examine the way in which different user actions influence TikTok's recommendations within users' "For You" feeds, and discuss the implications of our findings. Of course, there is a great variety of different user actions and characteristics that can influence the highly complex RS. In our analysis we focus on a number of those we see as most explicit: user location; user language settings; liking actions; following actions; video watching actions. Our analysis is thus not exhaustive and is rather a first step towards examining TikTok's RS. Additionally, the platform periodically introduces changes to the algorithm, thus any findings we have may be only accurate for a small time window. However, our methodology can be applied at different periods in time to trace the changes in the RS, and is applicable for the examination of platforms with features similar to TikTok's "For You" feed (e.g., YouTube Shorts or Instagram Reels).

2 RELATED WORK

2.1 Auditing Recommendation Systems

Due to the widespread application of recommendation algorithms, RS can have a serious impact on how humans receive information and ultimately perceive the world [2, 7, 46]. At the same time, "even those who train these systems cannot offer detailed or complete explanations about them or the neural networks they utilized" [3]. We therefore need scientific audits that shed light into the functionality of RS [38, 48]. As highlighted in a recent systematic literature review of algorithm audits [7], such studies can uncover problematic behaviors of RS and personalization algorithms such as the perpetuation of various biases [6], construction of filter bubbles [22, 43], personalization and randomization effects that can lead to users' unequal access to critical information [18, 28, 31], and price steering[19] [1].

There are different methodological approaches to algorithm auditing. According to [46], these are: (1) code audits, (2) noninvasive user audits, (3) scraping audits, (4) sock-puppet audits, and (5) collaborative audits. Our study falls into the fourth category as we mimic user behaviour via programmatic means, thus conducting what Sandvig et al. [46] refer to as a "classic" audit and following in the footsteps of other studies that examined how user characteristics and actions affect information distribution on online platforms [16–18].

2.2 TikTok-focused research

So far research on TikTok has been conducted along two main lines: with the focus on TikTok users and their behavior, and with the focus on TikTok as a platform, including some analysis of its algorithm. The research that falls into the first category has, for example, examined the relationships between grandchildren and grandparents on TikTok in relation to COVID-19 [40], analyzed political communication on TikTok [8, 34] and the ways news organizations adapt their narratives to TikTok format [52]. In the context of our study, however, the work that focuses on TikTok as a platform with an emphasis on its RS is more relevant.

One study has examined TikTok users' assumptions about the recommendation algorithm [30] and found "that it is quite common for TikTok users to evaluate app activity in order to estimate the behavior of the algorithm" as well as that content creators attribute the popularity (or lack of it) of their videos to TikTok's RS, and not to the video content. This study identified three main user assumptions about what influences the recommendation algorithm of TikTok on the content supply side: video engagement, posting time, and adding and piling up hashtags [30] and then, through an empirical analysis, confirmed that video engagement and posting time lead to a higher chance of the algorithm recommending a video. A few studies also described certain technical aspects of TikTok's algorithm. For instance, it has been outlined that once a new video is uploaded to TikTok, the system assigns descriptive tags to it based on computer vision analyses, mentioned hashtags, the post description, sound and embedded texts [12, 47, 53]. Afterwards, RS maps the tags to the user groups that match these tags, so that the recommendation algorithm can evaluate the next video to recommend from a reduced pool of videos [12]. Similarly, Zhao [57] concluded that ByteDance systematically categorizes a large number of content to better fit the user interests. Together with this method, ByteDance utilizes user's interest, identity, and behavior characteristics to describe a user and assign categories, creators, and specific labels to them [57]. Further, Zhao states that TikTok solves the matching problem of an RS in two steps. Namely, through recommendation recalling which retrieves a candidate list of items that meet user preferences and recommendation ranking which ranks the candidate list based on user preferences, item characteristics, and context [57]. Similar to Catherine Wang's theory about the TikTok recommendation algorithm [53], Zhao hypothesizes that TikTok uses the method of partitioned data buckets to launch new content [57]. In order to properly distribute a video, TikTok assigns newly uploaded videos to a small relatively responsive group of users (small bucket). Once the video received reasonable feedback measured by likes, views, shares, and comments surpassing a certain threshold it will be distributed to next level bucket with different users (medium bucket). This process will be repeated until a video no longer passes the threshold or lands in the "master" bucket to be distributed to the entire TikTok user community [57].

In contrast to the studies above that focus on the technical aspects of TikTok's RS innerworkings or on the possible factors that can increase the likelihood that a video will be recommended to a large pool of users, we examine the way users'[2] actions and characteristics affect the distribution of content on their "For You" feeds. Hence our analysis is centered on the content demand side rather than supply side. While the latter has been examined by the studies mentioned above, the demand side has so far been a subject of only few journalistic [27] but not scientific investigations.

We examine a variety of user actions and characteristics that may influence the recommendation algorithm, as noted in the Introduction. Based on the background information provided by TikTok itself regarding its RS [41] as well as on personalization-related research in general (e.g., [18, 28, 44]), we outline several hypotheses regarding the influence of surveyed personalization factors (user language, locations, liking action, following action, video view rate) on the users' feeds. These can be summarized as follows:

(1) If one user in a pair of identical users interacts with its "For You" feed in a certain way while its twin user only scrolls through its feed, the feeds of both users will diverge.
(2) Such divergence of the two users' feeds will increase overtime.
(3) Certain personalization factors have a greater impact on the recommendation system of TikTok than others.
(4) As a user interacts with specific posts in a certain way (e.g., likes them or watches them longer), that user will be served more posts that are similar to the ones it interacted with.
(5) As one of the two users interacts with its feed in a certain way, the engagement rate of the posts recommended to that

[1] For a detailed literature review of algorithm audits see [7].

[2] By users here and below we mean TikTok content consumers, not content creators.

C2

user will decrease, i.e. the number of views, likes, shares, comments of recommended posts will become smaller as the user will be served more "niche" content tailored to the user's inferred interests rather than generally popular content.

(6) Language and Location specific: Depending on the location and language a user uses to access TikTok, the user will be served different content.

3 METHODOLOGY

In this section we outline the general setup of the sock-puppet auditing experiments we conducted to assess the influence of different personalization factors on TikTok that was applicable to all experimental setups, regardless of the specific factors analyzed. Distinct factor-specific characteristics of the experimental setups are mentioned in the next section separately for each personalization factor-related experimental group. Same applies to the description of the analytical strategy.

3.1 Data Collection

In order to empirically test the influence of different factors on the recommendation algorithm of TikTok, we needed to create a fully controlled environment so we can isolate all the external personalization factors except the one we are testing in any given experimental setup [18]. Virtual agent-based auditing (or "sock-puppet" auditing [46]) is an appropriate methodology for creating such an environment while mimicking realistic user behaviour to assess the effects of different personalization factors [17, 51]. Thus, we created a custom web-based bot (virtual agent with scripted actions) that is able to log in to TikTok, scroll through the posts of its "For You" feed and interact with them, e.g. like a post. Similar to Hussein and Juneja [25], our program ran the ChromeDriver in incognito mode to establish a clean environment by removing any noise resulting from tracked cookies or browsing history that may originate from the machine on which the bot program was executed. The source code can be accessed on GitHub [3].

The scripted actions of the bot were executed as follows: first the program initialized a Selenium Chrome Driver session[4] with browser language set to English per default (depending on the test scenario, we adjusted the language; see details in Table 1), navigated to the TikTok website (https://www.tiktok.com), logged in as a specific user (login verification step was completed manually; we describe how user accounts were created below), and handled a set of banners to assure an error-free interaction with the user's "For You" feed; then it scrolled through a pre-specified number of posts and executed actions such as following or liking (as scripted for a specific experiment and "run" (execution round) of the program); while scrolling through the "For You" feed, the bot retrieved the posts' metadata from the website's source code and extracted more data from the request responses. In the testing rounds ahead of the deployment of the bots we established that every time TikTok's website was accessed it automatically preloaded about 30 posts to be displayed on the "For You" feed. Hereafter we refer to such groups of 30 posts as *batches*. As soon as the pre-specified number of batches[5] was scrolled through, the bot paused the last video and terminated the ChromeDriver session once all requested data was temporally stored to avoid unintentional interaction with the TikTok's feed. Afterwards all the data was stored in a PostgreSQL database hosted on Heroku. During our experiment we operated five local machines, four ran Windows 10 Pro and one macOS; as two users that were compared with each other (see below) always ran from the same local machine, the between-machine differences had no potential effect on our results. All machines were connected to the remote database.

For each run of the bot, we scripted a set of specifications which defined the characteristics of each run, e.g. web-browser language, test user, number of batches to scroll through etc. According to Yi, Raghavan, and Leggetter [56], web services can identify a user's location through their IP address. We therefore have assigned a dedicated proxy with a specific IP address to every test user due to three reasons: (1) every test shall be performed at a certain location, (2) to obscure the automated interaction, and (3) to link a specific IP address to a specific test user. We utilized proxies from WebShare [6] and acquired phone numbers from Twilio[7] to setup user accounts. We utilized user phone numbers instead of email-addresses as those would require a completion step on the mobile application. Similarly to [18, 20, 25], every test user was manually created using its dedicated proxy and incognito mode to reduce the influence of any external factors. Every machine executed one program run at a time which consisted of two bot programs being executed in parallel.

As noted in the Introduction, we aimed to establish the influence of several user actions and characteristics on TikTok's RS and thus the personalization on the platform's "For You" feed. We focus on the influence of the most explicit actions and characteristics (tested factors): following a content creator, liking a post, watching a post longer, and the language and location settings. To assess their influence on TikTok's RS, we conducted several experiments using the bot program as outlined above. We describe the experiments related to each of the tested factors below.

3.2 Experiment Overview

We created one experimental group with different experimental scenarios for every tested factor. For every scenario we have performed about 20 different runs which mainly consisted of two users (bots) executing scripted actions on one local machine in parallel. One of the two was the active and the other the control user. The active user performed a certain action, e.g. liking a post, while the control user only scrolled through the same number of batches as its twin user, looking at each post the same amount of seconds. We thus followed an approach similar to Hannak et al. [18] and Feuz, Fuller, and Stalder [16] by creating a second (control) user, that is identical to the active user except one specific characteristic/action - one of the tested personalization factors, - in order to measure the difference of the users' feeds by comparing the meta-data of the posts that both saw. If the posts on the feeds vary and do so more than we would expect due to inherent random noise (see [18]), the

[3]https://github.com/mboeke/TikTok-Personalization-Investigation

[4]In order to obscure the automated interaction of our bot program we followed the suggestions of Louis Klimek's article [29].

[5]3 by default for all experiments, though for some 5 batches were collected, as noted below and in Table 1.

[6]www.webshare.io

[7]www.twilio.com

C 3

difference can be attributed to the personalization of the recommendation algorithm of TikTok triggered by the tested factor. Every test scenario was executed twice a day, although the execution order varied, until all 20 test runs were completed.

3.3 Data Analysis

In order to analyse the results of our experiment we used four different analysis approaches.

First, we analyzed the difference between the feeds of two users by utilizing the Jaccard Index to measure the overlaps between posts, hashtags, content creators, and sounds between that each of the users encountered on their feed. Similar to previous work on measuring personalization online [18, 51], this approach allows us to identify to which degree the user feeds differ with respect to different metrics and attribute their variation to the influential factor being tested. Additionally, we compute the change trend in the discrepancies by fitting the obtained data to a linear polynomial regression.

Second, we analyze the number of likes, views, comments, and shares of a post. As noted by [30], one can evaluate a post's popularity on TikTok based on these metrics. We therefore examine these attributes to evaluate the popularity of individual TikTok posts recommended to the bot users, and also trace how average popularity of posts recommended to a user changes overtime (i.e., we expect that with time due to personalization the posts recommended to a user should become more tailored to their interests thus more "niche" and less popular on the platform as a whole).

Third, TikTok itself [42] as well as [13, 57] mention the importance of hashtags to the platform implying that content classification and distribution is heavily based on hashtags. We analyzed the reappearance hashtags as well as sounds and content creators on a given user's "For You" feed overtime to investigate whether TikTok picked up that user's interests as proxied by these post properties. Additionally, we cleaned the data before the analysis by removing overly common hashtags, e.g. "#fyp" (shortcut of the "For You" page) as those mentioned too frequently would obscure the real similarity - or absence of it - between different posts.

Fourth, we analyzed the similarity of two posts by analyzing the semantics of those posts' hashtags using a Skip-Gram model [35].

3.4 Ethical considerations

TikTok's Terms of Service (ToS) explicitly prohibit content scraping for *commercial purposes* [1]. As our audit is done for academic purposes only, without any commercial applications, we do not violate TikTok's ToS. Our bots have interacted with the platform as well as with the content creators (e.g., by liking/following them). However, as we used only few agents, we did not cause any disruption to the service and had only marginal, non-intrusive and completely harmless interactions with the content creators. Our research qualified as exempt from the ethical review of the University of Zurich's OEC Human Subjects Committee according to the official checklist.

4 EXPERIMENTS

All experiments were conducted between late June 2021 and mid-August 2021. In total, there were 39 successfully completed[8] experimental scenarios during which we collected the data on 30'436 different posts, 34'905 distinct hashtags, 21'278 different content creators, and 20'302 distinct sounds. In the sections to come we elaborate on the most significant findings for brevity reasons. We list all relevant details including the ID of each experimental scenario and corresponding bot users IDs in Supplementary Material in Table 1.

4.1 Controlling Against Noise

As introduced in section 2.1, when auditing algorithms one needs to identify potential sources of noise to assure any differences observed between users in experimental scenarios are due to personalization, and not inherent "noise" or randomization. In this section, we elaborate on the potential sources of noise and how we addressed them.

Accessing TikTok from different locations may result in different content being recommended. We control for this personalization by assigning dedicated IP addresses located within the same country and obtained from the same proxy provider for every pair of test users. As the device settings can be another influence to TikTok's RS, every machine uses the same ChromeDriver version and a proxy dedicated to a specific user to access TikTok.

TikTok points out that their "[...] recommendation system works to intersperse diverse types of content along with those you already know you love". They specifically state that they will "interrupt repetitive patterns" to address the problem of the filter bubble [42]. We need to control for this type of noise - the difference between two feeds that is triggered by the aforementioned design choices and inherent randomization and not the tested factor. In order to account for it and other potential sources of noise in the analysis, we created 11 experimental control scenarios, where none of the two users interacts with its feed in any way in order to measure the "default" levels of two users' "For You" feed divergence. To increase the robustness of our observations, we slightly varied the conditions of the control scenarios: some of our test scenarios collected five instead of three batches, or collected data from the first few posts of a feed while others did not. Our results reveal that there is no clear correlation between the level of users' feed divergence and collecting and not collecting the first few posts or collecting three vs five batches of posts. Thus, we treat these different settings as equivalent. Nonetheless, when accounting for noise in the analysis of experimental results for different tested factors (see below), we compared the observations for each tested factor scenario only with the observations of a control scenario fully corresponding to it (e.g., in terms of the number of batches of data collected). Using the data collected from the control scenarios, we computed a "noise value" (the level of divergence of two users' feeds when the users are identical and do not interact with their feeds in any specific way) for the number of different posts, hashtags,

[8]Beyond those 39 there were several runs we excluded from the analysis due to technical issues-related errors in the execution that could affect the results (e.g., when a bot got "stuck" on one post "watching" it for a long time which could affect the behaviour of the RS in undesirable ways). Such failed runs are listed together with successful runs in the overview Table 1 for reference but their IDs are marked in red.

C4

content creators, and sounds by averaging over differences across all test runs and scenarios. The percentage of different posts, content creators, hashtags, and sounds was 66.17%, 66.05%, 58.62%, and 64.47% for all scenarios collecting five batches. For scenarios that collected three batches these percentages corresponded to 69.74%, 68.15%, 59.63%, and 68.05%.

For brevity reasons here we present detailed results from only one of the 11 control scenarios (scenario ID 7), it however is similar to other control scenarios. Figure 1 shows strong fluctuations of the difference between the users' feeds, the most dominant being between test runs ID 2302 and 2534. We identified such drops in all test scenarios and figured that they regularly occur around the end of a week or weekend. Since TikTok continuously improves their recommendation algorithm [42], we believe that these drops must be related to software releases. We therefore accounted for these (presumed) software updates by averaging the values right before and after the drops to lift the graph as shown in figure 2. In figure 7 we observe that there are huge fluctuations in the levels of popularity (as proxied by likes and views) and engagement (proxied by shares and comments) of posts recommended by the RS. TikTok's algorithm seems to prioritize popular posts in the beginning, which is likely done to provoke a user feedback and thus overcome the cold-start problem. We averaged over the slopes of the trend lines of every difference analysis approach in order to compare the control and test scenarios. The corresponding values are provided in the Supplementary Material B. Hypothetically, if a tested factor indeed influences the recommendation algorithm, then the resulting feed should show stronger differences in its content than the ones of our control scenarios.

4.2 Language and Location

Setup. In order to show the influence of a language of the TikTok website and location from which the user accesses the service we created four different experimental scenarios (see Table 1 for the specifications). For each of those the bot only collected data, no test user performed any action on its feed. However, bot users in each pair were either running from different locations (manipulated via proxies) or had different language settings (set up via their TikTok profiles). Comparing the number of overlapping posts between user pairs that belonged to the same scenario we were able to identify the impact of a language and location. Scenario 12 and 13 contained two test user pairs each, one accessing TikTok from the US and the other from Canada, both in English. Unfortunately, however scenario 13 was excluded due to faulty bot behavior as noted in Table 1. Scenario 14 again consisted of two user pairs, one located in the US using English, the other in Germany with language set to German. For one user of each pair we switched the locations to Germany and the US back and forth to test if the RS "reacts" to the changes in the location immediately. In scenario 15 we focused on the influence of the language settings only. The experiment included four test user pairs. All accessed TikTok from the US, but each pair with one of the four languages: English, German, Spanish, and French. We decided to execute this experiment in the US as its population is reasonably large and according to Ryan [45] apart from English, Spanish, German, French belong to the four major languages spoken in that country.

Results. The heat maps in Figures 3, 4, and 5 visualize the averaged overlapping posts of each user of each corresponding test scenario across all test runs. Note that the negative values result from accounting for the overlapping noise of 35.38%. All three charts 3, 4, and 5 show that different locations have a strong impact on the posts shown by TikTok. For example, on the heat map in Fig. 3 both users 97_US_en and 98_US_en have a higher average of overlapping posts than the users 97_US_en and 99_CA_en. Figure 4 shows the same phenomenon even though the users switch their location in the meantime. This also implies that language does not influence the RS as strong as the location does. The heat map in Fig. 5 indicates that accessing TikTok using the same language setting does not always result in the highest overlap (e.g. comparing all users with 109_US_de). We learn that a user accessing TikTok from the US is likely to see more content in English than any other language regardless of the language settings, which makes sense as English is the country's official and most dominant language. This is the case for all examined languages except French - the feeds of users with French set as default language are more similar to each other than to users with other language settings. It seems as if TikTok interprets French to be more different to English, Spanish, and German than those three languages to each other.

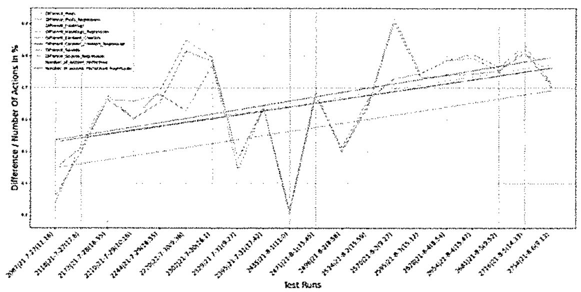
4.3 Like-Feature

Setup. As one of TikTok's influential factors, the like-feature could be interpreted as a proxy to understand user preferences, similar to a user rating [42, 58]. We created 11 different test scenarios incorporating different approaches of selecting the posts to like: randomly, based on user personas defined by set of hashtags[9], and those that matched specific content creators or sounds. With regards to the persona-based selection, we followed the approach of [16] to artificially create user interests based on a set of values, in our case using hashtags as a proxy to determine whether a video matches these pre-specified interests of a user or not. If at least one hashtag of the currently displayed post would matched the pre-defined set of hashtags corresponding to user interests, the user would like the post. The above referenced Table 1 specifies which scenario followed what kind of post-picking-approach.

Results. Overall, our analysis reveals that differences of feeds for scenarios that collected only three batches increase stronger than for the control scenarios. This, however, does not occur for scenarios that collected five batches, potentially indicating that the RS adapts the feed of a user trying to "infer" their interests even in the absence of any user actions, and this effect gets stronger the longer a user remains idle. Still, overall across all like scenarios (regardless of how the liking actions were specified), the users' feeds diverged stronger than in the control scenarios (as depicted in Table 2). That being said, the feeds in the scenarios for which active users were defined by only very few common hashtags did not diverge very much. We propose to run additional tests in future work with more specific, niche hashtags to investigate their feed change. Again we focus on scenario 21 as an example and omit details of the remaining

[9]For example, the set of hashtags of user 145 of scenario 39 is the following: ["football", "food", "euro2020", "movie", "foodtiktok", "gaming", "film", "tiktokfood", "gta5", "gta", "minecraft", "marvel", "cat", "dog", "pet", "dogsoftiktok", "catsoftiktok", "cute", "puppy", "dogs", "cats", "animals", "petsoftiktok", "kitten"]. All of these hashtags correspond to very popular interests, same was true for all persona scenarios.

C5



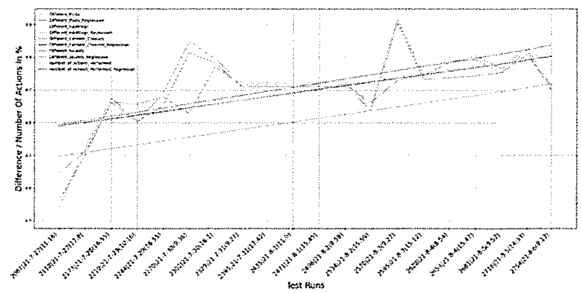


Figure 1: Difference of feeds per test run for test scenario 7 before accounting for drops.

Figure 2: Difference of feeds per test run for test scenario 7 after accounting for drops.

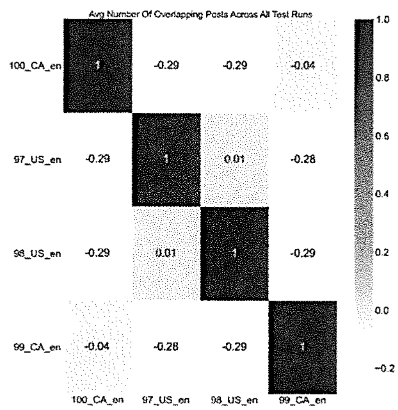


Figure 3: Results of test scenario 12.

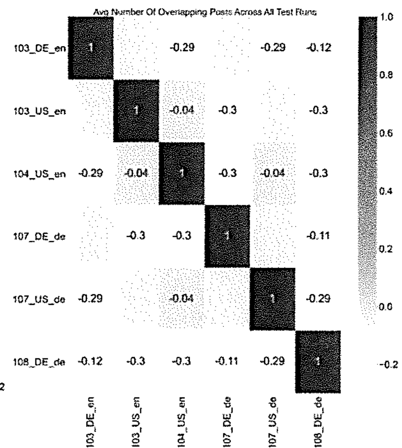


Figure 4: Results of test scenario 14.

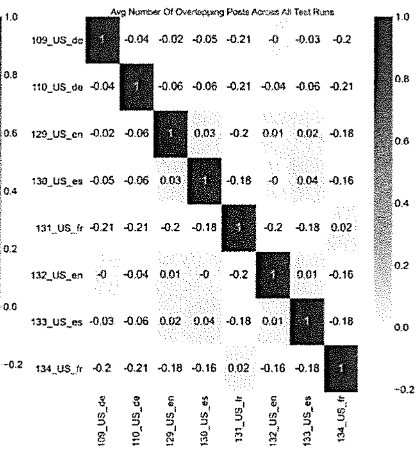


Figure 5: Results of test scenario 15.

scenarios for brevity reasons. The analysis of the feed difference and post metrics for scenario 21 reveal that the feeds become more different, show less popular posts in terms of likes and vies, and thus, imply that more personalized posts are fed to the active users than its twin control user. Similarly, the hashtag similarity analysis of scenario 21 reveals that the feed of user 123 becomes similar faster than that of control user 124. Also, the test scenarios where active users liked only certain content creators (scenarios 23 & 24) or sounds (25 & 26) showed a higher increase in differences compared to the appropriate control scenarios. The analysis of reappearing content creators or sounds for these scenarios also show that the content creators or sounds for which a post was liked reappeared more often than others.

We conclude that liking posts does influence the recommendation algorithm of TikTok. However, we figured that an arbitrary selection of posts to like does not have as strong an effect as persona-based picking, or based on a specific set of content creators or sounds.

4.4 Follow-Feature

Setup. We created six different test scenarios to test the follow-feature. For each one of them one of the user pairs followed only one random content creator every other test run. Again we had to exclude the scenario 29 as the bot got stuck.

Results. Our overall difference analysis as well as the hashtag similarity analysis let us conclude that following a certain content creator undoubtedly influences the recommendation algorithm (details in Table 3). Figure 6 related to scenario 28 further underpins this finding by displaying a greater variance of content creators for the control user 50 than the active user 49. Interestingly, three out of four content creators most frequently encountered by user 49 are not followed by this user. We suggest this might be due to their similarity to the creators followed by user 49 coupled by overall popularity (but not the latter alone as otherwise we would expect them to pop up in the control user's feed with similar frequency). However, our hashtag similarity analysis of scenario 28 shown in figure 8 again illustrates a strong influence of the follow-feature as the posts of the active user's feed become similar to each other faster than those in the feed of the control user (21% > 18%).

4.5 Video View Rate

Setup. With YouTube's design change in its recommendation algorithm that introduced accounting for the percentage a user watched a video, the overall watch time on the platform started rising by 50% a year for the next three years [39]. Google calls this metric

C6

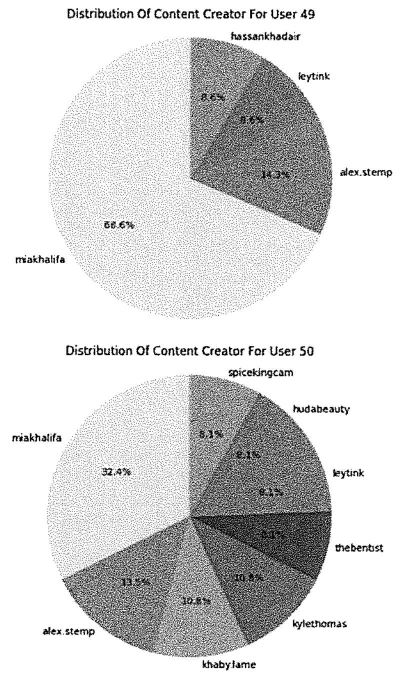


Figure 6: Distribution of content creators across all test runs for scenario 28.

the "video viewership" which measures the percentage that was watched of a certain video [21]. Given the importance of the feature on YouTube, we hypothesized it might also be relevant for the TikTok's RS system and set out to test this. We adjusted the "video viewership" metric as describe by Google to our purposes and call it the video view rate (VVR). We created ten different experimental scenarios to examine the influence of the VVR on TikTok's recommender system. The set of experimental scenarios was equally split into five that randomly picked posts and the other five based on a user persona. For both groups of test scenarios the share of video length that the bot users "watched" was varied between 25% and 400% (400% = watching a video four times), the details for each scenario are listed in Supplementary Material Table 1.

Results. Our analysis depicted in Table 4 reveals that the feed difference of the persona scenarios (those that "selected" videos to watch longer based on pre-specified sets of hashtags) increases significantly stronger than for other VVR scenarios allowing us to conclude that the TikTok recommendation algorithm reacts stronger to the VVR differences based on specific user profiles (the more niche the better) than on user profiles that randomly pick posts. Our results from the like-feature test scenarios align with these findings. Contrary to our assumptions, the feeds of scenario 33 with the active user watching only 25% of certain posts increase stronger in their difference than for scenario 35 with the active user watching 75% (averaged difference 0.85% > 0.56%). We observe the same with scenario 38 (active user watching 50%) and 40 (active user watching 100%). One explanation might be that TikTok RS "assumes" users decide within the first 25% (or 50% respectively) of the video duration whether they like the video or not. The remaining time is thus no longer relevant. Another reason may be that the feeds of scenario 33 just happened to be slightly more different from the beginning, and therefore, changed faster. Or the feed of user 77 may be more volatile than of user 81 as user 77 watches only 25% resulting in TikTok serving many different videos. Yet another explanation may be that watching 75% instead of 25% sends a stronger negative feedback. Looking at the hashtag semantics of the feeds for both scenarios reveals that the similarity of the feed from user 81 (slope: 10.92%) increases a lot faster than for user 77 (slope: 7.79%). Likewise, the hashtag similarity for user 91 (slope: 16.03%) grows quicker than for user 87 (slope: 7.98%). An additional indicator of personalization within the VVR tests that involve user personas is the number of posts that were watched longer as well as the time a bot needed to complete a test run. Our analysis revealed that user 91 watches increasingly more posts for an extended time frame with an average duration of 33.73 minutes than user 87 with an average duration of only 27.78 minutes.

Even though the feed difference analysis appears to increase stronger for users who watch less of a post, our findings allow us to conclude that not only watching a video longer than others influences the recommendations of TikTok's algorithm, but also the longer one watches the stronger it influences the algorithm.

4.6 Concluding Results

In this section we summarize the findings with respect to the previously introduced hypotheses. For the majority of all experimental non-control scenarios, the feeds become more different and continue to do so as the active user continues interacting with its feed (hypothesis 1 and 2). Furthermore, our data reveals that certain factors influence the recommendation algorithm of TikTok stronger than others. The order of the most influential factor to the least among those that were tested is the following: (1) following specific content creators, (2) watching certain videos for a longer period of time, and finally (3) liking specific posts. Interestingly, the influence of the video view rate is only marginally higher than the one of the like-feature. The number of performed and fully completed test scenarios as well as the number of collected batches may be one of the reasons. Another one may be the approaches to picking a post to interact with: on the one hand random picking of posts, which was identified as not a strong influential factor, and on the other persona-based picking, where the user were defined by very common and similar hashtags. The fact that watching a post for a longer period of time has a greater effect on TikTok's recommendation algorithm than liking it aligns with TikTok's blog post [42]. However, we can not confirm the findings of the WSJ investigation [27] as our data shows that following specific content creators influences the "For You" feed stronger than all the other tested factors. Elaborating on hypothesis four (increased within-feed similarity of content served to an active user) is not as straightforward. Overall, the follow feature scenarios indicate that the RS of TikTok indeed serves to the active user more posts of the content creators the user followed. The same is true for like feature where the user liked posts of certain content creators and/or with certain sounds. However, we do not identify a clear pattern for post attributes reappearing more often than others for the like- and VVR- tests where users

C7

picked posts randomly or based on predefined sets of hashtags. The first observation may again be due to the arbitrary selection. The second might be because of the hashtags that defined the personas are very popular and, thus, appear equally often for the active and corresponding control user. We plan on addressing this issue in future work by running tests with personas being defined by more specific, niche hashtags. However, the similarity analysis of the feeds reveals that in most cases the posts in the feeds of active users became similar faster than in the feeds of control users. We therefore consider hypothesis four to be true as well. Considering the averaged slopes of the combined post metrics, the feeds of active users do not always decrease faster than for the control user. We therefore reject hypothesis 5. Even though TikTok serves more personalized content it still recommends posts with very high numbers of views, likes, shares, and comments. Section 4.2 revealed that both language and location effect the TikTok posts recommended to a user (hypothesis 6).

5 DISCUSSION

In the past decade algorithmic personalization has become ubiquitous on social media platforms, heavily affecting the distribution of information there. The recommendation algorithm behind TikTok's "For You" page is arguably one of the major factors behind the platform's success [57]. Given the popularity of the platform [5, 37], the fact that its largely used by younger users who might be more vulnerable in the face of problematic content [54], as well as the central role TikTok's RS plays in the content distribution, it is important to assess how user behaviour affects one's "For You" page. We took the first step in this direction. In this section we outline the implications of our findings as well as the directions for future work.

Our analysis revealed that following action has the largest influence on the content served to the users among the examined factors. This is important since following is a conscious action, as contrasted for example to mere video viewing which could happen by accident or be affected by unconscious predispositions. One can watch something without necessarily liking what they see, especially in the case of disturbing or problematic content. Hence, according to our results users have some control over their feed through explicit actions. At the same time, we find that video view rate has a similar level of importance to the RS as liking action. This can be problematic: while likes can be easily undone and users unfollowed, one can not "unwatch" a video, thus the influence of VVR on the algorithm severely limits the users' control over their data and the behaviour of the algorithm. Given the proliferation of extremist content on the platform and TikTok's insofar insufficient measures to limit the spread of problematic content [54] as well as the high degree of randomization in the videos served to a user as identified by us, one can be potentially driven into filter bubbles filled with harmful and radicalizing content by simply lingering over problematic videos for a little bit too long. To alleviate this, we, similarly to [54, 57], suggest that TikTok should do more to filter out problematic content. Additionally, the platform could provide users with more options to control what appears in their feeds. For example, TikTok could add a list of inferred user interests available for control and adjustments to the user itself. TikTok already enables its users to update their video interests via settings, but only within few superficial categories. We suggest to provide a consistently updated list of inferred user interests using very detailed content categories based on which the user can always identify which interests the TikTok RS inferred from their interaction with the app. The user should also be able to adjust the list. According to [36] and [48], such an overview would seriously increase the degree of transparency and, thus, would benefit not only the user, but also TikTok.

The impressive accuracy of TikTok's recommender system (RS) mentioned by the literature (e.g. [4, 12, 30, 57]), could be used to effectively communicate important messages such as those on COVID-19 countermeasures [10], or place appropriate advertisements. However, such tools can also be easily misused for political manipulation [55], [34], [24] or distributing hate speech [54]. This can be exacerbated by the closed-loop relationship between users' addiction to the platform and algorithmic optimization [57] or filter bubbles. Our hashtag similarity analysis and the analysis of location and language-based differences imply the existence of such filter bubbles both at the level of individual interests but also at a macrolevel related to one's location. The findings of WSJ's investigation [27] also lend evidence to the formation of filter bubbles on TikTok. We therefore propose to countermeasure the creation of filter bubbles not only with recommendation novelty, but also by providing more serendipitous recommendations as this leads to higher perceived preference fit and enjoyment while serving the ultimate goal of increasing the diversity of the recommended content [33].

6 CONCLUSION

With this work, we aim to contribute to the increase in transparency of how the distribution of content on TikTok is influenced by users' actions or characteristics by identifying the influence of certain factors. We have implemented a sock-puppet auditing technique to interact with the web-version of TikTok mimicking a human user, while collecting data of every post that was encountered. Through this approach we were able to test and analyse the affect of the language and location used to access TikTok, follow- and like-feature, as well as how the recommended content changes as a user watches certain posts longer than others. Our results revealed that all tested factors have an effect on the way TikTok's RS recommends content to its users. We have also shown that the follow-feature influences the recommendation algorithm the strongest, followed by the video view rate and like feature; besides, we found that the location is a stronger influential factor than the language that is used to access TikTok. Of course, this analysis is not exhaustive and includes only the most explicit factors, while the algorithm without a doubt can be influenced by many other aspects such as, for instance, users' commenting or sharing actions. Nonetheless, with this work we hope to lay the foundation for future research on TikTok's RS that could examine other factors that can influence the algorithm as well as analyze the connection between the RS and the potential for the formation of filter bubbles and the distribution of problematic content on the platform in greater detail.

7 ACKNOWLEDGEMENTS

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C10

A EXPERIMENTAL SCENARIO DETAILS

Table 1: Different experimental groups and their individual scenarios: controlling against noise, language and location, like feature, follow feature, video view rate feature. The yellow highlighted users are the active users and red highlighted scenarios correspond to the failed ones.

Test Scenario ID	User IDs	Test Details
1	72, 73	Control: collecting 5 batches, collecting_data_for_first_posts = True
2	74, 75	Control: collecting 5 batches
3	93, 94	Control: collecting 5 batches, collecting_data_for_first_posts = True
4	95, 96	Control: collecting 5 batches
5	125, 126	Control : collecting_data_for_first_posts = True
6	137, 138	Control
7	139, 140	Control: collecting_data_for_first_posts = True
8	141, 142	Control
9	143, 144	Control
10	147, 148	Control: reuse_cookies = True
11	149, 150	Control: reuse_cookies = True
12	97, 98, 99, 100	Language = English; Location = United States and Canada
13	101, 102, 105, 106	Language = English; Location = United States and Canada
14	103, 104, 107, 108	Language = English and German; Location = United States and Germany
15	109, 110, 129, 132, 130, 133, 131, 134	Language = German, English, Spanish, French; Location = United States
16	45 , 46	Randomly liking 6 posts in batch 2, 3, 4, collecting 5 batches
17	59 , 60	Randomly liking 6 posts in batch 2, 3, 4, collecting 5 batches
18	61 , 62	Liking posts based on the user's persona defined by hashtags, collecting 5 batches
19	63 , 64	Liking posts based on the user's persona defined by hashtags, collecting 5 batches
20	70 , 71	Liking posts based on the user's persona defined by hashtags, collecting 5 batches
21	123 , 124	Liking posts based on the user's persona defined by hashtags
22	159 , 160	Liking posts based on the user's persona defined by hashtags, reuse_cookies = True
23	113 , 114	Liking posts of specific content creators
24	135 , 136	Liking posts of specific content creators
25	115 , 116	Liking posts with specific sound
26	117 , 118	Liking posts with specific sound
27	47 , 48	Follow a random content creator
28	49 , 50	Follow a random content creator
29	51 , 52	Follow a random content creator
30	53 , 54	Follow a random content creator
31	153 , 154	Follow a random content creator, reuse_cookies = True
32	155 , 156	Follow a random content creator, reuse_cookies = True
33	77 , 78	VVR: watching 10 random posts for 25% of their entire length
34	79 , 80	VVR: watching 10 random posts for 50% of their entire length
35	81 , 82	VVR: watching 10 random posts for 75% of their entire length
36	83 , 84	VVR: watching 10 random posts for 100% of their entire length
37	85 , 86	VVR: watching 10 random posts for 200% of their entire length
38	87 , 88	VVR: watching posts matching user persona for 50% of their entire length
39	145 , 146	VVR: watching posts matching user persona for 75% of their entire length
40	91 , 92	VVR: watching posts matching user persona for 100% of their entire length
41	151 , 152	VVR: watching posts matching user persona for 400% of their entire length, reusing_cookies = true
42	157 , 158	VVR: watching posts matching user persona for 400% of their entire length, reusing_cookies = true, time_to_look_at_post_normal = 0.5

C11

B DIFFERENCE ANALYSIS RESULTS

Table 2: Overview of average analysis metrics comparing control and like test scenarios.

Avg. Trend Line Slopes	Control Scenarios			Like Test Scenarios		
	3 Batches	5 Batches	All	3 Batches	5 Batches	All
Diff. Posts	0.42%	1.01%	0.59%	0.82%	0.88%	0.92%
Diff. Hashtags	0.28%	0.98%	0.65%	0.36%	0.77%	0.65%
Diff. Content Creator	0.23%	0.8%	0.73%	0.72%	0.73%	0.73%
Diff. Sounts	0.4%	0.54%	0.53%	0.78%	0.82%	0.87%

Table 3: Overview of average analysis metrics comparing control and follow test scenarios.

Avg. Trend Line Slopes	Control Scenarios		Follow Test Scenarios	
	3 Batches	All	3 Batches	All
Diff. Posts	0.42%	0.59%	2.03%	1.59%
Diff. Hashtags	0.28%	0.65%	1.79%	1.46%
Diff. Content Creator	0.23%	0.42%	1.73%	1.3%
Diff. Sounds	0.4%	0.53%	1.89%	1.53%

Table 4: Overview of average analysis metrics comparing control and VVR test scenarios.

Avg. Trend Line Slopes	Control Scenarios		VVR Test Scenarios			
	3 Batches	All	3 Batches	All	Random	Persona
Diff. Posts	0.42%	0.59%	0.75%	0.98%	0.67%	0.95%
Diff. Hashtags	0.28%	0.65%	0.62%	0.82%	0.59%	0.69%
Diff. Content Creator	0.23%	0.42%	0.51%	0.63%	0.41%	0.75%
Diff. Sounds	0.4%	0.53%	0.64%	0.84%	0.58%	0.81%

C ADDITIONAL FIGURES

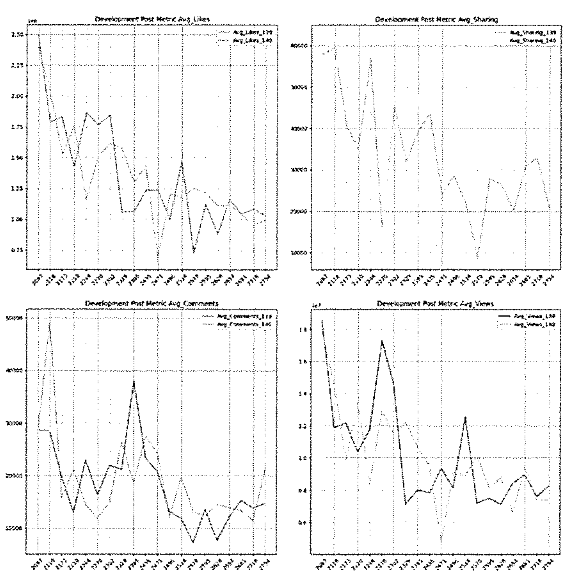

Figure 7: Post metrics (Likes-Shares-Comments-Views) changes for test scenario 7.

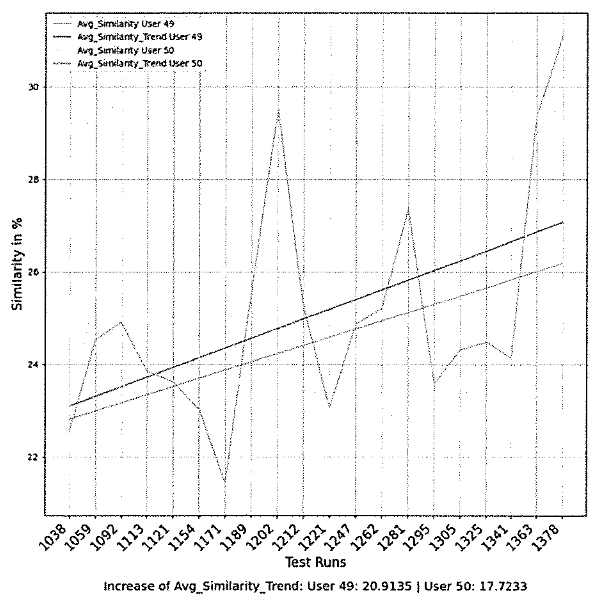

Figure 8: Hashtag similarity within feed of each user per test run for scenario 28.

Social Media Data Collection Can Lead to Violations of Privacy

Source D

Authors: Andre Oboler, Lito Cruz and Kristopher Welsh
Editor: Noah Berlatsky
Date: 2015
From: Are Social Networking Sites Harmful?
Publisher: Gale, a Cengage Company
Series: At Issue
Document Type: Viewpoint essay
Length: 3,557 words
Content Level: (Level 4)
Lexile Measure: 1200L

Full Text:

Article Commentary

Andre Oboler is chief executive officer of the Online Hate Prevention Institute and a postgraduate law student at Monash University. Kristopher Welsh is a lecturer in the School of Computing at the University of Kent. Lito Cruz is a teaching associate at Monash University and a part-time lecturer at Charles Sturt University. He holds a PhD in computer science from Monash University.

Social media data can be used to collect information about individuals by governments, businesses, journalists, employers, or social media platforms themselves. This data collection can result in numerous kinds of infringements of privacy. It could be used to manipulate voters, track activists, profile job applicants, or even reveal a user's physical movements. Social media platforms have given little consideration to the ethical issues raised. More needs to be done by both social media companies and users to prevent abuses of data.

Computational social science involves the collection, retention, use and disclosure of information to answer enquiries from the social sciences. As an instrument based discipline, the scope of investigation is largely controlled by the parameters of the computer system involved. These parameters can include: the type of information people will make available, data retention policies, the ability to collect and link additional information to subjects in the study, and the processing ability of the system. The capacity to collect and analyze data sets on a vast scale provides leverage to reveal patterns of individual and group behaviour.

The Danger of Data

The revelation of these patterns can be a concern when they are made available to business and government. It is, however, precisely business and government who today control the vast quantities of data used for computational social science analysis.

Some data should not be readily available: this is why we have laws restricting the use of wiretaps, and protecting medical records. The potential damage from inappropriate disclosure of information is sometimes obvious. However, the potential damage of multiple individually benign pieces of information being combined to infer, or a large dataset being analysed to reveal, sensitive information

D

(or information which may later be considered sensitive) is much harder to foresee. A lack of transparency in the way data is analysed and aggregated, combined with a difficulty in predicting which pieces of information may later prove damaging, means that many individuals have little perception of potential adverse effects of the expansion in computational social science.

> The risk posed by the ubiquity of computational social science tools ... poses serious questions about the impact that those who control the data and the tools can have on society as a whole.

Both the analysis of general trends and the profiling of individuals can be investigated through social sciences. Applications of computational social science in the areas of social anthropology and political science can aid in the subversion of democracy. More than ever before, groups or individuals can be profiled, and the results used to better manipulate them. This may be as harmless as advertising for a particular product, or as damaging as political brainwashing. At the intersection of these examples, computational social science can be used to guide political advertising; people can be sold messages they will support and can be sheltered from messages with which they may disagree. Access to data may rest with the incumbent government, with those able to pay, or with those favoured by powerful data-rich companies.

Politics and Beyond

Under its new terms of service, Google could for instance significantly influence an election by predicting messages that would engage an individual voter (positively or negatively) and then filtering content to influence that user's vote. The predictions could be highly accurate making use of a user's e-mail in their Google provided Gmail account, their search history, their Google+ updates and social network connections, and their online purchasing history through Google Wallet, data in their photograph collection. The filtering of information could include "recommended" videos in YouTube; videos selectively chosen to highlight where one political party agrees with the user's views and where another disagrees with them. In Google News, articles could be given higher or lower visibility to help steer voters into making "the right choice".

Such manipulation may not be immediately obvious; a semblance of balance can be given with an equal number of positive and negative points made against each party. What computational social science adds is the ability to predict the effectiveness of different messages for different people. A message with no resonance for a particular voter may seem to objectively provide balance, while in reality making little impact. Such services could not only be sold, but could be used by companies themselves to block the election of officials whose agenda runs contrary to their interests.

The ability to create such detailed profiles of individuals extends beyond the democratic process. The risk posed by the ubiquity of computational social science tools, combined with an ever-increasing corpus of data, and free of the ethical restrictions placed on researchers, poses serious questions about the impact that those who control the data and the tools can have on society as a whole. Traditionally, concerns about potential abuses of power focus on government and how its power can be limited to protect individuals; that focus needs to widen.

Social Media Data for Business

Social media systems contain particularly valuable information. This data derives its value from its detail, personal nature, and accuracy. The semi-public nature of the data means it is exposed to scrutiny within a user's network; this increases the likelihood of accuracy when compared to data from other sources. The social media data stores are owned and controlled by private companies. Applications such as Facebook, LinkedIn, and the Google suite of products (including Google search, YouTube, DoubleClick and others), are driven by information sharing, but monetized through internal

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analysis of the gathered data—a form of computational social science. The data is used by four classes of users: business clients, government, other users within the social media platform, and the platform provider itself.

Business clients draw on this computational social science when they seek to target their advertisements. Facebook, for example, allows advertisers to target users based on variables that range from standard demographics such as age, gender, and geographical location to more personal information such as sexual preferences. Users can also be targeted based on interests, associations, education level and employer. The Facebook platform makes this data (in aggregated form) available to advertisers for a specific purpose, yet Facebook's standard user interface can also be used as a general computational social science tool for other purposes.

> The very existence of social media can ... promote government's agenda.

To take an example, the Australian Bureau of Statistics (ABS) estimates the current population of Australia at 22.5 million. The Facebook advertising platform gives an Australia population (on Facebook) of 9.3 million; over 41 percent of the national population. As there is less coverage at the tails, Facebook has only 0.29 million people over 64, while the ABS says there are 3.06 million Australians over 65, the sample for some age ranges must be approaching the entire population and may provide a very good model as a computational social science tool. For example, research shows that about two percent of the Australia population is not heterosexual. From the Facebook advertising platform, we can readily [select] a population of Australians, aged 18 to 21, who are male, and whose sexual preference is for men. The platform immediately tells us the population size is 11,580 people. By comparing this to the total size of the Australian male Facebook population who expressed a sexual preference, we can see this accounts for 2.89 percent of this population, indicating that the data available to Facebook is of similar utility to that available to social scientists for research.

Data for Government

The second class of users of social media as computational social science tools is governmental. This is demonstrated by the U.S. government's demands to Twitter (via court orders) for data on Wikileaks founder Julian Assange and those connected to him. The court order was only revealed after Twitter took legal action to lift a court imposed censorship order relating to the requests. The Wikileaks affair demonstrates how government can act when it sees social media as acting against its interests.

The very existence of social media can also promote government's agenda. During the Iranian elections, for example, Twitter was asked not to take their service off-line for scheduled maintenance. In another example, the U.S. State Department provided training "using the Internet to effect social change" to Egyptian dissidents between 2008 and 2010, then sought (unsuccessfully) to keep social media access available during the January 2011 Egyptian anti-government protests. The Egyptian effort was defeated after Egypt responded by taking the entire country off the Internet, a move perhaps more in response to the U.S. than the protestors. While social media might enable activism, computational social science favours the state or at least those with power. Computational social science tools combined with social media data can be used to reconstruct the movements of activists, to locate dissidents, and to map their networks. Governments and their security services have a strong interest in this activity.

Social Media Data, Journalists, and Providers

The third class of actors are other social media platform users. Journalist Ada Calhoun has described as an epiphany that left her "freaked out" the realisation that anyone could research her just as she researched others while writing their obituaries. In her article, Calhoun reflected that some amateur experts on the anarchic message board 4chan, or professional experts working for government

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agencies, could likely find out far more than she could. The everyday danger that can result when anyone can research anyone else can be demonstrated through two scenarios:

> Scenario one involves Mary who has been a Facebook user for some years. Through Facebook Mary reconnected with an old friend Fred. As time went on, Mary and Fred grew closer and became a couple. One day Mary logged into her Facebook account and noticed that Fred has still not updated his details to say he is in a relationship with her. This makes Mary feel very insecure, and causes her to begin doubting Fred's intentions. Due to this discovery, Mary broke off her relationship with Fred.
>
> Joe applied to a company as a Human Resource team leader. The hiring manager, Bob, found Joe's resume appealing and considered him a good candidate. Bob decides to check Joe's Facebook information. On Joe's publically viewable wall, Bob sees several pictures of Joe in what Bob considers to be "questionable settings". The company never called Joe for an interview. Joe has been given no opportunity to explain, nor any explanation on why his application was rejected.
>
> Computational science can help a company like Facebook correctly profile its users, showing the right advertisements to the right people so as to maximize revenue.

Both Mary and Bob used Facebook as a computational tool to extract selected information as part of an investigation into the social dynamics of society, or in these cases, a particular individual's interactions with society. In this sense, Facebook could be considered a computational social science tool. Mary's inference may be based on a wider realisation that Fred's interactions with her are all in private and not part of his wider representation of himself. Bob may have drawn his conclusions from a combination of text, pictures, and social interactions.

These situations are far from hypothetical. Research released in November 2011 by Telstra, Australia's largest telecommunications company, revealed that over a quarter of Australian bosses were screening job candidates based on social media. At the start of 2012 the Australia Federal Police began an advertising campaign designed to warn the public of the need to protect their reputation online. The advertisement featured a job interview where the interviewer consults a paper resume then proceeds to note various positive attributes about the candidate; all seems to be going very well. The interviewer then turns to his computer screen and adds "and I see from your recent online activity you enjoy planking from high rise buildings, binge drinking, and posting embarrassing photos of your friends online". The advertisement is an accurate picture of the current approach, which takes place at the level of one user examining another. Computational social science may soon lead to software programs that automatically complete pre-selection and filtering of candidates for employment.

The final class or actor we consider are social media platform providers themselves. While Facebook provides numerous metrics to profile users for advertisers, far more data and scope for analysis is available to a platform provider like Facebook itself. Internet advertisements are often sold on a "cost per-click" (CPC) or "cost per-impression" (CPM—with M indicating costs typically conveyed per-thousand impressions). Thus, Facebook may maximize advertising revenue by targeting advertisements to achieve the greatest possible number of clicks for a given number of impressions. This maximization of the click-through rate (CTR) can be achieved using a wealth of hidden information to model which users are most likely to respond to a particular advertisement. Computational science can help a company like Facebook correctly profile its users, showing the right advertisements to the right people so as to maximize revenue. But what else can a company like Facebook or Google do? This depends on the data they hold.

Triangulation, Breadth, and Depth

While horizontal expansion of computational social science allows greater access to selected aggregate data, vertical expansion allows larger operators to add depth to their models. This depth is a result of triangulation, a method originally from land surveying. Triangulation gives a confirmation benefit by using additional data points to increase the accuracy and confidence in a measurement. In a research context triangulation allows for information from multiple sources to be combined in a way that can expose underlying truths and increase the certainty of conclusions.

Social media platforms have added to their data either by acquiring other technology companies, as Google did when acquiring DoubleClick and YouTube, or by moving into new fields as Facebook did in when it created "Facebook Places": a foursquare-like geolocation service. From a computational social science perspective, geolocation services in particular add high value information. Maximising the value of information requires a primary key that connects this data with existing information; a Facebook user ID, or a Google account name provides just such a key.

The *breadth of an account* measures how many types of online interaction the one account connects. It lets the company providing the account know about a wider slice of a user's life. Three situations are possible. The first involves distinct accounts on multiple sites and allows no overlap of data: what occurs on one site stays on that site. The second situation is where there is a single traceable login, for example your e-mail address, which is used on multiple sites but where the sites are independent. Someone, or some computational social science tool, with access to the datasets could aggregate the data. The third possibility is a single login with complete data sharing between sites. All the data is immediately related and available to any query the underlying company devises. It is this last scenario that forms the Holy Grail for companies like Facebook and Google, and causes the most concern for users.

The announcement by Alma Whitten, Google's Director of Privacy, Product and Engineering in January 2012 that Google would aggregate its data and "treat you as a single user across all our products" has led to a sharp response from critics. Jeffrey Chester, executive director of the Center for Digital Democracy, told the *Washington Post*: "There is no way a user can comprehend the implication of Google collecting across platforms for information about your health, political opinions and financial concerns." In the same article, Common Sense Media chief executive James Steyer states bluntly that "Google's new privacy announcement is frustrating and a little frightening".

> Accounts that are identity-verified, frequently updated, and used across multiple aspects of a person's life present the richest data and pose the greatest risk.

The *depth of an account* measures the amount of data an account connects. There are three possible situations. The first is an anonymous login with no connection to personal details, the virtual profile is complete in and of itself—it may or may not truthfully represent the real world. The second situation is an account where user details are verified, for example a university login that is only provided once a student registers and identification papers have been checked. A number of online services and virtual communities are now using this model and checking government issued identification to verify age. The third situation involves an account that has a verified identity aggregated with other data collected from additional sources, for example, a credit card provider knows who its customers are, as well as where they have been and what they have bought. The temporal nature of the data is also a matter of depth; your current relationship status has less depth than your complete relationship history.

Facebook's Timeline feature signifies as large a change to depth as Google's policy change does to breadth. Timeline lets users quickly slide to a previous point in time, unearthing social interactions that had long been buried. A Facebook announcement on 24 January 2012 informed the world that Timeline was not optional and would in a matter of weeks be rolled out across all Facebook profiles.

As Sarah Jacobsson Purewal noted in *PC World*, with Timeline it takes only a few clicks to see data that previously required around 500 clicks on the link labelled "older posts", each click separated by a few seconds delay while the next batch of data loads. Purewal provides a step-by-step guide to reasserting privacy under the new timeline regime, the steps are numerous and the ultimate conclusion is that "you may want to just consider getting rid of your Facebook account and starting from scratch". Though admittedly not scientific, a poll by Sophos, an IT security and data protection company, showed that over half those polled were worried about Timeline. The survey included over 4,000 Facebook users from a population that is likely both more concerned and more knowledgeable about privacy and security than the average user. If that wasn't telling enough, the author of the announcement, Sophos' senior technology consultant, Graham Cluley, announced in the same article that he had shutdown his Facebook account. Cluley's reasoning was a response to realizing exactly how much of his personal data Facebook was holding, and fatigue at Facebook's ever changing and non-consultative privacy regime.

All accounts have both a breadth and a depth. Accounts that are identity-verified, frequently updated, and used across multiple aspects of a person's life present the richest data and pose the greatest risk. The concept of a government-issued national identity card has created fierce debate in many countries, yet that debate has been muted when the data is collected and held by non-government actors. Google's new ubiquitous account and Facebook's single platform for all forms of social communication should raise similar concerns for individuals as both consumers and citizens....

Privacy and Caveat Emptor

In discussing the ethics of social science research, [Constance] Holden noted two schools of thought: utilitarianism (also known as consequentialism) holds that an act can only be judged on its consequences; deontologicalism (also known as non-consequentialism) is predominantly about absolute moral ethics. In the 1960s utilitarianism was dominant, along with moral relativism; in the late 1970s deontologicalism began to hold sway. In computational social science, the debate seems to be academic with little regard given to ethics. Conditions of use are typically one-sided without user input, although Wikipedia is a notable exception. Companies expand their services and data sets with little regard for ethical considerations, and market forces in the form of user backlashes [are] the first, and often only, line of resistance.

One such backlash occurred over Facebook's Beacon software, which was eventually cancelled as part of an out of court settlement. Beacon connected people's purchases to their Facebook account; it advertised to their friends what a user had purchased, where they got it, and whether they got a discount. In one instance, a wife found out about a surprise Christmas gift of jewellery after her husband's purchase was broadcast to all his friends—including his wife. Others found their video rentals widely shared, raising concerns it might out people's sexual preferences and other details of their private life. In addition to closing down Beacon, the settlement involved the establishment of a fund to better study privacy issues, an indication that progress was stepping well ahead of ethical considerations.

The *caveat emptor* view of responsibility for disclosure of personal data by social networking sites is arguably unsustainable. Through Beacon, retailers shared purchasing information with Facebook based on terms and conditions purchasers either failed to notice, or failed to fully appreciate. Beacon took transactions outside consumers' reasonable expectations. While Facebook was forced to discontinue the service, appropriate ethical consideration by technology professionals could have highlighted the problems at a much earlier stage.

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Source E

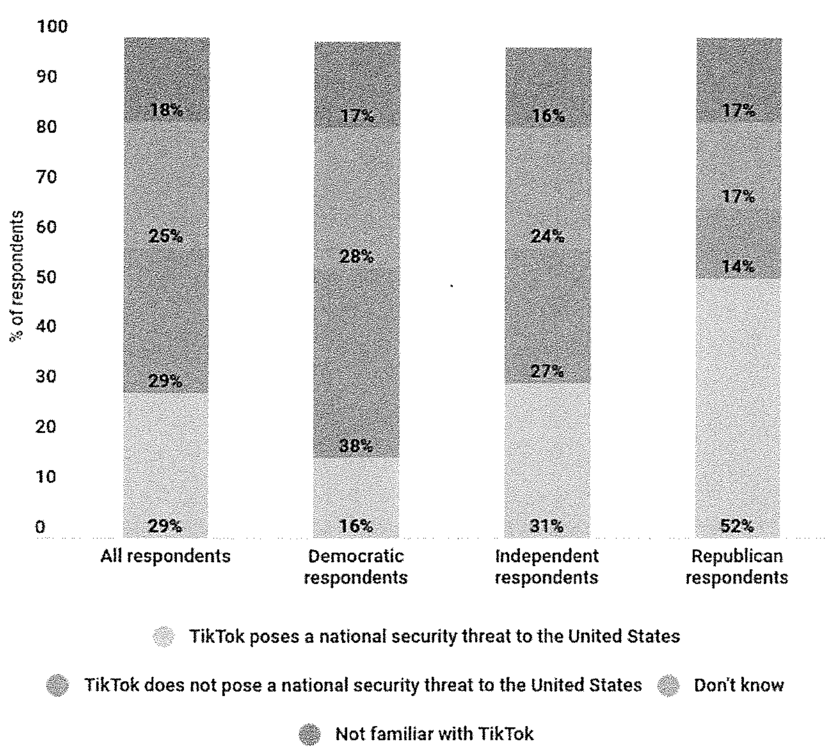
US Public Perception of TikTok as a National Security Threat, August 2020

Date: 2020
From: Gale Opposing Viewpoints Online Collection
Publisher: Gale, a Cengage Company
Document Type: Interactive infogram
Content Level: (Level 4)

Full Text:

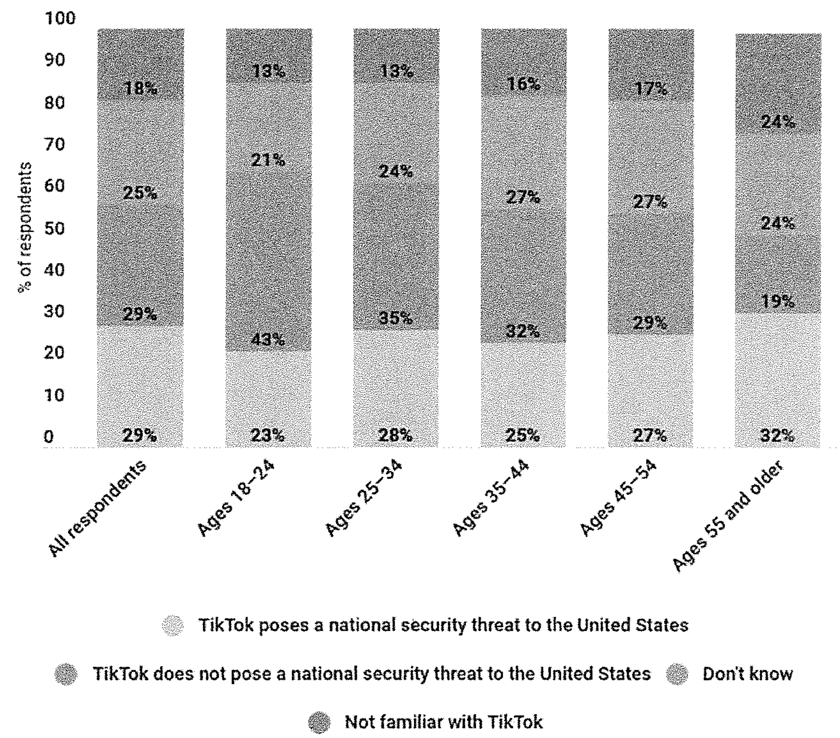
US Public Perception of TikTok as a National Security Threat, August 2020

By political affiliation

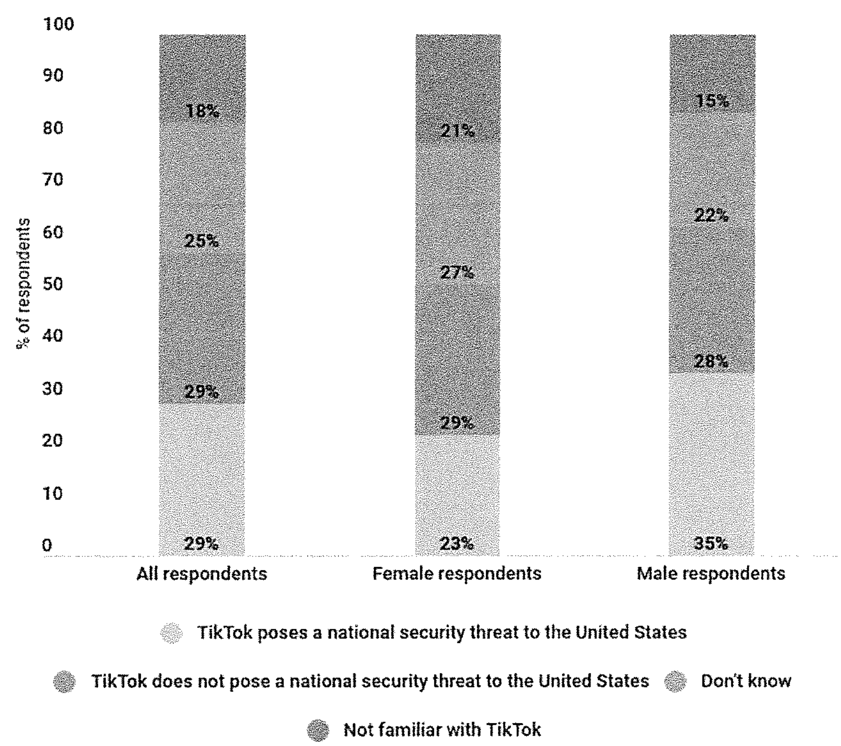


By age group

E1



By gender

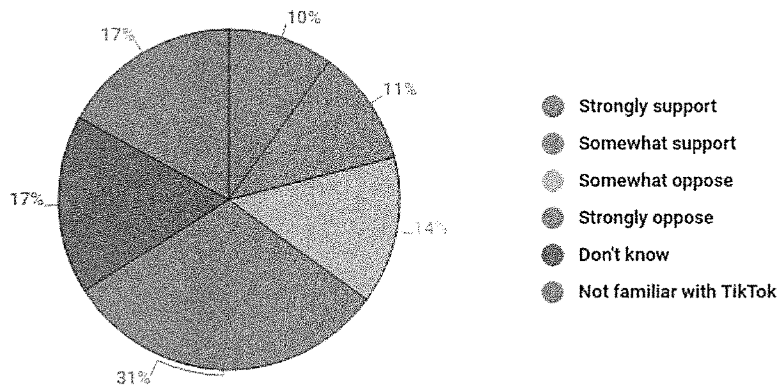


Note: Totals may not equal 100 percent due to rounding.

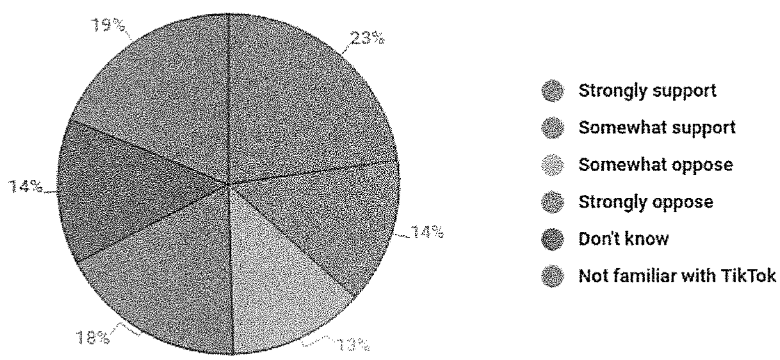
Support for the US Government Banning TikTok, by Political Affiliation

E2

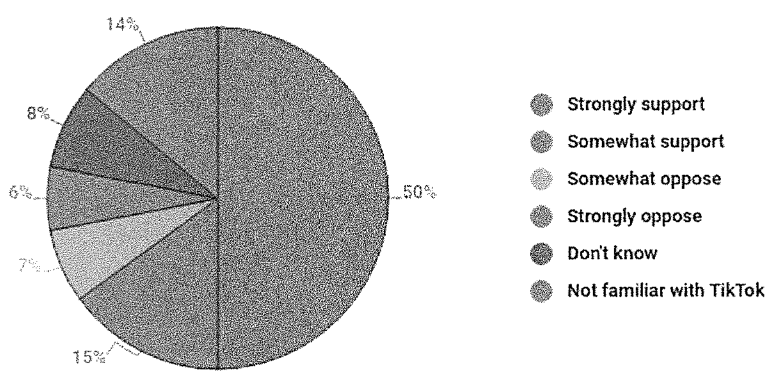
Democratic respondents



Independent respondents



Republican respondents



Note: Totals may not equal 100 percent due to rounding.

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E3

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Gale Document Number: GALE|YASWXT691441112

E4

Source F

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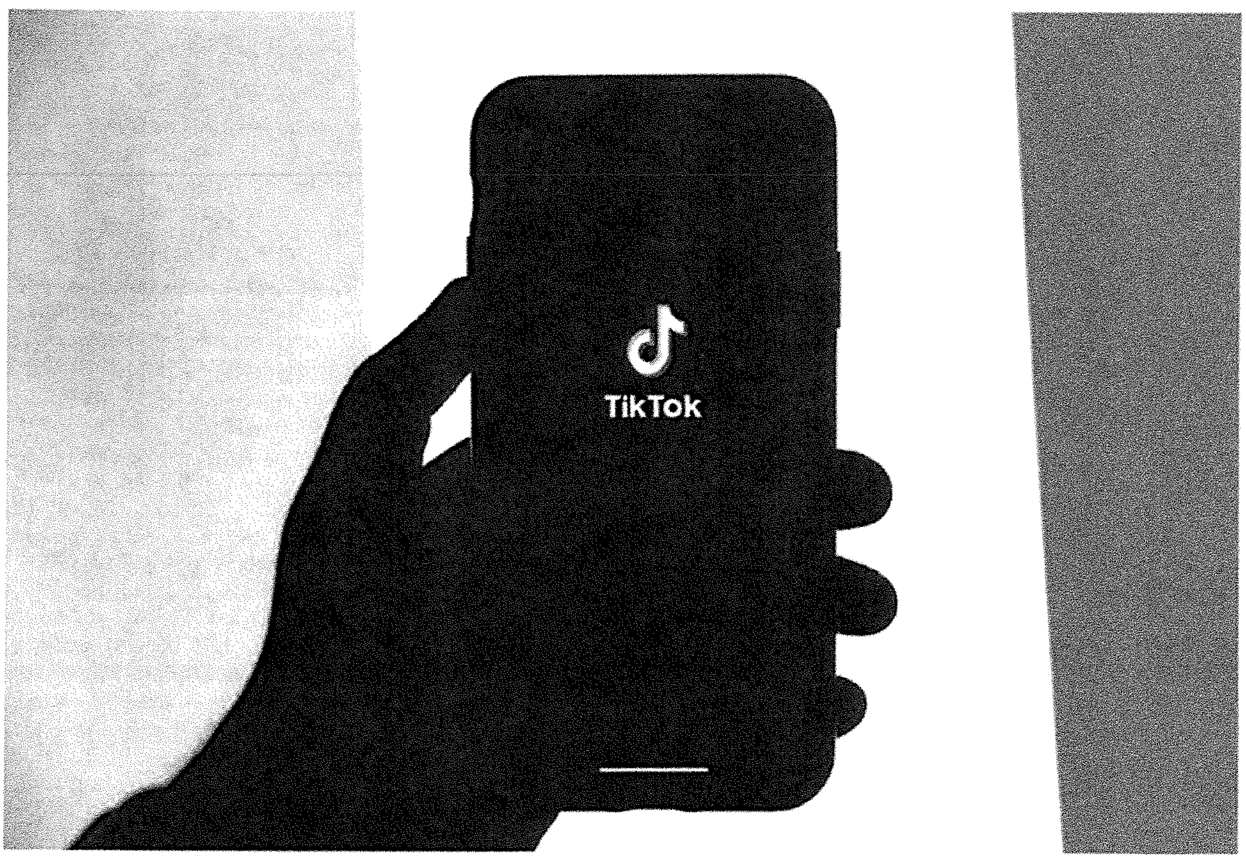
RADICAL TEACHER

A SOCIALIST, FEMINIST, AND ANTI-RACIST JOURNAL ON THE THEORY AND PRACTICE OF TEACHING

Reality check: How adolescents use TikTok as a digital backchanneling medium to speak back against institutional discourses of school(ing)

by William Terrell Wright



SOLEN FEYISSA VIA UNSPLASH.COM

I may as well have solemnly sworn I was up to no good when, just over ten years ago, as a high school student, I downloaded a soundbite onto my phone which played a shrill, mosquito-like sound that only young people could hear.

The night I came across this really quite annoying sound on the internet, my younger self immediately pounced on its possibilities. It happens that, as we age, our ability to hear high-pitched frequencies wanes through a process called presbycusis, a phenomenon observable in people as young as 18. Perhaps predictably, I took my phone to school the next day and played the soundbite on repeat in the middle of English class. A certain juvenile hilariousness ensued as my peers all winced in unison and looked about for the source of the sound while my teacher, deaf to its whine, attempted to figure out what had so rudely commandeered our attention.

I remember being captivated by this encounter. I played it once, maybe twice more throughout the day, quickly realizing how disruptive it was. But the notion that I had access to a secret frequency that our teachers were unable to access left an impression on me. It was a hidden channel, a form of covert telepathy. My imagination teemed with possibilities, and yet my younger self could have never predicted the rise of social media platforms such as TikTok, which grant today's young people the ability to create and circulate content on creative wavelengths that truly do transmit beyond the purview of most adults.

TikTok

For readers unfamiliar with the details, TikTok is a short-form video-making platform for iPhone and iOS where users create and share lip-sync, comedy, and talent videos. The app's website states that its "mission is to capture and present the world's creativity, knowledge, and moments that matter in everyday life" in such a way that "empowers everyone to be a creator directly from their smartphones" (https://www.tiktok.com). Within the past two years TikTok has become a global phenomenon, having been downloaded over two billion times (Carmen, 2020), with young people, overwhelmingly, its primary users. Launched by its parent company ByteDance in 2017, TikTok merged with the video-making app musical.ly later that year with the intention of capitalizing on their young userbase in the United States. The union proved a success, as TikTok went on to become the most downloaded app in the world in 2018. A feat it went on to repeat in 2019. The app then become embroiled in a series of international disputes in the latter half of 2020: most notably the South Korean-led pranking of the distribution of tickets for a Trump rally and the US-led charges that China may be using the platform as a means of overseas surveillance. That the app remains a subject of controversy remains clear.

The app itself immerses users with a seductive, casino-like design. When the app is opened, full-screen videos start playing immediately whether or not the user has any followers or has even created an account. The phone's clock disappears, transparent touch-controls are confined tidily to the margins, and a simple swipe of the finger dismisses one video for the next instantaneously. All is meticulously calibrated to ensure minimal distractions from the vibrant, unending stream of content available. As a result, the intention of a brief check-in all too easily lapses into a half-hour or more.

And yet for all its addictive properties, it cannot be denied that TikTok is still very much a wild west—both in the sense that it is loosely regulated and manifestly White (although video-makers use a lot of Black-produced music in their TikToks). Rampant stereotyping, often of a sexual or racialized nature, goes woefully unchecked. Copyright infringement, concerns over privacy and sexual predatorship, and reports of cyberbullying and racist abuse are disturbingly common. What is more, sharing one's voice on TikTok and other participatory mediascapes is also highly contingent on technological access and one's dexterity with dominant online discursive practices. And yet in spite of this, and perhaps most critically, TikTok's aggressive AI algorithms (i.e. users who enjoyed this content also enjoyed...) often shape users' feeds into digital walled gardens that effectively sequester perspectives and harden existing biases under the guise of plurality. This constellation of issues has yet to be addressed adequately—that is, in sustained, systematic, and proactive ways—and we (digital citizens, policymakers, administrators, teachers, and parents alike) can all do better.

As much as the user-generated content on TikTok reifies its fair share of problematic discourses, I have also found myself occasionally taken aback by the clever and subversive content its young users create, content which is then circulated, remixed, and taken up in various, unexpected ways. For certain, the skill with which previously published, often niche material becomes subject to multimodal recontextualization, juxtaposition, and commentary is impressive, especially given the enormous size of the TikTok community and the ever-shifting terrain of popular culture its users draw upon.

Despite this dynamism, in the eyes of many educators, TikTok is seen as a distraction at best and a bad influence at worst. Arguing against a blanketed disavowal, Moore (2011) argues that, "The issue with criticizing the objects of students' tastes, and by association often criticizing students' navigation through their unique media worlds, is the assumption that the negotiation of teacher/student authority applies to what is fundamentally a process of personal and social discovery" (p. 225). For the time being, at least, TikTok has entered into popular culture, and popular culture is quite clearly capable of shaping people's everyday beliefs and perceptions (Sellnow, 2018). At the same time, to complicate the situation further, it is important to keep in mind that "Youth culture needs to be tapped not co-opted" (Alvermann, 2012, p. 225), and that, when it comes to online mass media, "It is adolescents who curate, reinforce, and contribute most to these digital spaces and teachers may need to capitulate to the idea that they do not necessarily have the responsibility to teach them about their own worlds" (Fassbender, 2017, p. 266). While Vygotsky (1980) held that the largest impact on student learning comes from societal influences, students' cultures, and their peer groups, it has become increasingly difficult for educators to responsibly (much less authentically) tap into these potentials when an ever-increasing amount of young people's social interaction takes place online.

As a former English teacher and current literacy scholar, I wonder, in both personal and professional ways, how educators might reckon, variously, with the problems, popularity, and power of youth-dominated mediascapes such as TikTok. I certainly do not claim to know how to reconcile the often-competing observations spelled out here, but I do believe the tensions they typify are well worth educators' open-minded attention. I also believe that it is our responsibility as educators to be at least peripherally aware of what the young people in our classrooms are producing and consuming in their out-of-school lives.

This brings me to the focus of this article, which centers on how TikTok's adolescent users "speak back" to the discourses of school(ing). In considering this question, I refrain from offering ready-made solutions for educators or condoning the particular viewpoints expressed by any video or online trend. My aim is simply to offer up my observations of TikTok as a means to call attention to the ways school(ing), as a largescale, democratic project and socially constructed phenomenon, is being shaped *by* young people, *for* young people on a digital platform that backchannels a largely resistant attitude toward the institutional framing of school(ing) upheld by many adult educators today. I do so through a discussion of four viral, school-related trends that have proliferated on TikTok over the past two years. My hope is that educators might engage these moments of rupture and feelings of dissonance in considerate ways that do not combat or cheapen the experiences of the young people in classrooms but instead open up opportunities for understanding and dialogue.

Framing

For millions of students, TikTok operates as a kind of social backchannel. The term *backchanneling* has shifted from its linguistic roots in recent years to accommodate the advent of technological tools like texting and social media. Today, at least in scholarship, backchanneling is most often used to describe conversations that take place digitally during meetings, presentations, and classroom lectures (Seglem & Haling, 2018). My framing of backchanneling here, however, is more ubiquitous, referring, instead, to furtively-threaded lines of communication that make their way across spatiotemporal boundaries in a variety of contexts that scale cohesively from the intimate to the cultural. Online message boards, Reddit threads, YouTube channels, blogs, and memes all fall comfortably within my use of the term, so long as they operate as a channel of countervailing solidarity for a particular userbase.

My conception of backchanneling suggests that participatory mediascapes like TikTok may have considerably under-recognized effects in shaping the broader discourses of school(ing), particularly in the US. In describing the "discourses of school(ing)", I do not intend to evoke notions of dialogic exchange or even Gee's (2015) socially mediated "ways of being" within particular cultural groups. Instead, I use discourse in the post-structural sense to mean "a historically, socially, and institutionally specific structure of statements, terms, categories, and beliefs" (Scott, 1988, p. 35) which "systematically form the objects about which they speak" (Foucault, 1972, p. 49). In this way, "Discourse can never be just linguistic since it organizes a way of thinking into a way of acting in the world" (St. Pierre, 2000, p. 485). To put this concept to work, we can trace how the formation and function of school(ing) in the United States has been discursively constructed over the last century by drawing direct links from the assembly-line exploits of Fordism to our current era of neoliberalism, implicated in the heightened emphasis on standardization and efforts to commodify learning in privatized settings (Davies & Bansel, 2007).

I do not, however, take discourses to be totalizing in effect. Drawing on Butler's understandings of contingency (2013) and in particular the practice of "subversive repetition" (1990), wherein what is perceived to be given is routinely disrupted, I am instead suggesting an interpretation of discourse that is, at once, inescapable and ultimately malleable. Subjects in this case both reproduce and contest the various ways of being available to them in a state of ongoing, constitutive becoming. Here there are no stable meanings. Everything must always be questioned, attended to, and accounted for.

Relatedly, Döveling, Harju, and Sommer (2018) illustrate the online/offline entanglement between micro, meso, and macro memorial cultures (such as terrorist attacks and celebrity deaths) in order to describe how new media technologies such as TikTok influence and infiltrate social practices and cultural life via *digital affect cultures*—that is, "relational, contextual, globally emergent spaces in the digital environment where affective flows construct atmospheres of emotional and cultural belonging by way of emotional resonance and alignment" (p. 1). These digital affect cultures inevitably influence, reinforce, and produce sentiments that shape teachers' and students' lived behaviors in both the digital and physical worlds. Content on TikTok writhes and morphs to the tune of these affective flows. Whether hopping on a viral trend, riffing on a meme, celebrating the end of the school year, or referencing blockbuster films, TikTok users remain keenly up to date in creating "culture-specific communities of affective practice" (p. 1). These affective intensities resonate across spatiotemporal boundaries to produce meaning and change. What "happens" online, in other words, immanently alters the course of lived reality. It is therefore imperative that educational theorists and practitioners reckon more thoroughly with participatory mediascapes such TikTok so as to better understand and account for the ways educational discourses are being shaped by those whom we often least assume: the students themselves.

Viral Trends

The four trends in the discussions that follow have each gone viral on TikTok at some point over last year and a half. I have chosen to focus in on these four trends to demonstrate how users' engagement with the platform enters into sociocultural, political, and economic dialogue that is both relevant to school(ing) communities and the larger discourse(s) surrounding education in the US. Given the now-mainstreamed culture of neoliberalism in US schools (tending to dwell primarily on test scores and positive PR), I consider how TikTok might represent a compelling, if complicated, counter-narrative—that is, as a vibrant community of loose, constellating affiliations that could very well signal a future for responsive engagement with networked technologies in the context of 21st century schooling.

Acronyms

One of the most popular school-related trends to have proliferated on TikTok is the creation of acronyms intended to (re)inscribe meanings of commonly used educational words. "School," for instance, is frequently alleged on TikTok to stand for Six Cruel Hours Of Our Lives, a perhaps unsurprising indictment for those acquainted with traditional depictions of school(ing) in mass media (Trier, 2006). Similarly, "Homework" is said to stand for Half Of My Energy Wasted On Random Knowledge, a loaded characterization fundamentally averse to educators' goals to make the content they teach meaningful for their students. And finally, contrary to former American democratic presidential nominee Andrew Yang's suggestion that "math" be taken to mean Make America Think Harder, the average TikTok user has observed time and again that "math" stands for Mental Abuse To Humans.

Potential impressions of melodrama aside, these associations do not come from a vacuum. Something about the educative project we are a part of has created conditions where massive amounts of young people actively produce and relate to such sentiments. Perhaps, when we recall what it was like to be adolescents ourselves, these feelings may even sound familiar. Beyond providing us with insights—or perhaps reminders—into how school(ing) is experienced and perceived by young people, such instances also afford us opportunities to look anew at how and why we teach the ways that we do. If students, at the end of the year, have learned to dislike the subject we teach more than when they came to us, then we have done them an unequivocal disservice. There of course are no simple solutions or easy targets to point fingers at. What is plain, however, is that we still have work to do, especially when it comes to empathizing with our students and inspiring them in intrinsic ways.

Finally, it is important to bear in mind that language and ideas often have slippery relations. We need look no further than the host of hotbed words (facts, socialism, etc.) which are actively being contested on sociopolitical levels that scale cohesively from policy on down to the personal. While youth's discursive grumblings on TikTok might seem inconsequential by comparison, the formulation and spreading of these resistive acronyms are prime examples of youth participating in ongoing constructions of meaning. Whether in Webster or Urban Dictionary, words must be attended to. As youth readily engage in reading and writing their words/worlds (Freire & Macedo, 2005), educators who choose to sit idly or dismissively by miss out on opportunities to participate with them in the attempt to render a more fulfilling, less cynical tomorrow.

#callingteachersbytherefirstname [sic] 825.6k views

#callingteachersbytherefirstname [sic] is another viral trend in which students go about school calling teachers by their first names in order to film their reactions. A typical video consists of a mashup of a half-dozen or more short clips that cut off as soon as the teacher's face registers the tiny, unexpected breach in decorum. Teachers' reactions vary from irate to dumbfounded to pleasantly surprised, while we, the viewers, serve as witnesses to this break in a teacher's self-composure.

The trend, while only a gest, to be sure, nevertheless prods gently against age-old power dynamics that exist between students and their instructors. On the surface, the humor derives from its disruption of the seriousness and formality of the school setting. But between the lines is also the soft, subversive thrill of seeing the resident hierarchy flattened, in only for a moment. Under this polite guise, a hardened signifier of deference and respect is playfully cast aside. Suddenly an address to a superior becomes the nonchalant hailing of an equal.

These students, playfully knocking against the discursive protocols we have built for them, may be said to be questioning any number of things. What constitutes respect, for instance? Why do adults care so much about maintaining certain distinctions? Where are the lines that should and should not be crossed? Does taboo come in shades of grey? Or: perhaps deep down they are just seeking glimpses of who their teachers really are underneath that professional exterior of theirs. Are we willing to show it to them?

#publicschoolcheck 9.5m views

#publicschoolcheck is one of TikTok's most viral trends. To participate, students compile a series of clips that represent what they perceive to be the most shoddy, rundown, or pedestrian qualities of their school. Common subject matter for these montages includes "out of order" signs on bathroom stalls, STD prevention flyers, graffiti, close ups of school lunches, and shaky panoramas of cafeterias, hallways, and school grounds. As a rule, the intro to the song "Stoner" by Young Thug plays over the video.

On the surface, these students do not seem to be drawing a deliberate critical eye to the material conditions of their schools; it appears, rather, that they are simply having fun by cataloguing their experience to playfully commiserative ends. And yet these attempts to identify representations of "ordinary" (if largely suburban) public school environments nevertheless wind up providing an intriguing commentary on the spaces in which we ask our young people to learn. Such a stance falls into even greater relief when held up against the countering #privateschoolcheck, where private-school students show off lines of sports cars in the student parking lot, in-school Starbucks, pristine sporting venues, and lavish, TV-lined cafeterias. Such contrasting portrayals demonstrate that students are in fact keenly aware of the ways in which adults do or do not value (at least monetarily) the dignity of physical environments in which learning is expected to take place.

#belldoesntdismissyou 1.9m views ("The bell doesn't dismiss you. I do.")

This last trend likely requires the least amount of introduction. The bell rings, students all stand to leave, and the teacher shouts, "The bell doesn't dismiss you. I do." On TikTok, this immanently-recognizable moment is characterized as a routine power trip. Content creators ask, "then what is the bell for?" or claim that teachers have no power in this case because they are "required by law" to let students leave when the bell rings. Other users illicit humor by juxtaposing their reenactments with dramatic showdown music from popular entertainment sources such as *Dragon Ball Z* or *Avengers*. In this way, a challenge is set up: *it's all of us versus you*. From the auspices of TikTok, what might have remained a minor frustration in the lives of young people transforms into a broad-based nexus of contention, a rallying point no longer experienced in isolation. The everyday is made epic.

While an element of humor of course underscores many, if not most, of these depictions, it is interesting to consider why such a statement—"The bell doesn't dismiss you. I do."—garners so much attention in the first place. It is, after all, a moment of tension, where power hangs in the balance, when a teacher's "time is up" and students feel it is their prerogative to flock to the halls and joke with friends, listen to music, or kiss their significant others.

While the routines and teaching style of a given educator is (and should be!) their own, it is nevertheless important for teachers to be mindful of how their statements are being perceived and, in this case, taken up. There may be a time and a place for such hardline demonstrations of authority, but if we are indeed unwittingly circulating tired clichés, then we must consider checking ourselves in an attempt to resist doing so, in order that we might seem less like automatons and more like the authentic human beings our students need us to be.

Finally, I want to make clear that "The bell doesn't dismiss you. I do" is far from the first flashpoint phrase adolescent students have been in league against. Years ago now, a high school student of mine wrote a poem called "Mitochondria are the powerhouse of the cell". In the poem, the title phrase was repeated robotically at the end of each stanza. The student and I had a candid relationship and often spoke together after class. It was here that he told me the phrase was based on a popular meme that most students knew all too well, although he suspected most teachers did not. Indeed, online, the phrase "mitochondria are the powerhouse of the cell" is mocked as an example of the impractical information taught in schools, the irrelevant "third things" (Gambell & Sumara, 1996) students are expected to hardwire into their brains for test day. While there may be advantages to insisting our students learn particular facts, educators should, at the same time, attempt to avoid abetting obtuse caricature-building in whatever ways possible.

Discussion

Of course TikTok will not be around forever. Many, including Casey Newton of *The Verge* (2019), are already predicting its demise. Alternatively, as with Facebook, its user demographic could shift if more and more adult users begin to migrate to the platform. There will no doubt, however, be other apps, other means of transmission, which young people take up. Traditionally, whether it was a clubhouse, a favorite performance venue, or a friend's basement, unsupervised spaces have provided important enclaves for young people to experiment with their identities and their relationship to the world around them. Since young people's lives have begun transitioning into digital spaces, however, there has been an ever-retreating ragged edge where young people gather to create and communicate with each other online. This expressive frontier has taken many forms over the years—Facebook, Twitter, Tumblr, Yik Yak, Vine, Snapchat, TikTok, to name a few—and yet the expressive energy of young people inevitably finds new outlets to flourish when one platform or another comes under threat from the co-opting forces of adultism. A few such platforms, such as Reddit and YouTube, have managed to stick around, diversifying themselves into large enough platforms that various communities, young and old, willingly or not, wind up compartmentalized into wholly-contained online ecosystems—a separate but related issue that is beyond the scope of this article to address, one which is nevertheless responsible, in part, for the proliferation of "fake news" and the reinforcement of political tribalism.

There may also be a need to expand classical definitions of activism in order to better account for the complexity of civic participation within 21st century participatory mediascapes. Setting oneself ablaze, standing in front of tanks, marching with picket signs, or placing flowers in the barrel of a soldier's rifle come to mind as emblematic images of activism. But perhaps, as Butler (2010) writes, "the "act" in its singularity and heroism is overrated… [as it] loses sight of the iterable process in which a critical investigation is needed" (p. 184). Certainly the everyday courage of minoritized and non-conforming young people who risk their wellbeing to speak and be seen on social media are not to be taken lightly. Nor are students who upload mobile footage of their school security officers using violent force against their peers. These are forms of activism, too. But even on a less immediate note, one also cannot overlook the popularity of crowd-sourced GoFundMe pages, patron-supported YouTube channels, and online Reddit threads (where creators connect directly with fans), which, in many ways, typify a collective desire among younger generations to bypass intermediaries or bureaucracies in whatever ways they can. One might certainly include here, as well, the "more playful style of activism...emerging through [the] appropriative and transformative dimension of participatory culture" (Jenkins, 2016, p. 2), such as those proliferating on TikTok, which are not about making a stand so much as finding countless, invisible allies with which to secretly resist.

Indeed, all of these examples demonstrate that youth "are often political insofar as they aim to influence or change existing power relations" (Brough & Shresthova, 2012). It is these small everyday revolutions, which become habits and trends, that Shukaitis (2009) describes as "movement[s] through and of the entire social field [that] are nearly impossible to describe without imposing closure on them as open and constantly fluctuating processes" (p. 16). These interstitial movements, in many ways, escape signification. And it may well be the fact that they are difficult to pin down that leads to their eventual widespread affirmation, familiarity, and adoption.

As an educator myself, I am well aware and have written about (Wright, 2020) the ways in which hardline schooling environments that are beholden to test scores and good PR are often run in such a way that is restrictive to and, in many cases, outright adverse toward pedagogical explorations of the very same networked technologies that continue to shape the world we know in profound and momentous ways. As such, I want to suggest that deciding with finger-in-ear certainty to foreclose even the possibility of proactive institutional engagement with these technologies too often leaves today's youth fending for themselves in the digital environments that most affect them. In the wake of the Covid-19 pandemic especially, platforms such as TikTok are leaned on heavily as stand-ins for the sort of loose, affiliated interactions described here. In a time of social distancing, backchanneling, in effect, has become much easier, and new trends are already starting to emerge. To be clear, I do not believe that schools should take over or even necessarily monitor the TikTok feeds of their students; rather, I am suggesting that all of us—teachers, researchers, and administrators alike—might more empathetically tune into the subjective frequencies of young people's experiences in schools (at least, as best we can), so that we might better understand and account for the ways in which we, ourselves, might be perpetuating students' clear frustration and discontent with the ways school(ing) environments function in their lives.

Curiously, whether a wholesome step forward or another instance of existing power structures subsuming and thereby sterilizing whatever radical energies speak up against it, afterschool TikTok clubs (where teachers and students collaborate to create school-appropriate content) started to crop up across the US before the pandemic struck (Lorenz, 2019). Plenty of catchy dances and pep rally prep, to be sure, but also, perhaps, an opportunity to enter into dialogue with students about issues of online representation, the unpredictable power of virality, and the ways in which we all might think and do otherwise—whether together or apart, in the open or in secret.

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Political and social activism have been part of the internet since the World Wide Web went public in August 1991. As the internet's role in communication and commerce has grown, its importance as a tool for activism has also expanded. Issue-oriented organizations, businesses, governments, political candidates, charities, and politically active individuals all use the internet as a crucial tool for bringing awareness to social and political issues. The internet can boost activism by raising funds, influencing voters, recruiting people for offline events, and providing means of communication among activists.

Though the internet has enabled activists to spread information and generate awareness, critics of internet activism have argued that it is less effective than traditional activism at bringing about change. Further, participation in online activism has been characterized as performative, with some social media users accused of adopting causes to improve their image without actually advancing the cause. The internet also helps authorities track and monitor activists, creating issues related to privacy and civil liberties.

Main Ideas
- Activists can use the internet in a variety of ways to share information about issues. These include websites, email, social media apps like Facebook, Twitter, and TikTok, and livestreaming on platforms like Twitch or YouTube.
- Social media has been particularly useful for quickly spreading information through "viral" posts, photos, and videos that reach a large number of people and motivate them to respond with action.
- In the 2010s internet activism became a vital component to large-scale offline actions such as charity fundraisers, political campaigns, and mass protest movements.
- Risks of internet activism can include harassment or even prosecution in countries with few free speech protections. Opposing activists may also try to publicize the identities of online activists to incite others to harass or physically attack them or cause them to lose jobs or social status.
- Critics suggest that online activism too often becomes an ineffective substitute for enacting real change on important issues.

Improving Communication and Awareness

Most political organizations use the internet primarily for communication. An organization can share information by posting an update on its website, sending a mass email to a mailing list, suggesting an idea or linking an article on Facebook or Twitter, or sharing images and videos on apps like Instagram and TikTok. Members of the public can express their support by reacting with a "like" or "favorite," leaving a comment, or sharing the information with members of their social networks. People can also show support for a cause through symbolic gestures on social media, such as changing a Facebook profile picture to promote a specific movement or organization. In addition, activists can create and share their own online petitions on websites such as Change.org and iPetitions.

The internet can also be used to spread firsthand information that might not otherwise receive coverage from media outlets. For example, in June 2019 Animal Recovery Mission, a group combating animal abuse, released a video showing employees mistreating calves at Fair Oaks Farms in Indiana, which went viral. The video was covered in local and national news media, and a boycott of Fair Oaks Farms's Fairlife milk products followed, along with a criminal investigation and civil lawsuit.

While these tactics bring awareness to issues, critics note that they do not always solve the problems they were meant to address. In response to the murder of George Floyd and the Black Lives Matter protests that followed, two Black music executives proposed #TheShowMustBePaused for June 2, 2020, to disrupt the workweek and hold the music industry accountable for profiting off of Black artists. However, as their idea spread, it evolved into #BlackOutTuesday and quickly went viral, with everyone from celebrities to large corporations posting black squares on Instagram and other social media. Critics questioned how posting a black square helped the cause and noted that the use of the #BlackLivesMatter hashtag with the squares prevented people from using the hashtag to find information about the protests. Corporations faced allegations of performative activism for releasing public statements of support without acknowledging their own racist history or instituting substantive changes in their operations.

Expanding Participation

Information available online can also facilitate discussion of political issues. In the 2010s hashtags on Twitter and other sites have been used to publicize and inform followers about issues, a practice termed *hashtag activism.* Twitter hashtags have been used for charitable purposes such as the 2014 #IceBucketChallenge. Participants shared videos of themselves dumping ice water over their heads to bring awareness of amyotrophic lateral sclerosis (ALS) and raise funds, ultimately providing more than $115 million to the ALS Association to support patient needs and research. Though the original organizer of the challenge, Pete Frates, died of ALS in 2019, researchers reported that the money raised had funded promising research into new treatments for the disease. Hashtags also have been used to show support and share experiences, as in the use of the #MeToo hashtag in 2017 to publicize the number of people who have faced sexual harassment.

Internet activism can be especially effective when it combines an action that is easy and quick to perform and rewarding to share. For example, after an Oklahoma rally for President Donald Trump was scheduled for June 21, 2020, TikTok users began to suggest that people use the online system to reserve free tickets for the event that they would not use. Iowa political activist Mary Jo Laupp posted a TikTok video about the prank. Her video amplified the call and reached thousands of teens, who reserved tickets and then posted videos about it, making humorous excuses about why they would not attend. Because the information mainly spread among TikTok users, the movement remained unnoticed by the wider public and the media. The Trump campaign posted several social media messages boasting of an expected high turnout after millions of tickets were reserved, however only around 6,200 people actually attended the event.

Online activism frequently extends beyond the internet. Movements use Facebook, Twitter, and email lists to organize face-to-face meetings and demonstrations. In addition, activists may hold private meetings using group messaging apps such as Slack, Discord, or Zoom. Some of the most successful movements have combined online activism with in-person participation. In the months before the 2020 Democratic primaries, the youth-oriented environmental group Sunrise Movement gained attention online through viral videos of their protests and their endorsements of candidates who supported Green New Deal proposals. They then recruited volunteers to work for those candidates' campaigns through fundraising and phone banking.

Livestreaming through apps like Periscope, Facebook Live, and Instagram Live allowed Black Lives Matter protesters in May and June 2020 to share real-time video of their marches and encounters with police. Twitch, a site usually used to livestream video game play, was also used to share protest footage. Viewers who could not attend protests in person could participate virtually; some activists also monitored multiple livestreams to advise participants on police movements and blocked streets around protest areas.

Conservative Internet Activism

Conservative political groups and activists have also made use of internet activism. For example, anti-tax advocate Grover Norquist has long used email and social media to organize rallies against state and federal taxation, pressure politicians to take his "Taxpayer Protection Pledge," and mobilize followers to call and email politicians on issues or legislation.

The alt-right political movement, encompassing various far-right and nationalist groups, has made extensive use of the internet to publicize their views through YouTube videos, Facebook groups, and anonymous forum sites like 4chan and 8chan. In May and June 2020 activists used social media to organize protests against mask-wearing requirements and in favor of early reopening of businesses in the wake of the novel coronavirus disease 2019 (COVID-19) pandemic.

In the months leading up to the 2020 elections, prominent Republican political operatives who opposed the 2016 election of Donald Trump organized the Lincoln Project to battle against his re-election. The group produced videos criticizing controversial actions and statements by Trump, often within hours of the incidents. While the videos saw limited use as paid advertising on cable networks and websites, most of their reach was viral through online shares on social media.

Hacktivist Groups

In its most extreme form, internet activism can involve using and subverting computer networks for political purposes. These activities are sometimes referred to as *hacktivism.* Like the term hacking, from which it derives, hacktivism may include a range of legal and illegal activities. Many hacktivist groups favor free speech and oppose authoritarian governments; some argue that hacktivist activity should be decriminalized as a legitimate form of protest. Their techniques include sabotaging the websites of targeted governments and organizations, often through denial-of-service attacks, which immobilize a server by flooding it with requests.

Internet activists have also stolen data from secure servers and released this information to the public. Two of the best-known hacktivist groups are Anonymous and WikiLeaks. WikiLeaks is a whistleblowing organization that makes leaked classified documents available to the public, first gaining prominence in 2010 by releasing documentation of United States activities in Afghanistan and Iraq that included evidence of war crimes. Following Wikileaks's releases of hacked emails from Hillary Clinton's campaign for the US presidency in 2016, the organization was accused of falling under the influence of foreign governments. WikiLeaks has also targeted the personal information of US Immigrations and Customs Enforcement (ICE) officers in 2018 in response to that agency's immigrant detention policies.

Anonymous takes a more active role in subverting computer systems; its members have attacked the secretive Church of Scientology and declared war on the terrorist group the Islamic State. Members of Anonymous have also participated in the Occupy and Black Lives Matter movements. In June 2020 Anonymous leaked a large trove of records from police departments across the United States. The documents included internal memos, email addresses and passwords, and intelligence documents.

Critical Thinking Questions

- In what ways does internet activism differ from more traditional forms of activism, and how are they similar?
- What do you think are the most important strengths and weaknesses of internet activism?
- What are some possible risks of participating in online activism? Would these risks deter you from participating?

Risks and Concerns

Internet activism can be risky. Social media can be monitored by political opponents and law enforcement. It is difficult to erase the record of things that are said and shared online. Email messages can often be recovered even after they have been deleted, and social media posts can be captured with a screenshot even if they are later taken down. "Doxing," the practice of publicizing internet users' true identities and contact information, can be used to enable harassment or even physical attacks on people.

Internet activism can also be subverted by foreign agencies seeking to sow dissent and confusion in other countries. Though multiple Russian organizations and individuals have been indicted in US federal courts for interference in the 2016 elections, intelligence and cybersecurity experts have warned that the 2020 elections faced similar attacks. In particular, they pointed to the use of memes and untrue or exaggerated news stories to disrupt the campaigns. One tactic involves establishing Facebook groups and social media accounts that appear to be US-based local organizations, which then attempt to mount in-person protests in US cities.

The effectiveness of internet activism has been questioned. Critics have coined a derogatory term, *slacktivism*, to describe online activities that take minimal effort but reward participants with the feeling of having accomplished something positive. However, others argue that online activism generates energy that then gets translated into on-the-ground organizing. The role of online activism, they contend, is to increase public awareness of what is being done or needs to be done offline.

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G3