It’s Not Good #ForYou: Exploring the Influence of Social Media Algorithms on Youth Media Consumption and Diet Culture

A Research Paper submitted to the Department of Engineering and Society

Presented to the Faculty of the School of Engineering and Applied Science
University of Virginia • Charlottesville, Virginia

In Partial Fulfillment of the Requirements for the Degree
Bachelor of Science, School of Engineering

Isabella Heintges

Spring 2025

On my honor as a University Student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments

Advisor

Rider W. Foley, Department of Engineering and Society

The Role of Recommendation Algorithms in Content Promotion on Social Media

"A lot of times, people don't know what they want until you show it to them," (Jobs, 1998). In an era of pervasive digitization, many aspects of daily life are migrating to online platforms, thereby transforming the way people interact with goods, media, and services. This shift has given rise to highly sophisticated recommender systems, a subset of machine learning employed to "guide the user in a personalized way to interesting or useful objects in a large space of possible options" (Burke et al., 2011, p. 14). Social media platforms have integrated these complex systems, capitalizing on their ability to shape user preferences, often before individuals are fully aware of their own desires.

Social media is woven into the fabric of modern society, altering the ways by which individuals connect, communicate, and engage with the world around them. Of those on social media platforms, youth aged 13-17 represent a significant demographic and are particularly susceptible to influence. Among this age group, 95% reported actively using a form of social media, with a third admitting their use to be almost constant (U.S. Department of Health and Human Services, 2023). Algorithms play a leading role in shaping the content young audiences see online, promoting material based on prior interactions to maximize engagement (Narayanan, 2023). While these systems are celebrated for crafting a personalized digital feed, concerns have emerged regarding repetitive youth exposure to harmful content on social media, specifically in relation to health messaging. TikTok, one of the most popular social media platforms, uses a sophisticated recommendation algorithm to deliver personalized content on each user's #ForYou page, often highlighting posts that circulate these health-related topics. Even though not all of this material is negative, TikTok's algorithm "keep[s] users glued to their screens" and entraps young audiences in a rabbit hole of posts that normalizes unrealistic body ideals and dieting, thereby harming their mental health and physical well-being (Sousa, 2024).

The role of recommendation algorithms in social media, and their role in promoting harmful health messages can be analyzed using the framework of infrastructure, as presented by Susan Leigh Star in her work “The Ethnography of Infrastructure” (1999). Conceptually, infrastructure is envisioned as a system of substrates, further shaped by present social and cultural factors. By exploring the systems and structures that facilitate the recommendation process on social media platforms, I can better determine the negative effects on young audiences. In this research paper, I will use Star’s framework to argue that platforms invisibly recommend content, in a standard fashion. I will highlight that unhealthy health messages are promoted to young users by these systems, which are embedded in the platform and affect broader societal beliefs. To explore how recommendation algorithms amplify negative health messaging to younger audiences, I have chosen to focus on TikTok’s algorithm due to its notable personalized nature. I will begin with a case analysis involving the creation of two separate accounts on the platform, tracking how user interactions influence the platform’s recommendations. Following this, I will contextualize the results by referencing existing research to reinforce the effects on adolescents, of viewing such content. In today’s digital landscape, social media platforms shape the perceptions and behaviors of young audiences by leveraging user preferences to curate content. With this influence in mind, this paper examines the role of recommendation algorithms on social media and assesses the extent to which they contribute to the adoption of negative behaviors among youth, particularly in relation to diet-culture.

Algorithm Knows Best: The Function of Recommender Systems in Social Media

While seemingly self-governing, the content displayed on one's social media feed is carefully curated by a recommender system developed and implemented by the platform. Unlike general search engines, recommender systems produce results that vary depending on the user, even for another identical input. These artificial intelligence technologies function by analyzing a user's long- and short-term activity alongside their stated preferences (Schafer et al., 2007). In addition to user-specific data, these systems leverage Big Data to suggest content imperceptibly (NVIDIA, 2025). They are designed to learn and continuously refine their predictions about an individual's characteristics on a case-by-case basis.

Design and Function of Modern Recommender Algorithms

Recommender systems, which power social media algorithms, are typically built using one of two main approaches: collaborative filtering or content-based filtering (Maruti Techlabs, 2021). While social media platforms often develop hybrid algorithms that incorporate elements of both models, user content suggestion primarily relies on the collaborative filtering (CF) model due to its efficiency, accuracy, and ability to deliver personalized recommendations (Ni et al., 2021) (Figure 1).

Collaborative Filtering (CF) Models. CF algorithmic processes function under the assumption that "people with similar tastes will rate things similarly" (Schafer et al., p. 300), and involve developing a user-item rating matrix to identify users with similar interests (Ni et al., 2021). This matrix contains values that reflect a user's preference for a given item and is based upon both explicit and implicit user feedback (GeeksforGeeks, 2024). Explicit feedback refers to the input directly inputted by the user, while implicit feedback involves behavior tracked by the system, like clicks, views, or time spent. Using these values, the algorithm computes a "weighted sum of the ratings for items most similar" to the item in question (Schafer et al., p. 304). Algorithmic recommendations are based on these similarity ratings and prediction calculations (Dou et al., 2016). CF filtering models can be further categorized into user-based and item-based approaches, depending on their application, see Figure 2.

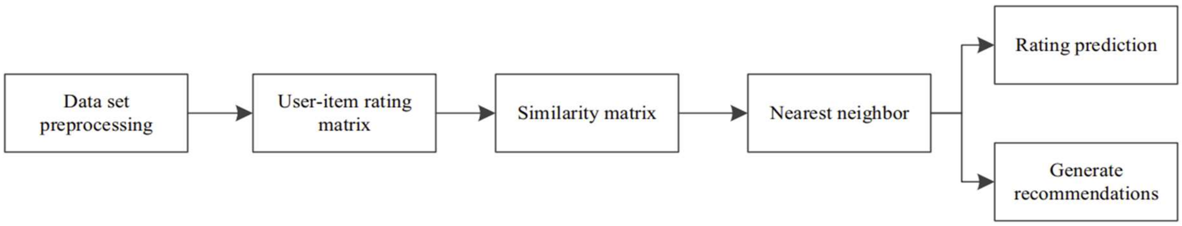

Figure 1. Collaborative filtering (CF) model architecture (Schafer et al., 2007).

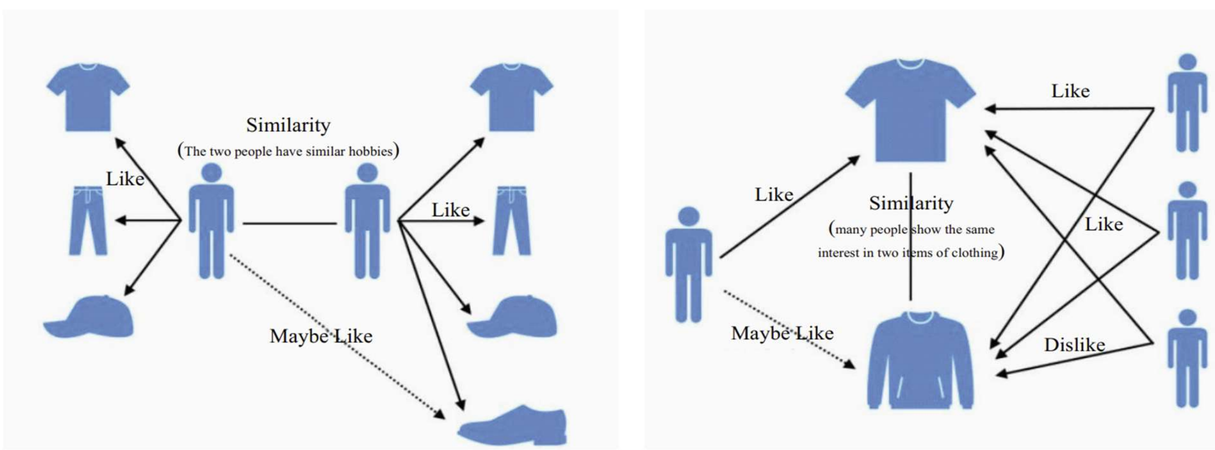

Figure 2. User-based collaborative filtering modeling (left) and item-based collaborative filtering modeling (right) (Ni et al., 2021). Note: User-based CF systems recommend items by identifying users with similar preferences, while item-based CF systems analyze relationships between items to suggest content similar to what a user has previously liked.

Content-Based Filtering (CBF) Models. While collaborative filtering (CF) models generate recommendations by analyzing user behavior, content-based filtering (CBF) models rely solely on the characteristics of user and item profiles to make recommendations (Aaweg, 2024). User profiles are created by the CBF system by analyzing the features of previously used content. To indicate "products with similar characteristics to those chosen by the user in the past" (Hossain et al., 2022, p. 3), the model matches this generated user profile with similar content profiles. A CBF system then recommends items with closely related features, see Figure 3.

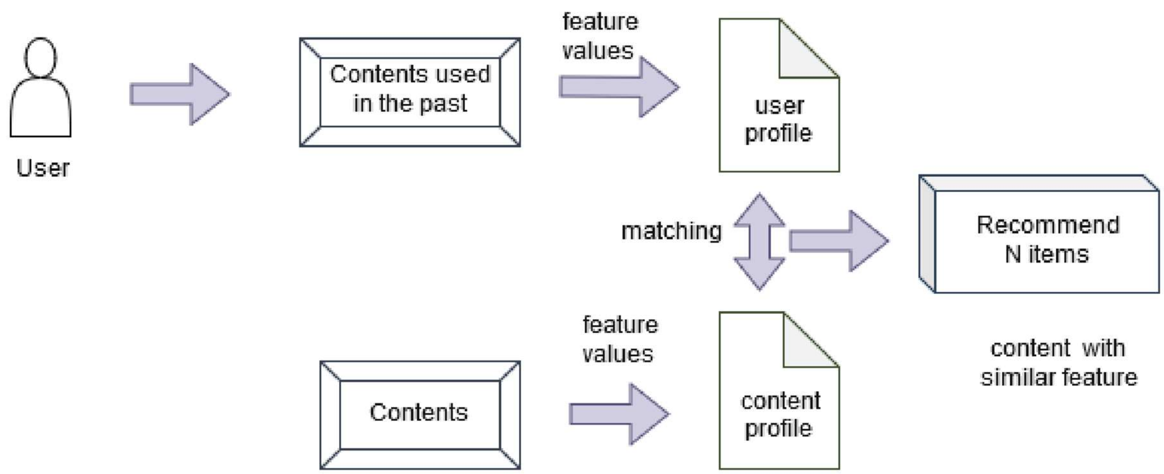

Figure 3. Content-based filtering (CBF) model architecture (Murel & Kavlakoglu, 2024).

On social media platforms in particular, a hybrid filtering system is regularly employed to deliver user-specific content, which combines both collaborative filtering and content-based filtering processes. These hybrid algorithms produce "more accurate and efficient recommendations than a single technique" (Hossain et al., 2022, p. 3), as each filtering method compensates for the limitations of the other, enhancing the model's overall performance. TikTok, a popular platform for sharing short-form videos, has developed a highly effective hybrid algorithm that personalizes user content, which contributes to the application's "addictive quality" and overall success (D'Souza, 2025).

Algorithmic Allure: TikTok's Model for Maximizing Retention

Globally, TikTok has rapidly become one of the most popular social media platforms, soaring from 55 million monthly active users in January 2018 to 1 billion by September 2021—an 18-fold increase in less than four years (Backlinko, 2025). This explosive growth is driven by its highly engaging algorithm, which keeps users on the app longer than any other leading social network. Of those online, about a third of TikTok's users fall into the 10-19 age range, with 22% of teenagers in the United States spending 2-3 hours daily on the app (Wallaroo, 2024; Duarte, 2024). Content discovery on TikTok is centered around the app's #ForYou page, "a personalized feed of content based on [user] interests and engagement" (TikTok, 2025a). This endless stream of curated media is propagated by the platform's algorithm: a hybrid recommender system that implements collaborative filtering and deep learning models to tailor user suggestions (TrulyDigital Media, 2024). This system "select[s] from a large collection of eligible content" and ranks media based on its "prediction of how likely [a user will] be interested in each" (TikTok, 2025b). In the ranking process, TikTok's algorithm considers "fantastic volumes of data" (Smith, 2025), but gives greater weight to user interactions, content information, and user information in suggesting content. While little is known about the exact design of this recommendation engine, TikTok's engineers in Beijing revealed that the algorithm optimizes two closely related metrics in personalizing content: retention and time spent, see Figure 4 (Smith, 2025). TikTok's addictive algorithm has sparked widespread discussion regarding the elusive intricacies of its design and its negative effects on young users.

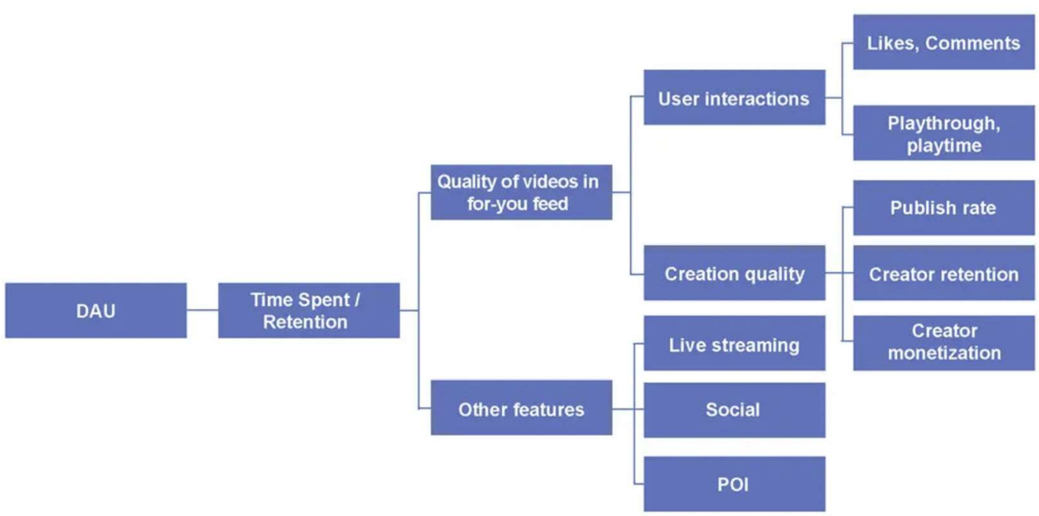

Figure 4. The goals of TikTok's algorithm (Smith, 2021). Note: This chart was reproduced based on original platform documents and included in the New York Times article referenced.

Susan Leigh Star’s Framework of Infrastructure

Infrastructure, commonly regarded to be the foundational framework responsible for general systems and structures, is reconceptualized by Susan Leigh Star in “The Ethnography of Infrastructure” (1999). Star defines infrastructure, not as a noun, but as an approach to analyzing the relational, ecological phenomenon that mediates how technologies interact with and shape society. Because infrastructure is both created and used by individuals across different contexts, Star emphasizes that technologies take on different meanings depending on their perception by those who interact with them. Her ethnographic approach highlights the importance of understanding these varied perspectives, as circumstance shapes how technologies are understood, judged, and integrated into daily life. Given that “[w]e shape our buildings; thereafter, they shape us” (Bernstein et al., 2023, p. 1), I will draw upon Star’s framework in my research to analyze TikTok’s recommendation algorithm. Among the nine characteristics Star identifies as defining features of infrastructure, I argue that visibility upon breakdown, embeddedness, and reach are the three most relevant. To understand how an algorithm functions within and impacts adolescent digital culture, I will explore these aspects of infrastructure in the context of amplified, negative health messaging on social media.

Algorithms are Invisible, Until They Are not

TikTok’s recommendation algorithm, like many physical infrastructures, operates seamlessly in the background as it suggests user-specific content. Yet, as Susan Leigh Star (1999) explains, infrastructure is “normally invisible” until it breaks (p. 382). In the case of TikTok, the algorithm’s once-hidden presence becomes highly visible through its harmful effects on adolescent users, particularly through the promotion of diet-culture.

Diet culture refers to "the collective beliefs and practices that promote the pursuit of weight loss as the ultimate marker of health and well-being" (National Alliance for Eating Disorders, 2023). It perpetuates a harmful narrative that prioritizes thinness, appearance, and body shape, while encouraging behaviors like calorie restriction, negative self-talk, and the categorization of foods as strictly *good* or *bad* (Daryanani, 2021). As these ideas become increasingly normalized, weight and beauty are considered as the primary indicators of health, contributing to the rise in disordered eating behaviors among adolescents. Over the past 50 years, epidemiological studies have documented a significant increase in eating disorders among young girls (Morris & Katzman, 2003), with a 107.4% increase in adolescent diagnoses between 2018 and 2022. During this same period, the number of related healthcare visits in the United States more than doubled for individuals under the age of 17 (Bergman, 2025). This surge of both eating disorder diagnoses and healthcare visits is linked to the COVID-19 pandemic, and the increased time adolescents spent on social media (Giragosian, 2024). While medical professionals are still unsure how these disorders manifest, online platforms clearly expose young users to harmful content that threatens their mental and physical well-being.

The problem? Diet-culture is incredibly sneaky. On social media, posts promoting unrealistic body standards and harmful weight loss behaviors are often disguised as fitness tips or wellness advice. In recent years, platforms like TikTok have faced criticism for amplifying such content, making the once invisible nature of recommendation systems incredibly apparent. As the platform attempts to "promote content attractive to users who fit a certain demographic or lifestyle" (Bergman, 2025), those searching for health-related topics are flooded with posts on weight loss, extreme dieting, and intense workouts. Attorney Matthew Bergman of the Social Media Victims Law Center (2025) highlights the seriousness of this issue:

> The algorithms on platforms like TikTok and Instagram direct vulnerable kids to unsolicited dangerous and harmful content, including videos and user groups encouraging eating disorders. These companies are aware of the harm it causes, particularly in young girls, with images and videos promoting unhealthy eating.

As adolescents innocently explore topics related to dieting and fitness, TikTok's algorithm no longer functions in the background, it is exposed as an active mechanism that contributes to real-world consequences. Though not all health-related content is inherently harmful, the repetitive exposure facilitated by the algorithm distorts young users' perceptions of health and body image, reinforcing diet culture and encouraging damaging behaviors.

Algorithms are Embedded into Digital Platforms

Infrastructure is often taken for granted, as it is seamlessly integrated into the routines, tools, and systems people use daily. Star (1999) defines embeddedness as a key feature of infrastructure, describing it as "sunk into and inside of other structures, social arrangements, and technologies" (p. 381). In the context of social media, algorithms are not just tools—they are structurally embedded into the platforms themselves. On social media platforms, algorithms function as the "technical means of sorting posts based on relevancy instead of publish time" (Golino, 2021). From development onward, they are interwoven into the architecture of the application. TikTok's recommendation system acts as the very system through which the platform operates, deeply integrated into the domain's interface, user behavior, and content production cycles. It is this embeddedness of TikTok's algorithm that poses an issue, as users often do not distinguish between different aspects of the app, which challenges the autonomy of young audiences.

Regarding artificial intelligence, user autonomy refers to “the ability of individuals to control their interactions” with digital systems (AIPanelHub, 2024). Despite TikTok’s global popularity, the platform has faced growing scrutiny for undermining this autonomy, as many users “often remain unaware of why certain videos are recommended to them” (Zhou, 2024, p. 203). The embedded nature of the algorithm makes it difficult for adolescent users to critically assess how their viewing habits shape future content, operating with what Cuello (2024) describes as “inherent complexity and lack of transparency.”

In the context of negative health messaging, this lack of awareness is particularly concerning. Many users do not realize that their engagement with content related to dieting, fitness, or beauty standards is guided and further intensified by the platform’s recommendation system (Nunes, 2024). Each interaction prompts the algorithm to refine its suggestions, reinforcing a narrow and often harmful stream of content. This self-perpetuating cycle makes it increasingly difficult for users to break free from these curated pathways. Through this process, TikTok’s infrastructure not only dictates what users see, but subtly shapes how they understand their interests, identities, and behaviors. The algorithm’s embeddedness ensures that its influence is constant yet largely unnoticed, acting as an invisible hand guiding adolescents toward content that can distort perceptions of health and self.

Algorithms Broadly Affect Societal Practices

TikTok’s algorithm exhibits extensive reach, both spatially and temporally, aligning with Star’s notion that infrastructure extends beyond isolated events or single-site practices. The influence of the recommendation system is not confined to one video or moment of interaction; rather, it spans long periods of user engagement and transcends geographic boundaries. For young users, a single interaction with a misleading health post can trigger a chain of recommendations that persist over time, gradually developing an online environment dominated by similar content. This process fosters digital echo chambers, where users are continually presented with ideas "that only [echo] their own views and beliefs," (Bojic, 2024, p. 104). Further, the scope of the algorithm's influence allows harmful content to spread globally, reaching vast audiences with little oversight. As Gao et al. (2022) note, this process creates filter bubbles that narrow the user experience and limit exposure to diverse or corrective information. Star's concept of reach highlights the sustained, far-reaching impact of TikTok's algorithm, which shapes user perceptions and behaviors in profound and lasting ways.

Being an active component in this narrative, TikTok's algorithm is examined in this study as an infrastructural system that guides the experience of the user, rather than functioning as a neutral tool. Given that recommender systems operate as "a relational property, not as a thing stripped of use" (Star, 1999, p. 380), it is essential to examine these technologies within the broader context of user engagement, institutional structures, and digital culture, to better understand how they propagate negative health messaging.

Research Question and Methods

The research question I am exploring is: *How does TikTok's recommendation algorithm shape young users' behaviors and exposure to negative health messaging, particularly in relation to diet culture?* An application brought to fame by its coveted recommendation algorithm, TikTok more than succeeds in delivering personalized content to users. Alongside leveraging vast amounts of data collected, the recommender systems employed by this platform are central to how content is delivered, giving them significant power in influencing adolescent perceptions and behavior (Smith, 2025). As numerous social media platforms attempt to mirror the algorithmic success of TikTok, it has become crucial to critically examine the systems responsible for this personalized content stream. By exploring how TikTok's algorithms dictate content exposure, it is possible to better understand how social media platforms influence user engagement with negative health messaging, particularly among vulnerable, young audiences.

To examine the evolving role of TikTok's recommendation algorithms in subjecting young users to harmful health-related content, I will conduct my analysis using a mixed-methods approach, drawing from the processes outlined by Anandhan et al. (2018). I will conduct a case analysis involving the creation of two separate TikTok accounts on my mobile device. The first account will serve as the control user and engage with a broad range of content, while the second will act as the test subject, actively seeking content related to dieting and fitness. Both accounts will interact with the posts and creators suggested by the platform. Over a 10-day period, I will track how TikTok's systems adjust its recommendations based on the engagement patterns of the two accounts, collecting information regarding the searched results and the content recommended by the #ForYou page. Daily, on both the control and test profiles, the following tasks will be completed:

1. Search five hashtags, as based upon each account's engagement patterns.
2. Like ten searched posts, as prompted by the searched hashtag.
3. Follow five creators, as prompted by the searched hashtag.
4. Interact with ten posts on the #ForYou page.

On each account's *Search* tab, I will enter a specific hashtag and like the top two recommended posts. For the control account, hashtags will be randomly generated to ensure diverse engagement and for the test account, they will reflect buzzwords related to harmful health messaging, focusing on dieting and fitness. Each hashtag will be searched once per account with no repeats across profiles. After liking the second post, I will follow its creator. This consistent engagement pattern enables a controlled comparison of algorithmic responses.

Daily, I will record the five hashtags searched and five creators followed per account, along with each creator's username, content type, follower count, and engagement metrics.

Over the 10-day period, the process of searching hashtags, liking posts, and following users will shape the #ForYou pages of each account. To compare the resultant differences between them, I have interacted with the first ten posts suggested to each account daily and tracked the subject matter of each video. Having compiled all relevant information, I additionally conducted a thematic content analysis of the posts displayed on each account's #ForYou feed. To simplify and standardize the posts previously recommended to each account, labels were defined and assigned to realize patterns between the amplitude of harmful messaging and user engagement patterns. This study explores how TikTok's algorithm curates content recommendations based on user interactions, aiming to assess the degree of autonomy young users have in shaping their digital experiences. By systematically tracking engagement patterns across two distinct accounts, this research investigates how TikTok's recommender system reinforces negative health messaging, potentially shaping young users' perceptions of body image and diet culture.[1]

Results: TikTok's Algorithmic Influence on Content Exposure

TikTok's recommendation algorithm plays a powerful and iterative role in shaping young users' engagement with health-related content, particularly in relation to diet culture and body image. The platform's recommender system quickly personalizes an account's content stream based on the initial interactions of the user, creating a feedback loop that reinforces exposure to specific themes over time. As a user engages with diet, fitness, and weight-loss-related content,

[1] Based on the described methods, all source code used to generate relevant figures is available at: https://github.com/bellaheintges/its-not-good-for-you

TikTok's algorithm amplifies these topics, fostering a homogeneous content landscape. This pattern of algorithmic reinforcement reflects key aspects of Star's (1999) infrastructural framework, particularly the system's embeddedness and capacity to operate invisibly until its consequences, such as the promotion of harmful health narratives, become visibly apparent.

Over the 10-day period, the test account's #ForYou page became progressively saturated with posts promoting caloric restriction, extreme dieting, and body transformation narratives. This content was continuously subjected to the test user in a manipulative manner, as the algorithm amplified posts disguising these negative practices as aspirational, or forms of self-improvement. In contrast, the control account maintained a more diverse mix of content. By the study's conclusion, the test account had been exposed to nine times more diet-focused and body-centric content than the control account, ultimately suggesting that TikTok's recommendation systems embed the productivity goals of the company, prioritizing user engagement rather than well-being. These findings indicate that the algorithm acts as infrastructure, invisibly funneling users into highly specific content silos based on early engagement patterns. This process exposes users to repetitive and harmful messaging, rather than moderating it. For young, impressionable users, this self-reinforcing cycle raises significant concerns, as the prevalence of negative content can contribute to disordered eating patterns, body dissatisfaction, and unhealthy relationships with food and exercise. The results of this study highlight the urgent need for greater transparency and accountability in social media recommendation systems to prevent the unintended amplification of harmful health perceptions.

Searched Interactions: Hashtags Browsed, Posts Liked, and Creators Followed

To begin, two new Gmail accounts were created to serve as the basis for separate TikTok profiles, as the platform requires contact information upon registration. Given TikTok's extensive and often opaque data collection practices—including access to phone numbers, search histories, and browsing activity—it was crucial to isolate each account from one another and from the researcher to minimize external influences and preserve validity (Fung, 2023; TikTok, 2025). Discovery permissions were disabled on both accounts during setup to further ensure separation. The accounts were named Jane Control (@janecontrol2010) and Jane Test (@janetest2010), each using the same open-source stock image as a profile photo (Figure 5).

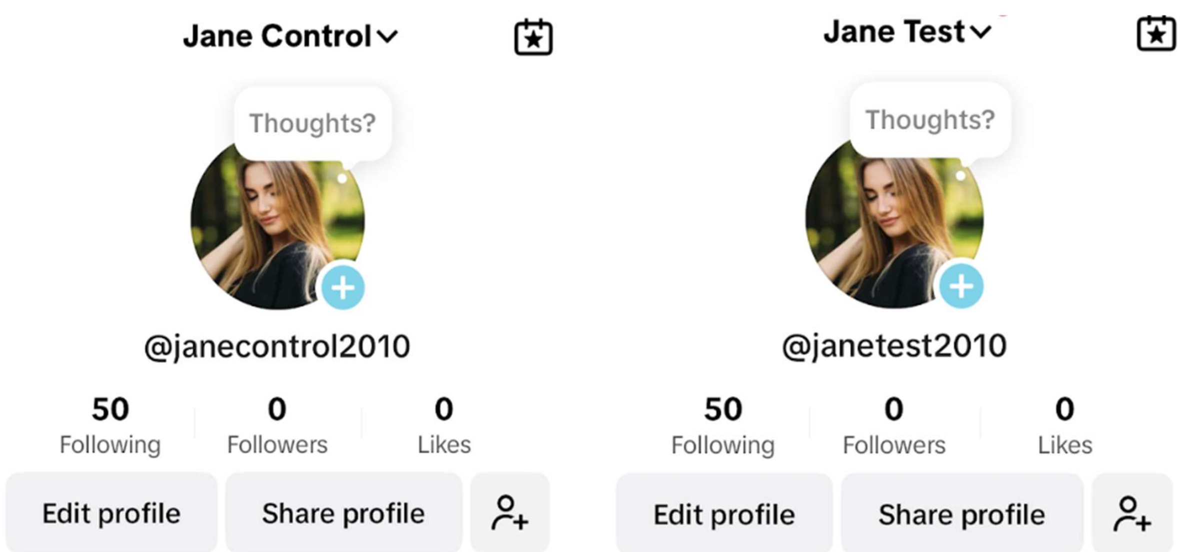

Figure 5. The control account TikTok user profile (@janecontrol2010) and test account TikTok user profile (@janetest2010).

Over the 10-day period, by searching varied keywords, the control account engaged with a broad range of topics and followed diverse creators spanning lifestyle, art, and general wellness influencers. Alternatively, by focusing its search on diet- and fitness-related hashtags, the test account primarily engaged with content centered on weight loss, dieting, fitness, and body aesthetics. Consequently, this variable account followed a more limited group of creators, with their corresponding platforms promoting narratives strictly aligned with these themes. Corresponding to the day of the study, information involving the hashtags searched and creators followed on each account was aggregated (see **Appendix A**). Further, to better understand how

TikTok returns content based on a user's search query, relevant information corresponding to all creators followed on both accounts was tabulated (see **Appendix B**).

Control Account Interactions. Given that the control account's queries were based upon randomly generated hashtags, the profiles followed by Jane Control covered a broad range of topics (see Table B1 in **Appendix B**). These creators posted material related to travel, nature, animals, DIY projects, art, and general entertainment. Notably, rather than being based on popularity, the accounts followed by Jane Control had significant variation in their engagement levels. Smaller creators followed by the control account had a mere 1,000 followers, while others reported a following over four million. Interestingly, while some of the more *'basic'* creators followed had amassed millions of likes, niche users that shared specialized content yielded lower engagement metrics. These differences in account visibility suggest that the profiles suggested to TikTok users are not solely based on their general popularity, but rather user compatibility, furthering the embeddedness of their function.

Test Account Interactions. Unlike Jane Control's exposure to a diverse range of content, Jane Test followed users that posted incredibly similar material, as her search queries were narrower in subject matter (see Table B2 in **Appendix B**). Unlike the control account, the test account primarily followed creators that posted material related to topics like weight loss, fitness, nutrition, and body image. Generally, this account only engaged with users that had a concentrated focus on certain health-related themes, unlike the diverse portfolio of followers associated with the control account. The limited scope of creators followed by Jane Test was expected, as the hashtags searched on the test account were based upon search criteria much narrower. Alongside similarities related to the material shared by each followed creator, many users analogously had substantial followings, with some amassing millions of followers and likes. Among these creators with higher popularity, many promoted content that was almost-identical, sharing posts encompassing dieting strategies, workout routines, and aesthetic-focused content. Interestingly, several of the popular creators followed by this test account emphasized extreme dieting methods that incorporated strict calorie restrictions, reinforcing the test account's consistent exposure to potentially harmful health messaging.

#ForYou Page Recommendations

The content that appeared on each account's #ForYou Page was closely tied to the various hashtags searched and corresponding creators followed. Disregarding the first day of the study—since user engagement had not yet influenced the content—both accounts each viewed 90 total posts on their corresponding #ForYou pages, totaling 180 unique videos. Of 21 identified themes in the content propagated, an overarching thematic keyword was subjectively assigned to each of the 180 posts, as based on an interpretation of the post's content. While it was possible for a video to span multiple thematic categories, each post was given a single assignment based on the dominant messaging observed. The frequency of each theme was then aggregated, and its percentage out of the total content viewed was calculated (see **Appendix C**).

Comparison of Recommended Content Themes. TikTok's algorithm recommended a diverse range of content to the control account, resulting in an even distribution across categories, see Figure 6. On the control account's #ForYou page, while posts related to beauty were viewed most frequently, no single category was overwhelmingly dominating. In contrast, the test account displayed a skewed distribution of content, interacting with a higher concentration of posts related to diet (20%) and fitness (12.22%). Posts related to vanity (10%) appeared five times more frequently than in the control account, reinforcing the body-focused narrative shaped by the hashtags searched. The unbalanced concentration of the content exposed to the test account highlights the algorithm's responsiveness to user engagement patterns. While it was the user responsible for demonstrating an initial interest in topics relating to diet and fitness, TikTok's algorithm actively propagated disproportionate content tied to these queries. This intensifying exposure raises concern regarding the system's nature to foster an unhealthy engagement style, as the algorithm amplifies content that encourages appearance-driven ideals (Figures 7 & 8).

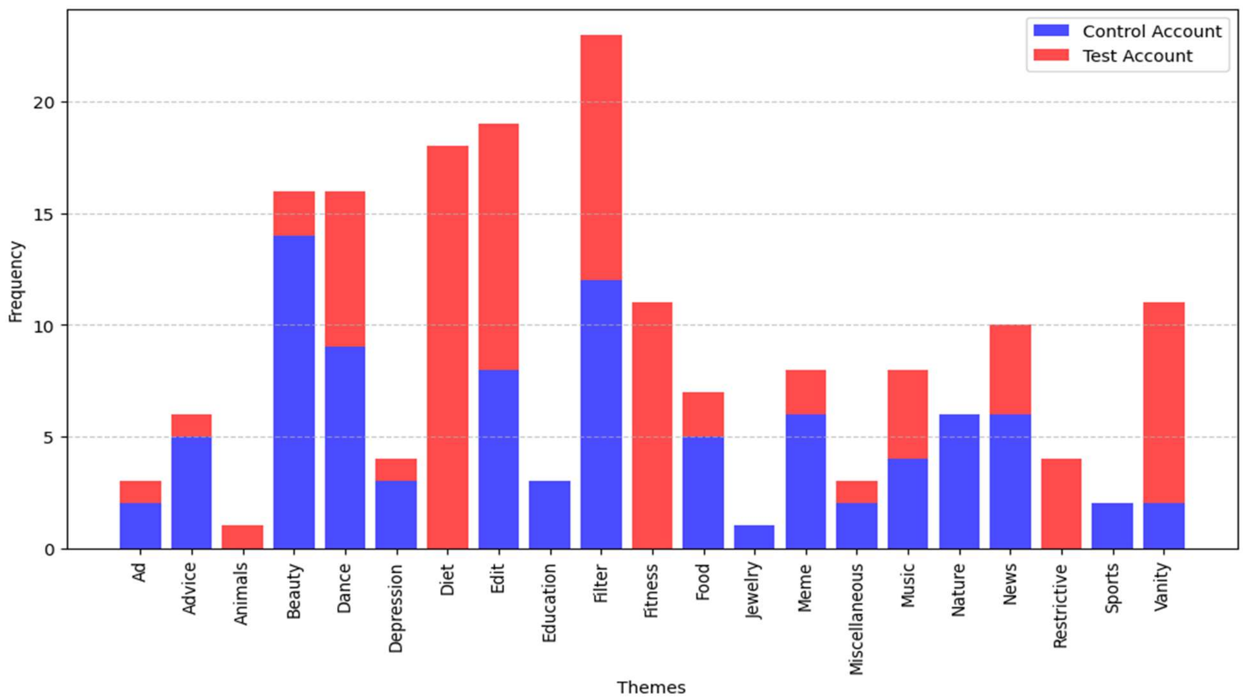

Figure 6. Frequency and distribution of themes in content recommended on each account's #ForYou page.

Recommended Content Over Time. This pattern of disproportional content recommendation becomes even more evident when examining how the accounts' exposure evolved over time. Over the 10-day period, a stark disparity emerged in the patterns associated with each account's exposure to negative health-related content. The control account experienced minimal fluctuations in the percentage of negative content viewed per day, remaining close to zero for much of the study (Figure 7). Conversely, the test account saw a sharp and sustained increase in exposure, with negative content responsible for 60% or more of daily viewed posts for the entire second half of the study.

Just as the daily percentages highlight the intensity of the negative themes recorded, Figure 8 further emphasizes the cumulative impact of this exposure. By the conclusion of the study, the test account had viewed 43 posts categorized as negative—essentially half of the 90 videos shown over the 10-day period. In contrast, the control account only documented five. This significant gap highlights how TikTok's recommendation algorithm invisibly reinforces harmful content over time, compounding the impact of early engagement patterns. The steady rise in the test account's cumulative exposure to negative, diet-related content suggests not just isolated algorithmic decisions, but a broader pattern of content reinforcement with an incredible scope.

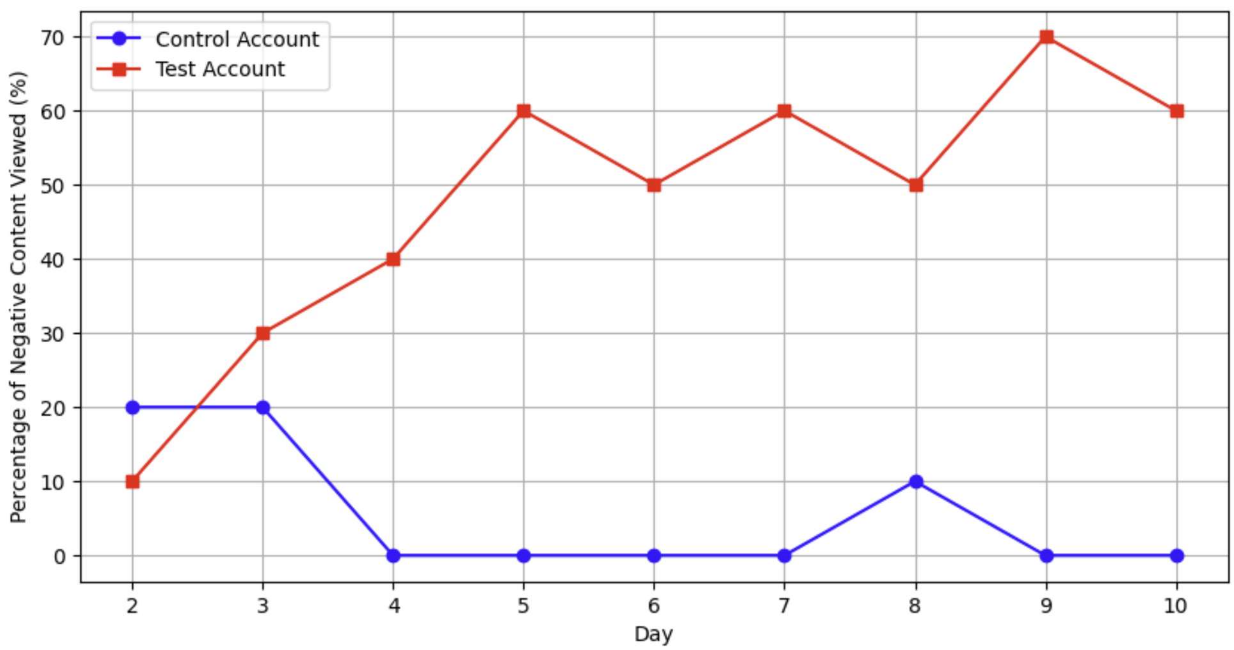

Figure 7. Percentage of negative content viewed per day across both accounts' #ForYou pages. Note: Posts categorized under the themes of fitness, diet, vanity, depression, and restriction were included as relevant criteria.

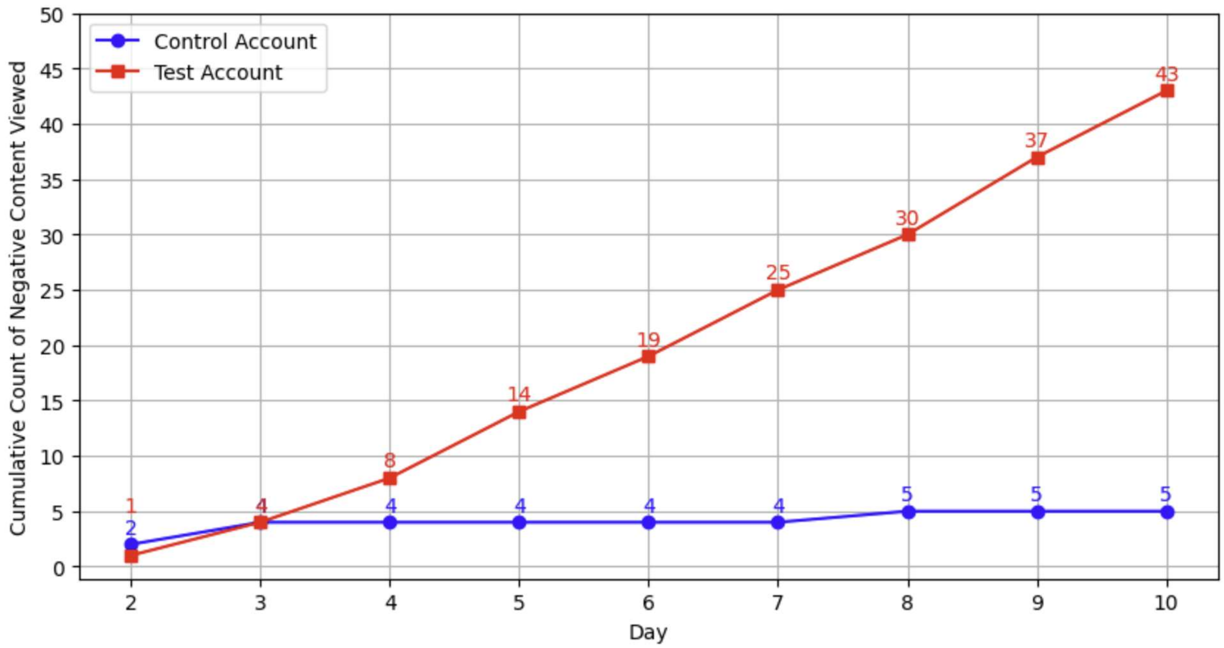

Figure 8. Cumulative negative content viewed over the 10-day period across both accounts' #ForYou pages. Note: Posts categorized under the themes of fitness, diet, vanity, depression, and restriction were included as relevant criteria.

While not all content categorized under fitness, diet, and vanity was explicitly negative, it collectively contributed to a narrative that could be unhealthy for adolescent viewers. For example, within the diet category, Jane Test frequently encountered content promoting recipes for weight loss. On Day 6, she viewed a post demonstrating how to make high-protein pancakes. Although a seemingly healthy recipe, the underlying concern is that children are engaging with content centered on weight loss. At the end of the same video, the creator emphasized the appeal of the recipe by noting that each pancake contained only around 45 calories. While the pancakes themselves may be nutritious, the implication that a 150-calorie breakfast is sufficient for young audiences is egregious and highlights the harm of this deceptive content.

Integrating Existing Research: Infrastructure and Adolescent Vulnerability

The findings of this study strongly align with existing literature on adolescent digital engagement, particularly in relation to algorithmic influence on health perception and body image. As Papageorgiou et al. (2022) highlight, it is the innate invisibility of social media recommendation algorithms that capitalize on the vulnerability of young audiences, as they aim to increase user engagement. The algorithm's once unforeseen role is made strikingly clear in the results of this study, as TikTok's algorithm actively subjected the test account to a narrowed stream of body- and diet-focused media (Figure 8). Gillespie (2018) considers this amplified feed to be a characteristic trait of engagement-based systems, as the recommendation systems embedded in social media platforms regularly prioritize emotional and behavioral engagement over user well-being.

As suggested by the findings of this research, the active nature of algorithms poses threat to adolescents on a broader scale. As individuals are unknowingly guided to interact with damaging health narratives, as seen in Jane Test's case, there exists a risk of increased body dissatisfaction and lowered self-esteem (Papageorgiou et al., 2022). On TikTok in particular, Conte et al. (2024) reported additional concerns, concluding that the exposure to certain content actively contributes to both increased psychological distress and negative self-comparisons among teenage users. In addition to fostering this negative behavior, Wiley et al. (2023) found that repeated exposure to appearance-focused content is associated with an increased risk of disordered eating habits. As Jane Test reported an increase in diet-focused content as the study progressed, it is reasonable to consider that an actual user would experience similar negative effects on their well-being. Through the infrastructural lens, by reinforcing idealized body standards and fostering self-comparison, TikTok's algorithm functions far beyond isolated interactions, encouraging problematic usage patterns, disordered eating behaviors, and the misinformed narrative of diet-culture.

Discussion

The findings of this study support existing theories of recommender system operation, while underscoring the negative impact content reinforcement has on adolescent well-being. The stark contrast in the content propagated on each #ForYou page further emphasizes the embeddedness of the invisible algorithm guiding TikTok's platform, serving as the infrastructure guiding user exposure to negative, health-related content. By reinforcing past engagement patterns, the recommendation system systematically narrows a user's digital environment, perpetuating a repetitive content stream that "shape(s) social and cultural formations and directly impact(s) individual lives" (Beer, 2009, p. 994). The results collected in this study highlight the structure of TikTok's algorithm, designed "to get people addicted," which has a great potential to foster an unhealthy digital environment for young users (Smith, 2021).

While this research presents notable information regarding the function of TikTok's algorithm in subjecting users to diet and body-related content, there exists several limitations. First, the short 10-day observation period limited the study's ability to assess long-term trends in the exposure of content. Since TikTok's algorithm continuously adapts its suggestions based on user interaction, a longer study could reveal whether the system's reinforcement of content intensifies, stabilizes, or diversifies over time. Additionally, this study relied on only two accounts, meaning that the effects of differing engagement styles could not be captured, nor their influence on content suggestion. Another limitation involves how account engagement was conducted, as user interactions were standardized and manually controlled to ensure consistency in the data collection process. Realistically, users organically navigate on social media platforms in a more sporadic manner. The scoring of suggested material would be further affected by these interaction patterns, whether scrolling passively or pointedly searching for content.

To improve this study, it is necessary to address the limitations observed, which would produce more realistic results. Extending the study duration beyond its original 10-day period would enable me to track the long-term algorithmic effects, in hope of better understanding algorithmic changes over time. In the same fashion, I would increase the number of test accounts and widen the ranges of engagement patterns, to gain a more comprehensive understanding of TikTok's algorithm. Aside from broadening the collection of platform-related data, to better develop an understanding of the user, I would conduct additional means of primary data collection. Surveys and interviews would provide more insight into user realities, and how they are influenced by TikTok's algorithm. Combining the case analysis results with this information would establish the relationship between the platform's algorithm and the user perspective. Enacting these changes in future research would improve my results, reflecting greater depth and reliability within my findings, while additionally exploring TikTok's influence from the user perspective.

This study highlights the powerful role of TikTok's recommendation algorithm in shaping online user environments, particularly in reinforcing diet and body-related narratives among young users. More broadly, these findings underscore the active nature of social media algorithms, as they shape how users engage with, interpret, and internalize health-related content. As young users unknowingly immerse themselves in an endless stream of appearance-driven material, the embeddedness of social media algorithms becomes increasingly concerning. This self-reinforcing cycle of amplifying content that promotes diet culture poses a significant threat to adolescents, especially as the reach of algorithmic influence transcends physical distances. Conducting this research has deepened my understanding of recommendation systems, particularly within the context of social media platforms. Overall, I now feel more informed about how my own interaction patterns influence the content I encounter online. With this in mind, to ensure user well-being, I plan to advocate for ethical design and transparency in algorithm development.

Conclusion

This study demonstrates that TikTok's recommendation algorithm does not passively reflect user interests but actively reinforces and narrows content exposure, particularly in ways that amplify harmful health messaging. This endless cycle of diet, fitness, and vanity-related content raises concerns about how algorithmic infrastructures shape adolescent perceptions of health. Moving forward, future research should explore the long-term effects of such exposure, demographic variations in algorithmic reinforcement, and potential interventions that promote content diversity to better understand the broader impact of these systems. These findings also highlight the need for social media platforms to implement safeguards within their recommender systems, such as transparency features, content diversity quotas, or user-controlled algorithmic settings, to reduce the amplification of potentially harmful content.

Ultimately, this research reveals an unsettling truth: not everything you view online is entirely within your control. On social media, it is impossible to determine the influence of recommendation algorithms, making it necessary to remain aware of the systems shaping your online experience. To curate a less intensified feed and reduce the likelihood of reinforcing harmful content, I would suggest consciously engaging with a wide range of topics and perspectives. With these systems increasingly integrated in countless aspects of daily life, it is crucial to safeguard user mental and physical well-being.

References

Aaweg, I. (2024, March 16). *Recommender Systems: Collaborative Filtering and Content-Based Filtering*. Medium. https://ogre51.medium.com/recommender-systems-collaborative-filtering-and-content-based-filtering-20785d50d56f

AIPanelHub. (2024, December 2). *User Autonomy in AI: Key Challenges*. https://www.aipanelhub.com/post/user-autonomy-in-ai-key-challenges

Anandhan, A., Shuib, L., Ismail, M. A., & Mujtaba, G. (2018). Social Media Recommender Systems: Review and Open Research Issues. *IEEE Access, 6,* 15608–15628. https://doi.org/10.1109/access.2018.2810062

Backlinko. (2025, January 23). *TikTok Statistics You Need to Know*. https://backlinko.com/tiktok-users

Beer, D. (2009). Power through the algorithm? Participatory web cultures and the technological unconscious. *New Media & Society, 11*(6), 985–1002.

Bergman, M. (2025, January 3). *Social Media's impact on eating disorders in children and teens*. Social Media Victims Law Center. https://socialmediavictims.org/mental-health/eating-disorders/

Bernstein, M., Christin, A., Hancock, J., Hashimoto, T., Jia, C., Lam, M., Meister, N., Persily, N., Piccardi, T., Saveski, M., Tsai, J., Ugander, J., & Xu, C. (2023). Embedding Societal Values into Social Media Algorithms. *Journal of Online Trust and Safety*, *2*(1). https://doi.org/10.54501/jots.v2i1.148

Bojic, L. (2024). AI alignment: Assessing the global impact of recommender systems. *Futures*, *160*, 103383. ScienceDirect. https://doi.org/10.1016/j.futures.2024.103383

Burke, R., Felfernig, A., & Göker, M. H. (2011). Recommender Systems: An Overview. *AI Magazine, 32*(3), 14. https://doi.org/10.1609/aimag.v32i3.2361

Conte, G., Iorio, G.D., Esposito, D., et al. (2024, October 16). Scrolling through adolescence: a systematic review of the impact of TikTok on adolescent mental health. *European Child & Adolescent Psychiatry.* https://doi.org/10.1007/s00787-024-02581-w

Cotter, K. (2021). "Shadowbanning is not a thing": black box gaslighting and the power to independently know and credibly critique algorithms. *Information, Communication & Society, 26*. 1-18. 10.1080/1369118X.2021.1994624.

Cuello, F. (2024, August 14). *Why machine learning models are black boxes*. TrendSpider Learning Center. https://trendspider.com/learning-center/why-machine-learning-models-are-black-boxes/

Daryanani, A. (2021, January 28). *"Diet culture" & social media*. UCSD Recreation. https://recreation.ucsd.edu/2021/01/diet-culture-social-media/

de Valle, M. K., Gallego-García, M., Williamson, P., & Wade, T. D. (2021). Social media, body image, and the question of causation: Meta-analyses of experimental and longitudinal evidence. *Body Image*, *39*, 276–292. https://doi.org/10.1016/j.bodyim.2021.10.001

Duarte, F. (2025, February 24). *Average time spent on TikTok statistics (2024)*. Exploding Topics. https://explodingtopics.com/blog/time-spent-on-tiktok

D'Souza, D. (2025, January 20). *TikTok: What it is, how it works, and why it's popular*. Investopedia. https://www.investopedia.com/what-is-tiktok-4588933

Dou, Y., Yang, H., Deng, X. (2016). A Survey of Collaborative Filtering Algorithms for Social Recommender Systems. *2016 12th International Conference on Semantics, Knowledge and Grids (SKG)*, 40-46, https://doi.org/10.1109/SKG.2016.014

Dragan, R. (2016, March 23). What Steve Jobs Taught Me About Customer Feedback. *Medium.* https://medium.com/learn-ium/what-steve-jobs-taught-me-about-customer-feedback-8f7e982505a6

Fardouly, J. & Vartanian, L.R. (2016). Social media and body image concerns: Current research and future directions. *Current Opinion in Psychology, 9*, 1-5. https://doi.org/10.1016/j.copsyc. 2015.09.005

Fung, B. (2023, March 24). *TikTok collects a lot of data. but that's not the main reason officials say it's a security risk.* CNN. https://www.cnn.com/2023/03/24/tech/tiktok-ban-national-security-hearing/index.html

Gao, R., Shah, D., & Hube, C. (2022). *Algorithmic curation and echo chambers: How recommendation systems reinforce user preferences.* Journal of Digital Media & Society, 8(3), 423.

GeeksforGeeks. (2024, September 3). *Recommendation system in Python*. https://www.geeksforgeeks.org/recommendation-system-in-python/

Gillespie, T. (2018). Custodians of the Internet: Platforms, Content Moderation, and the Hidden Decisions That Shape Social Media. *Yale University Press.* 10.12987/9780300235029.

Giragosian, L. (2024, February 26). *Reducing the impact of eating disorders on adolescent girls*. ASTHO. https://www.astho.org/communications/blog/reducing-the-impact-of-eating-disorders-on-adolescent-girls/

Golino, M. (2021, April 24). *Algorithms in Social Media Platforms*. Institute for Internet & the Just Society. https://www.internetjustsociety.org/algorithms-in-social-media-platforms

Hossain, I., Palash, M., Sejuty, A., Tanjim, N., Nasim, M., Saif, S., Suraj, A. (2022). A Survey of Recommender System Techniques and the Ecommerce Domain. *Front.Comput.Sci.* http://dx.doi.org/10.48550/arXiv.2208.07399

Maruti Techlabs. (2021, August 17). *What are the types of recommendation systems*. Medium. https://marutitech.medium.com/what-are-the-types-of-recommendation-systems-3487cbafa7c9

Mercado, M. (2021, July 22). *So this is how TikTok knows so much about you*. The Cut. https://www.thecut.com/2021/07/tiktok-algorithm-knows-me.html

Merriam-Webster. Infrastructure. In *Merriam-Webster.com dictionary*. Retrieved March 20, 2025, from https://www.merriam-webster.com/dictionary/infrastructure

Morris, A. M., & Katzman, D. K. (2003). The impact of the media on eating disorders in children and adolescents. *Pediatrics & child health*, *8*(5), 287–289. https://doi.org/10.1093/pch/8.5.287

Murel, J., & Kavlakoglu, E. (2024, December 19). *What is content-based filtering?*. IBM. https://www.ibm.com/think/topics/content-based-filtering

Narayanan, A. (2023, March 9). *Understanding Social Media Recommendation Algorithms*. Knight First Amendment Institute. https://knightcolumbia.org/content/understanding-social-media-recommendation-algorithms

National Alliance for Eating Disorders. (2023, July 27). *The surprising history of Diet Culture*. https://www.allianceforeatingdisorders.com/the-surprising-history-of-diet-culture/?gad_source=1&gclid=Cj0KCQjwhr6_BhD4ARIsAH1YdjDxyZKzTx04kjJpRWyqqpB4YeT-WIZ_R2lq3R4r4CsRjpasMK39wqYaAk7MEALw_wcB

Ni, J., Cai, Y., Tang, G., Xie, Y. (2021, October). Collaborative Filtering Recommendation Algorithm Based on TF-IDF and User Characteristics. *Applied Sciences, 11(20),* 9554. http://dx.doi.org/10.3390/app11209554

Nunes, M. (2024). Chapter 11: Algorithmic Agency, Automated Content, and User Engagement on TikTok. *The De Gruyter Handbook of Automated Futures: Imaginaries, Interactions and Impact*, 175-190. https://doi.org/10.1515/9783110792256-011

NVIDIA. (2025). *Recommendation System.* https://www.nvidia.com/en-us/glossary/recommendation-system/

Papageorgiou, A., Fisher, C., Cross, D. (2022, June 27). "Why don't I look like her?" How adolescent girls view social media and its connection to body image. *BMC Women's Health, 22(261).* https://doi.org/10.1186/s12905-022-01845-4

Raiter, N., Husnudinov, R., Mazza, K., & Lamarche, L. (2023). TikTok promotes diet culture and negative body image rhetoric: A content analysis. *Journal of Nutrition Education and Behavior*, *55*(10), 755–760. https://doi.org/10.1016/j.jneb.2023.08.001

Schafer, J. B., Frankowski, D., Herlocker, J., & Sen, S. (2007). Collaborative Filtering Recommender Systems. *The Adaptive Web, 4321,* 291–324. https://doi.org/10.1007/978-3- 540- 72079-9_9

Smith, B. (2021, December 5). *How TikTok Reads Your Mind*. The New York Times. https://www.nytimes.com/2021/12/05/business/media/tiktok-algorithm.html

Sousa, M. (2024, November 15). *Oops, I gave my algorithm an eating disorder.* Fashion Journal. https://fashionjournal.com.au/health/social-algorithm-eating-disorder/

Star, S. L. (1999). The Ethnography of Infrastructure. *American Behavioral Scientist, 43(3),* 377–391. https://doi.org/doi/10.1177/00027649921955326

Strickland, S. R. (2024). *TikTok and Eating Disorders: Delineating Directional Associations Between "What I Eat in a Day" Videos and Disordered Eating.* https://repository.lib.fsu.edu/islandora/object/fsu:911244

TikTok. (2025a). *Getting Started – For You.* https://support.tiktok.com/en/getting-started/for-you

TikTok. (2025b). *Privacy Policy*. https://www.tiktok.com/legal/page/us/privacy-policy/en

TrulyDigital Media. (2024, May 2). *The Algorithm Behind TikTok: How It Works and Why It's So Addictive.* Medium. https://medium.com/@trulydigitalmedia/the-algorithm-behind-tiktok-how-it-works-and-why-its-so-addictive-51b956eaab25#:~:text=TikTok%20uses%20 collaborative%20filtering%20to,one%20user%20to%20the%20other

U.S. Department of Health and Human Services, Office of the Surgeon General. (2023). *Social media and youth mental health: The U.S. Surgeon General's advisory*. https://www.ncbi.nlm.nih.gov/books/NBK594759/

Wallaroo. (2024, May 7). *Tiktok statistics – everything you need to know.* https://wallaroomedia.com/blog/social-media/tiktok-statistics/#:~:text=The%20percentage%20of%20U.S.%2Dbased,All%20data%20via%20Comscore.

Wiley et al. (2023). Social media and body image: The role of appearance-ideal content in disordered eating behaviors. *International Journal of Eating Disorders, 56*(2), 241-257.

Zhou, R. (2024). Understanding the Impact of TikTok's Recommendation Algorithm on User Engagement. *International Journal of Computer Science and Information Technology*, *3*(2), 201-208. https://doi.org/10.62051/ijcsit.v3n2.24

Appendix A

Day	Hashtag Searched	Creator Followed	Day	Hashtag Searched	Creator Followed
1	#friends	ernieqfish	1	#keto	organicallyaddison
	#love	darxycracra		#vegan	dr.vegann
	#mushrooms	vivispamm_0		#abs	veganchefmaya
	#ocean	physicians_formula		#lowcalorie	nobodyknowsmereally.vent
	#water	serenebloomm		#sugarfree	bruh_justhot
2	#robot	trendy_viewz	2	#skinny	helptoweightloss
	#spectrum	saranne_wrap		#lowcarb	lowcarblove
	#lung	instituteofhumananatomy		#water	johnderting
	#ball	charitymermaidpirate		#eggwhites	scaseyfitness
	#star	elysianescape		#trainer	blankitacisneros
3	#monopoly	amarynax_	3	#nutrition	stephgrassodietitian
	#animals	thefeatheryflock		#macros	bart.wgsd
	#laser	guinutil		#portioncontrol	petecataldo
	#vision	sicr3t.acc0unt		#healthy	appleuser3995580
	#circle	andrewivx2.0		#BMI	dr.tommymartin
4	#respect	silviogabriel77	4	#wl	kiraswldiary_
	#grow	wavyy.bvby		#plant-based	shakaylafelice
	#queen	user381929201		#protein	dr.rachelpaul
	#drill	stxmx		#binge	dr.kojosarfo
	#grill	grillz.queen		#detox	mamaaronn
5	#mosaic	theartrevival	5	#exercise	channy.fit
	#happy	isla.moonadevntures		#workout	l.ssvnrise
	#frog	pampermoony		#caloriecounting	ericrobertsfitness
	#scrapbook	taylortysenn		#BMR	rachel.steward.fitness
	#snowman	wrizzposts69		#body	forgedbyfit
6	#flicker	.im_n0t_a_pers0n	6	#mindfuleating	cnpfitness_
	#orbit	littlepoisontree		#yoyodiet	findfoodfreedom
	#velvet	modernbymb		#zerocalorie	nickrosenski
	#lipstick	briohni		#thin	slavicglan
	#paint	messybynature2025		#scale	emma.currivan
7	#money	linkyanime	7	#thigh	patrickhongfit
	#respect	are.you.okay.15		#highcardio	thewodfather
	#cherry	azziyaaa_		#hourglassfigure	heloomelloo
	#pickle	cookiterica		#loseweight	iampeachye1
	#soccer	sporf		#bodyfat	skydoesfitness
8	#real	e.l_083848	8	#fatburn	ray2fitness
	#necklace	theholynecklace		#fasting	i.f_fitness
	#pig	_gabeybabey		#lean	iamnotrealbleat
	#lipstick	mydlvz1		#shredded	thebuffunicorn
	#jupiter	astrospaceq		#caloriedeficit	dikarter
9	#gingerbread	themainstreetduo	9	#mealprep	meeraefirkins
	#hat	rancherhatstore		#fitbod	ugcwithkaytelynn
	#ball	soccer_5711		#fastmetabolism	nutrition.corner_
	#witch	empathvibez		#thinarms	fine..fashion2
	#penguin	whitecatt03		#under100cal	jessicaplayfair
10	#money	tealoes2up	10	#skinnylegend	millyondollargirl
	#apple	apple.mood		#restricting	hannahholthealth
	#computer	wzzqo		#lowfat	sororitynutritionist
	#geography	jordan_the_stallion8		#cuttingcals	rumorzachariaa
	#ring	getrealwithalix		#fatloss	fitnfineewithpenelope

Appendix A. Hashtags searched on the control account (left) and test account (right), along with the corresponding creators followed.

Appendix B

Table B1.

Information Regarding the Creators Followed by the Control Account

Day	Creator Followed	# of Followers	# of Likes	Creator Content
1	ernieqfish	2025	22200	Travel-related, fishing, hiking
	darxycracra	285	60600	Various
	vivispamm_0	N/A	345000	Various
	physicians_formula	45900	157100	Makeup products, brand page
	serenebloomm	41800	7600000	Sunsets, beaches
2	trendy_viewz	719500	47000000	Popular content/news
	saranne_wrap	305000	15000000	Various
	instituteofhumananatomy	10700000	113800000	Information about the body
	charitymermaidpirate	86000	2200000	DIY crafts and tutorials
	elysianescape	115000	6400000	Edits of stars, space, sky
3	amarynax_	3833	1300000	Various
	thefeatheryflock	332	8773	Pet bird videos
	guinutil	1800000	49400000	Scary edits
	sicr3t.acc0unt	66	9563	Love edits/manifestation
	andrewivx2.0	4300000	120700000	How to...
4	silviogabriel77	1900000	94400000	Various edits
	wavyy.bvby	671700	13200000	Various
	user381929201	19900	8400000	Aesthetic edits
	stxmx	17700	912300	Drill dancing videos
	grillz.queen	496500	23000000	Grillz/jewelry making
5	theartrevival	144700	18700000	Arts over time
	isla.moonadevntures	1800000	34400000	Passion for nature
	pampermoony	732400	19300000	Famous frog account
	taylortysenn	284	2487	Scrapbooking
	wrizzposts69	66800	3000000	Meme account
6	.im_n0t_a_pers0n	795	37300	Gaming edits
	littlepoisontree	228	55800	Various edits
	modernbymb	220100	3600000	Fashion brand
	briohni	68000	9600000	Makeup reviews
	messybynature2025	1637	39600	Acrylic painting
7	linkyanime	8699	43600	Random edits
	are.you.okay.15	498600	39600000	Random edits
	azziyaaa_	98600	5400000	Random ideas
	cookiterica	3200000	146800000	Cooking recipes
	sporf	851400	28700000	Viral home-sports vids
8	e.l_083848	27600	4600000	Edits/memes
	theholynecklace	52500	2000000	Christian jewelry brand
	_gabeybabey	851200	56400000	Pet pig account
	mydlvz1	24600	3500000	Mom lifestyle account
	astrospaceq	4000000	197900000	Space edits
9	themainstreetduo	114100	26700000	Couple on Disney adventures
	rancherhatstore	103800	1300000	Hat store in TX
	soccer_5711	14800	924200	Homemade soccer vids
	empathvibez	9550	21000	Eclectic witch
	whitecatt03	90800	15800000	Animal videos/facts
10	tealoes2up	117400	3700000	Money edits
	apple.mood	44600	1600000	Apple tech. products promo
	wzzqo	7118	1100000	Meme/random edit posts
	jordan_the_stallion8	13900000	630500000	Advice/speaking to camera
	getrealwithalix	3838	320600	Fashion, health, wellness

Note. The creators listed above correspond to those on the left side of Appendix A, based on the hashtags previously searched.

Table B2.

Information Regarding the Creators Followed by the Test Account

Day	Creator Followed	# of Followers	# of Likes	Creator Content
1	organicallyaddison	80300	3100000	Nutrition & recipes
	dr.vegann	43600	7500000	Vegan health
	veganchefmaya	71200	49500	Healthy cooking
	nobodyknowsmereally.vent	N/A	N/A	Dieting & weight loss
	bruh_justhot	7019	619100	Fitness motivation
2	helptoweightloss	9491	464200	Weight loss tips
	lowcarblove	2000000	23000000	Low-carb diet
	johnderting	4600000	110600000	Nature & travel
	scaseyfitness	2800000	28400000	Fitness & health
	blankitacisneros	64600	2700000	Personal training
3	stephgrassodietitian	2200000	33900000	Dietitian advice
	bart.wgsd	12100	124200	Workout tips
	petecataldo	750	14200	Health coaching
	appleuser3995580	88	59	General fitness
	dr.tommymartin	2500000	53800000	Doctor insights
4	kiraswldiary_	1551	91000	Weight loss journey
	shakaylafelice	164400	3200000	Plant-based lifestyle
	dr.rachelpaul	688700	8400000	Nutrition science
	dr.kojosarfo	2500000	73400000	Mental health & well-being
	mamaaronn	11100	674500	Detox & cleanse
5	channy.fit	251300	4400000	Strength training
	l.ssvnrise	11400	377700	Bodybuilding
	ericrobertsfitness	1500000	39200000	Fitness motivation
	rachel.steward.fitness	259900	5900000	Workout routines
	forgedbyfit	8882	19800	Body transformation
6	cnpfitness_	N/A	N/A	Food freedom
	findfoodfreedom	672900	7500000	Mindful eating
	nickrosenski	234000	23700000	Zero-calorie foods
	slavicglan	779	37800	Thinspiration
	emma.currivan	21000	523100	Weight management
7	patrickhongfit	245000	4100000	Personal fitness
	thewodfather	331	3561	CrossFit training
	heloomelloo	492900	20800000	Beauty & body trends
	iampeachye1	1500000	70000000	Weight loss journey
	skydoesfitness	853900	13900000	Muscle building
8	ray2fitness	38400	1300000	Fat burning
	i.f_fitness	12100	83000	Intermittent fasting
	iamnotrealbleat	34500	1500000	Caloric deficit
	thebuffunicorn	502600	28700000	Strength & conditioning
	dikarter	188	802	Extreme dieting
9	meeraefirkins	330	1457	Meal prepping
	ugcwithkaytelynn	3518	81800	Body toning
	nutrition.corner_	10400	161400	Healthy lifestyle
	fine..fashion2	148500	9600000	Fashion & aesthetics
	jessicaplayfair	21500	1000000	Weight loss myths
10	millyondollargirl	38100	1000000	Slimming techniques
	hannahholthealth	45500	2000000	Restrictive dieting
	sororitynutritionist	391600	8300000	Caloric control
	rumorzachariaa	136000	4700000	Cutting phase
	fitnfineewithpenelope	443300	2800000	Fitness & wellness

Note. The creators listed above correspond to those on the right side of Appendix A, based on the hashtags previously searched.

Appendix C

Theme	Control #ForYou		Test #ForYou	
	Count	% of Content	Count	% of Content
Ad	2	2.22%	1	1.11%
Advice	5	5.56%	1	1.11%
Animals	0	0.00%	1	1.11%
Beauty	14	15.56%	2	2.22%
Dance	9	10.00%	7	7.78%
Depression	3	3.33%	1	1.11%
Diet	0	0.00%	18	20.00%
Edit	8	8.89%	11	12.22%
Education	3	3.33%	0	0.00%
Filter	12	13.33%	11	12.22%
Fitness	0	0.00%	11	12.22%
Food	5	5.56%	2	2.22%
Jewelry	1	1.11%	0	0.00%
Meme	6	6.67%	2	2.22%
Miscellaneous	2	2.22%	1	1.11%
Music	4	4.44%	4	4.44%
Nature	6	6.67%	0	0.00%
News	6	6.67%	4	4.44%
Restrictive	0	0.00%	4	4.44%
Sports	2	2.22%	0	0.00%
Vanity	2	2.22%	9	10.00%
Total	**90**		**90**	

Appendix C. Overall theme distribution in the content viewed on each account's #ForYou page. Note: For each account, *the % of Content* statistic was calculated by taking the theme's total *Count* and dividing by 90—the total number of recommended posts viewed per account.