Impact of Tik Tok on Society

Examing How Gender Affects Social Media Use on TikTok & Overcoming Data Collection Barriers with a Focus on Gender, eating Disorders, and Conspiracy

Progress Report 3

December 6th, 2024

Marie Check (261091388)

Max-Henri Chanut (261036357)

Greta Zu (261099681)

Adele Khiiarova (261133165)

Abstract

Our study investigates the influence of TikTok's search functionality on the recommendations presented on its ”For You Page” (FYP), with a focus on sensitive topics such as eating disorders, conspiracy theories, and gender. To address limitations of prior research, we designed a novel methodology involving targeted bots, custom algorithms, and user surveys to evaluate the relationship between search inputs and FYP recommendations. Our analysis centers on key metrics, including the prevalence of hashtags, creators, and tags of interest from the search phase in FYP content.

The results reveal that hashtags used during searches moderately influence FYP content, with 46% of FYP videos containing hashtags from search results. However, this influence is heavily topic-dependent, and our findings do not support the hypothesis that TikTok's algorithm creates silos of negative content. Notably, creators identified in the search phase have negligible impact on FYP recommendations, suggesting that hashtags are the primary linking mechanism.

We also uncover an alarming ease with which users can access harmful content through minimal search manipulation, such as misspelling banned keywords. While this study does not establish a causal link between exposure to negative content and FYP recommendations, it highlights TikTok's limited content moderation in search results. These findings underscore the platform's potential for both positive engagement and harm, emphasizing the need for improved filtering mechanisms and stricter algorithmic governance to safeguard users, particularly in sensitive contexts.

This report concludes with recommendations for further research on the psychological and societal impact of exposure to harmful content and strategies to enhance the transparency and accountability of TikTok's recommendation system.

1 Introduction

1.1 Motivation

Nowadays, social media platforms like TikTok play an increasingly prominent role in shaping cultural norms, influencing behaviors, and spreading information. However, these platforms are also susceptible to promoting harmful content or amplifying sensitive topics in certain ways. Previous studies have shown that social media algorithms can exacerbate body image issues, perpetuate gender stereotypes, and fuel conspiracy theories (Bivens, Rena et al. 2016; Enders, A. M. et al, 2021; Santarossa, S. et al, 2017). The study of TikTok's recommendation system is particularly relevant in understanding its influence on societal issues such as *eating disorders*, *gender perceptions*, and *conspiracy theories* (Maes, C., Vandenbosch, L., 2022).

Our motivation comes from the desire to investigate how TikTok's recommendation system might contribute to these societal impacts. Specifically, we aim to:

- Understand whether TikTok's algorithm reinforces or amplifies user engagement with sensitive or controversial topics.
- Explore the correlation between user interactions with specific content and the algorithm's recommendations on the *For You Page (FYP)*.
- Address the ethical and societal implications of algorithm-driven content recommendations.

This project is inspired by the broader need to ensure accountability in algorithmic systems (Reviglio, U., Agosti, C., 2020), particularly as they relate to public health, misinformation, and social equity. Our approach not only seeks to improve the understanding of TikTok's algorithm but also to provide a framework for analyzing other recommendation systems with similar societal concerns.

1.2 Previous work

Our project builds on prior efforts of students to analyze TikTok's recommendation algorithm. The previous team developed a scraping framework that combined bots with an algorithm to prioritize watching videos related to specific topics of interest. Their algorithm, informed by survey responses, was designed to focus on videos matching predefined themes, such as eating disorders, gender issues, and conspiracy theories.

Despite these efforts, their work faced significant obstacles. Their bots analyzed each video in real-time to determine its relevance, but this approach ultimately altered the TikTok algorithm's behavior. Instead of focusing on the target topics, TikTok began recommending a wide variety of unrelated content. Consequently, the data collected was inconsistent and insufficient for understanding the platform's recommendation patterns in relation to sensitive topics.

The previous team's work highlighted key challenges:

- The inability to efficiently target and collect data relevant to the predefined topics without algorithmic interference.
- Difficulty in isolating specific patterns in TikTok's recommendations due to the broadening of suggested content.

By recognizing these limitations, we wanted to design an improved data collection strategy. Our approach focuses on pre-specified topics via search-based methods, with bots specialized in a specific topic. This allows for more targeted and reliable data to assess correlations between watched and recommended content.

2 Project description

2.1 Survey

To inform and refine our approach, we conducted a survey that gathered 107 responses, primarily from individuals aged 18 to 24 (90%). The survey was designed to gather insights into TikTok usage patterns, content preferences, and user behavior, all of which were integral to shaping our algorithm and methodology.

One of the key objectives of the survey was to understand how users interact with TikTok videos. Respondents were asked how often they engage with videos by liking, saving, commenting, following creators, or refreshing the page. The results revealed that liking and saving were the most common forms of interaction, with 51.9% and 25.7% of users, respectively, indicating these behaviors. Commenting, following, and refreshing videos were significantly less frequent. Based on these findings, we decided to incorporate liking and saving interactions into our algorithm, rounding the probabilities to 50% and 25% respectively, to simulate realistic user behavior in our bots.

The survey also highlighted the types of content most popular among users. Categories such as *music*, *food*, and *memes* emerged as the most frequently viewed topics. However, to maintain focus on our research objectives, we prioritized the topics of *eating disorders*, *gender issues*, and *conspiracy theories*. These topics were specifically chosen for their societal relevance and potential to uncover the algorithmic behaviors surrounding sensitive content.

When asked about their usage of TikTok's features, respondents majoritarily identified the *For You Page (FYP)* as the most utilized page, followed by the *Search Page*. Other pages such as *profile*, *inbox*, and *following* were deemed negligible. This insight directly influenced our data collection strategy, where our bots were programmed to first explore the *Search Page* to collect topic-specific videos before moving to the *FYP* to analyze recommendations.

Another noteworthy finding was that 60% of respondents reported encountering political content on TikTok, and 64% of them believed that this content aligned strongly with their personal beliefs. This finding underscored the need to understand how TikTok's algorithm reinforces user-specific content preferences, an area our project sought to address through analyzing the recommendation patterns.

The survey also collected recommendations for creators associated with our topics of interest (*eating disorders*, *gender issues*, and *conspiracy theories*). While this data was valuable, we opted not to add it into our bot's algorithm. Searching for creators often yielded a narrower range of videos compared to using hashtags, which provided a broader and more diverse dataset. As a result, our bots searched for hashtags over creator names to identify relevant content.

The insights gained from the survey were very important in choosing our methodology. The emphasis on liking and saving behaviors ensured our bots mimicked typical user interactions, enhancing the reliability of our data. Similarly, prioritizing the *Search Page* and *FYP* aligned with user preferences, maximizing the relevance of collected data. By focusing on hashtags rather than creators, we achieved a broader sampling of videos, allowing for a more comprehensive analysis of TikTok's recommendation algorithm.

2.2 Bots

Since the previous team had already created many bot accounts, we simply took a few from the previous *bots.json* list of accounts, double checked that the accounts were still active, and put them into a new *bots_working.json* file. Our experiments were conducted on this smaller pool of bots, where we also renamed them according to their purposes: *bot_conspiracies_neutral, bot_gender_positive, bot_gender_negative, bot_eating_positive, bot_eating_negative.*

As explained in the previous section, we chose to stop focusing on well-known creators for the topics of interest. Instead, we implemented *non-tags* to filter out irrelevant or ambiguous content. These *non-tags* were created by using the tags of the bot with the opposite sentiment. For example, if the bot was looking for videos that were positive in terms of eating, the *non-tags* were derived from the negative sentiment bot's tags, such as "foodforweightloss". This approach ensured that videos tagged with sentiments contrary to the intended focus of the bot were skipped. This decision was made when we observed that creators occasionally used opposing tags, like "anorexia," to discuss how to avoid the eating disorder. In the context of our experiment, we wanted to avoid collecting videos with positive explanations for anorexia under "negative eating videos" and vice versa.

Our selection criteria for the tags were based on a combination of research for commonly used TikTok tags related to our topics of interest and a manual review of TikTok videos.

For eating disorders, the approach differed for positive and negative tags. For positive tags, we primarily conducted manual searches on TikTok, observing the type of videos associated with various tags and selecting three tags that yielded the most positive and unambiguous results. For negative tags, we relied on common trends and techniques observed on TikTok: a popular negative trend (*eatthisnotthat*), a frequently used negative keyword (*weightloss*), and a technique to bypass TikTok's moderation (*howtogeteatingdisode*—a misspelled version of "how to get an eating disorder") (*Bringing light to the dark side of TikTok's algorithm*, n.d.). This methodology ensured the tags were both relevant and aligned with the intended sentiment of each bot.

For gender, the approach to finding positive tags informed the negative tags and vice versa. For positive tags, we manually searched on TikTok for tags that we believed produce positive content. For example *feminism*, although related to a positive concept did not always yield positive videos. Searching for the tag *feminism* would produce a mixture of results both for and against the concept. Some tags commonly written on videos that came up were *womenempowerment* (an overwhelmingly positive tag) and also *alphamale* (an overwhelmingly negative tag). On the opposite side, searching for *toxicmasculinity*, a tag thought to produce negative results, would yield videos with tags such as *toxicmasculinitydoesntexist* (an overwhelmingly negative tag) and *mensmentalhealthmatters* (an overwhelmingly positive tag). This methodology ensured that the videos associated with the positive and negative bots' hashtags would be overwhelmingly positive and negative, respectfully.

For the conspiracy topic, our approach was different. Because the idea of "positive conpiracies" and "negative conspiracies" are extremely vague and hard to define, we simply chose 3 topics which often have conspiracies around them.

The following tables shows the tags we used for each bot, demonstrating the tags as well as the non-tags:

Bots	**Tags**	**Non-Tags**
`bot_conspiracies_neutral`	"sports conspiracy", "political conspiracy", "celebrity conspiracy"	NA
`bot_gender_positive`	"womenempowerment", "genderequality", "mensmentalhealthmatters"	"toxicmasculinitydoesntexist", "alphamale", "feminismisbad"
`bot_gender_negative`	"toxicmasculinitydoesntexist", "alphamale", "feminismisbad"	"womenempowerment", "genderequality", "mensmentalhealthmatters"
`bot_eating_positive`	"mealprep", "healthfood", "healthymealideas"	"foodforweightloss", "eatthisnotthat", "howtogeteatingdisode"
`bot_eating_negative`	"foodforweightloss", "eatthisnotthat", "howtogeteatingdisode"	"mealprep", "healthfood", "healthymealideas"

Table 1: Tags and Non-Tags Used for Bots

2.3 Algorithm

Each bot in our system followed a defined sequence of actions to collect data systematically from TikTok. The steps were as follows:

1. Log in to the assigned TikTok account using the existing login code from the previous team's implementation.
2. Manually solve the CAPTCHA challenge presented during login.
3. Navigate to the search page by clicking the search button on the TikTok interface.
4. Enter the first pre-assigned tag in the search bar and execute the search.
5. Click on the first video in the search results.
6. For the next 20 videos:
   - Skip the video if the it contains any *non-tags*, but still collect the metadata below.
   - Watch the video for 20 seconds if it doesn't contain any *non-tags*.
   - Like the video every 2 videos and save it every 4 videos..
   - Collect metadata such as the creator, music, description, hashtags (extracted directly from the description), and the date and time of viewing.
7. Repeat the above steps for the second and third tags assigned to the bot.
8. After processing all three tags, exit the search scrolling page.
9. Navigate to the *For You Page* (FYP).
10. Scroll through 20 videos on the FYP, spending approximately 3 seconds on each video. Collect the same metadata as above (creator, music, description, hashtags, date, and time).
11. Exit the TikTok application.

While the core Python code logic was inherited from the previous team, significant modifications were necessary due to TikTok's dynamic web interface. TikTok frequently updates its HTML structure, which changed the XPaths required for Selenium automation. This was one of the most significant challenges we faced, as it necessitated constant inspection of the HTML structure using Chrome's developer tools to identify the correct links and paths.

Additionally, we developed new code components to improve and expand the bot functionality, including:

- Extracting hashtags from the video description.
- Implementing scrolling behavior on the search results page..
- Avoiding videos tagged with *non-tags*.
- Automating the like and save actions for videos at specified intervals.

The goal of these enhancements was to allow us to gather more relevant and precise data for our study.

3 Experiments

To ensure a robust and systematic collection of data, we conducted three runs for each of the five bots. The data from each experiment was saved into separate CSV files for analysis. Each experiment was designed to last approximately 30 minutes, during which the bot executed its predefined sequence of actions, as described in the previous section.

We also ran a bot to scrape data off 20 for you page videos, without going on the search page before, to use as reference during our analysis of the results.

Given TikTok's platform constraints, certain precautions were taken during the execution of the experiments to mitigate errors and ensure continuity.

After each experiment, a cooldown period was enforced before reusing the same bot. This was necessary to avoid the error message: *Maximum amount of attempts reached*, which TikTok displayed when the same bot was used repeatedly without sufficient delay.

We also ensured to respect a delay between experiments using different bots. Based on our observations, we hypothesized that TikTok may detect and restrict bot activity through mechanisms such as monitoring IP addresses or other signals of automated behavior. By spacing out experiments, we aimed to reduce the likelihood of detection and restriction.

4 Results

The following tables present the results of our experiments, summarized across four key metrics for each experiment.

- **FYP Videos with Hashtags from Search:** This metric represents the percentage of videos scraped from the "For You Page" (FYP) that contained hashtags also present in at least one video from the "Search" page during the same experiment. To compute this, we ran a Python script on each CSV file to count the matching hashtags, calculated the average per video in Excel, and then divided the result by 20.
- **FYP Videos with Hashtags of Interest from Search:** This metric indicates the percentage of FYP videos containing hashtags of interest that also appeared in at least one video from the Search page during the same experiment. Hashtags of interest exclude generic tags such as *fyp*, *trend*, *viral*, and *for you*. We derived this by manually filtering the matching hashtags from the first metric to retain only those of interest.
- **Videos from Search with Tags to Avoid:** This metric quantifies the percentage of videos scraped during the search phase that contained any *non-tags*, leading to the bot skipping over the video during it's run.
- **FYP Videos with Creators from Search:** Similar to the first metric, this represents the percentage of FYP videos featuring creators who also appeared in at least one video from the Search page during the same experiment.

These metrics collectively offer insights into the relationship between the content retrieved via targeted Search queries and the recommendations observed on the FYP, helping assess the algorithmic impact of specific hashtags and creators.

Category	FYP Videos with Hashtags from Search (%)	FYP Videos with Hashtags of Interest from Search (%)
Total Percentage	46.0%	10.0%
Reference Percentage	28.0%	2.0%

Table 2: Percentage Statistics: Hashtags from Search

Category	Videos from Search with Tags to Avoid (%)	FYP Videos with Creators from Search (%)
Total Percentage	1.3%	0.3%
Reference Percentage	0.0%	0.3%

Table 3: Percentage Statistics: Tags to Avoid and Creators from Search

Bot Category	FYP Videos with Hashtags from Search (%)	FYP Videos with Hashtags of Interest from Search (%)
Eating Positive Percentage	33.3%	11.7%
Eating Negative Percentage	50.0%	5.0%
Gender Positive Percentage	73.3%	26.7%
Gender Negative Percentage	21.7%	3.3%
Conspiracies Percentage	51.7%	3.3%

Table 4: Bot Percentage Statistics: Hashtags from Search

Bot Category	Videos from Search with Tags to Avoid (%)	FYP Videos with Creators from Search (%)
Eating Positive Percentage	0.0%	1.1%
Eating Negative Percentage	4.4%	0.0%
Gender Positive Percentage	0.6%	0.0%
Gender Negative Percentage	1.7%	0.0%
Conspiracies Percentage	0.0%	0.0%

Table 5: Bot Percentage Statistics: Tags to Avoid and Creators from Search

5 Analysis

The analysis of the results focuses on the relationship between the Search and FYP data for hashtags, hashtags of interest, tags to avoid, and creators. The following key observations can be drawn from the tables:

Hashtags from Search

Table 2 highlights the overall importance of hashtags from the Search page in influencing FYP content. The Total Percentage of FYP videos containing hashtags from Search is 46.0%, with 10.0% of those containing hashtags of interest. In contrast, the Reference experiment shows significantly lower values at 28.0% and 2.0%, respectively. These findings suggest that searching for hashtags have a measurable influence on the FYP but vary in effectiveness depending on the topic.

We acknowledge that the metric **FYP Videos with Hashtags from Search** is not very relevant due to the amount of generic tags contained in the majority of Tik Tok videos (”fyp”, ”trend”,...).

However, the **FYP Videos with Hashtags of Interest from Search** metric shows the percentage of videos of the exact same topic as the videos looked up during the search phase. The difference between the Reference experiment and the topic specific ones is notable. However, we see that the ”Positive” experiments have a higher percentage for that metric, while the ”Negative” experiments have a low percentage. We unfortunately here fail to demonstrate that Tik Tok creates silos of negative thoughts by feeding negative content in the For You Page of users searching for it.

Tags to Avoid

Table 3 reveals that tags to avoid are minimal in both the Total and Reference experiments, with percentages of 1.3% and 0.0%, respectively. This indicates the effectiveness of our tags design in excluding irrelevant content during the Search phase. However, some variability is observed in the bot-specific results (Table 5), with Eating-negative bots showing the highest percentage of tags to avoid (4.4%). Indeed, the topic of eating disorders was the one containing the most videos with conflicting tags during our manual analysis. However, the conflicts are negligible and we do not assume them to have impacted the results negatively.

Creators from Search

The influence of Search creators on FYP recommendations appears extremely limited. As shown in Table 3, the Total and Reference percentages are both low at 0.3%. Bot-specific results (Table 5) similarly show really minimal influence, with most percentages close to 0.0%. This can be explained by the fact that we looked up Hashtags as keywords for the Search phase, and disregarded creators. Hence, we fail to show that Tik Tok might feed a user videos from the same creators over and over.

Facility to Find Negative Videos

We wanted to highlight the ease with which negative videos can be found, even for new accounts such as those created for the bots. TikTok's Search page lacks effective filtering mechanisms, allowing users to easily access harmful content. Although certain keywords, like "eating disorder," are banned, simple techniques such as misspelling hashtags (e.g., replacing letters with numbers or symbols, or removing letters like we did) or searching for negative trends and keywords successfully expose users to such content.

The accessibility of negative videos raises serious concerns. These videos display no warning messages and do not diversify as users scroll. Furthermore, the negativity of the videos does not diminish over time, which could perpetuate harmful cycles of content consumption. While we failed to show a direct link between negative content on the Search page and FYP recommendations, the immediate availability of such videos poses a risk to vulnerable users, such as teenagers or individuals with mental health challenges. This highlights an area where TikTok's content moderation policies and algorithms could be improved to mitigate exposure to potentially damaging material.

Key Insights

While the analysis highlights that TikTok algorithm's does focus on hashtags as a linking mechanism between Search and FYP videos, we fail to demonstrate that it encourages consumption of negative topics through the FYP to users deliberately looking for it. We also note the influence of creators is negligible, and tags to avoid are effectively filtered.

However, the "Facility to Find Negative Videos" subsection underscores an alarming observation: the ease with which harmful content can be accessed on the platform, even by new users. This accessibility, coupled with the lack of warnings or content diversification, raises important questions about TikTok's role in fostering a safe online environment.

The results underline the complexity of TikTok's recommendation system and the need for topic-specific strategies to analyze and mitigate risks.

6 Future work

The key insight underscored in the "Facility to Find Negative Videos" section lends an insight into future work which could expand on the question of TikTok's facility to search negative content. It was observed that searching for the hashtags "weightloss", "eatingdisorder" and "anorexia" would produce a trigger warning or block the content altogether. However, by modifiying the spelling, users would have access to negative content that the trigger warnings warned against. Although opinions on the use of trigger warnings in media are mixed, experts argue that they encourage content transparency and informed consent (Charles, A. et al, 2022). A large-scale review of several studies associating social media use and mental health stated that several studies concluded that extended social media use can exacerbate mental health issues such as anxiety and depression. Thus, the study concludes that medical professionals and social science researchers should take this impact into account for their patients (Karim, F. et al, 2020). From a technical standpoint, it is important to alleviate the pressure that social media causes upon mental health. A future research study should investigate this insight and establish how TikTok users can skirt the platform's trigger warnings and content blocks to view the negative content they seek out. This could be achieved by first searching negative words to establish a specific list of hashtags blocked by TikTok. Then, the algorithm would then search modifications of these words and collect data of the videos presented on the search page. Using the video data collected, the results should be analyzed to establish if TikTok's content warnings do not prevent users from searching negative content. The motivation and conclusion of this study would be to provide recommendations to social media platforms to establish wider content blocks and warnings.

7 Conclusion

TikTok is a social media app that not only plays a role in shaping minds and influencing behaviors, but also has such a vast reach. The platform had around 1.3 billion monthly users as of 2023 (Iqbal, M., 2024). Given the widespread platform interaction combined with social media's addictive qualities, it is important to study the extent to which TikTok can influence users through thought silos. This experiment found that TikTok did not favor negative content after the algorithm collected data from videos on the *For You Page*. In fact, for all 3 categories investigated–eating disorders, gender, and conspiracy–the FYP had higher rates of positive gender and eating content than conspiracy and negative eating disorder and gender content.

The importance of such findings is relevant to inform social media use limitations and education as well as further research to determine how extensive a user's search should be to create negative silos of thought. This experiment suggests that TikTok does not create negative silos of thought related to eating, gender, and conspiracy. However, the limitation of this study was the depth and breadth of the experiment. Further research could test bots on more keywords per category as well as scrolling the *Search* and *For You Pages* for more than 20 videos, as this study did.

8 Statement of contributions

Max Chanut

As a COMP400 student, I contributed to the survey, code, experiments, analysis and report. The survey was done as a group. For the code, I inspected the Tik Tik webpage to update all the links necessary for Selenium to access information while scraping, I coded the get_video_info() function which involved collecting the hashtags, updated the Video class in Video.py, and overall adapted the previous team's code to run our algorithm. I ran experiments for eating disorders 1,2,3; conspiracy 2,3; and the reference experiment. I took care of the analysis, coding the results_analysis.py and results_summary.py scripts, and then manually annotating the summary_table.csv. For the report, I wrote the Introduction, Project Description, Experiments, Results, Analysis.

Marie Check

This semester as a COMP396 student, I contributed to the survey, code, experiments, and report. The survey was a group effort, as we all contributed ideas for questions. For the code, my main responsibility was in the *search* function. I generalized the code to search for any keyword in the *tags* attribute of each bot, rather than a specific word. Additionally, I introduced the *non_tags* to *bots_working.json*. Then, I modified the *scrolling_through_search_results* function to have the bot avoid interacting with videos that contained *non_tags*. For the experiments, I researched and tested gender hashtags and non tags. I was also responsible for running the gender experiments, and I ran the first conspiracy experiment. Finally, in the report, I contributed the section about the gender hashtags, Future Work, Conclusion, Works Cited, and in-text citations.

Greta Zu

As a volunteer this semester, I contributed to parts of the survey, the bots setup and the report. We worked together on the survey to contribute questions and I also looked at the creators and tags since I mainly worked on setting up the bot accounts for the experiments. I went through the bot accounts to identify the active and functional ones and researched tags and non-tags we could use to help our experiment process. Since I was working with the bots, I also helped write the bots section in the report as well as referencing sources and literature we looked at throughout our project.

Adele Khiiarova

As a shadow contributor, I assisted in defining the survey questions, configuring the bot setup, and identifying references for the final report.

9 Works Cited

Bivens, R. & Haimson, O. L. (2016). Baking gender into social media design: How platforms shape categories for users and advertisers. Social Media + Society, 2(4). https://doi.org/10.1177/2056305116672486

Bringing light to the dark side of TikTok's algorithm. Virtual Eating Disorder Treatment & Therapy. (n.d.). https://withinhealth.com/explore/tiktok-research

Charles, A., et al. (2022). Typology of content warnings and trigger warnings: Systematic review. PLOS ONE, 17(5). https://doi.org/10.1371/journal.pone.0266722

Enders, A.M., Uscinski, J.E., Seelig, M.I. et al. The Relationship Between Social Media Use and Beliefs in Conspiracy Theories and Misinformation. Polit Behav 45, 781–804 (2023). https://doi.org/10.1007/s11109-021-09734-6

Harriger, J. A., Thompson, J. K., Tiggemann, M. (2023). Tiktok, TikTok, the time is now: Future directions in social media and Body Image. Body Image, 44, 222–226. https://doi.org/10.1016/j.bodyim.2023.01.005

Iqbal, M. (2024, October 10). Tiktok revenue and Usage Statistics (2024). Business of Apps. https://www.businessofap
tok-statistics/

Karim, F., et al (2020). Social media use and its connection to Mental Health: A Systematic Review. Cureus. https://doi.org/10.7759/cureus.8627

Maes, C., Vandenbosch, L. (2022). Adolescent girls' instagram and TikTok use: Examining relations with body image-related constructs over time using random intercept cross-lagged panel models. Body Image, 41, 453–459. https://doi.org/10.1016/j.bodyim.2022.04.015