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Original article

Scrolling to heal or hurt? TikTok's impact on eating disorders

Erika De Marco[1], Giorgia Polizzotto[1], Sara Catellani[1,2], Lorenzo Bassi[1], Stefania Traina[1], Mattia Marchi[1,2], Gian Maria Galeazzi[1,2], Luca Pingani[1,2]

[1]*Department of Biomedical, Metabolic and Neural Sciences, University of Modena and Reggio Emilia; Italy;* [2]*Dipartimento ad Attività Integrata Salute Mentale – Dipendenze Patologiche, Azienda USL, IRCCS di Reggio Emilia; Reggio Emilia Italy*

SUMMARY

Background and Objectives

Social media, particularly TikTok, plays a pivotal role in shaping perceptions of feeding and eating disorders (FEDs). While it offers recovery-oriented content, it also exposes users to harmful narratives that may normalize disordered eating patterns. Understanding how FED-related content engages users is crucial for informing digital health strategies and content moderation policies. This exploratory study aimed to explore the impact of TikTok short videos on FED-related discourse, analysing how different content types of influence user engagement and whether recovery-focused messages generate higher interaction than weight-loss or pro-anorexia (pro-ana) content. Rather than providing a platform-level estimate, the dataset represents an exploratory snapshot of the Italian TikTok landscape during the collection period.

Methods

An observational cross-sectional study was conducted, involving three independent researchers who analysed 202 TikTok videos collected via 13 predefined FED-related hashtags. Videos were classified based on thematic content (pro-recovery, pro-ana, anti-pro-ana, or neutral) and emotional appeal, while engagement metrics (views, likes, comments, shares, saves) were statistically analysed. To account for the large variance in video age (mean ≈ 530 days, SD ≈ 343), all engagement metrics were normalized by the number of days each video had been online, resulting in per-day averages (e.g., views/day, likes/day). Undownloadable or muted videos (n=58) were excluded, which may have biased the dataset toward content that passed TikTok's moderation filters.

Results

Recovery-focused videos were the most prevalent and received significantly higher engagement than pro-ana videos specifically promoting weight-loss behaviours (p=.003). Emotional expression was positively correlated with increased user interaction (p=.007). Additionally, creators with larger follower bases achieved greater engagement (p < .001). No significant differences were observed in broader comparisons between pro-ana and pro-recovery content, although these analyses were likely underpowered.

Conclusion

Our results underscore TikTok's ambivalent role in FED discourse: while it amplifies recovery-oriented narratives, harmful content persists. Strengthening content moderation and digital health strategies is crucial to foster safer online spaces for vulnerable users.

Key words: TikTok, social media, feeding and eating disorders, mental health, recovery

Luca Pingani
E-mail: luca.pingani@unimore.it

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Introduction

Feeding and Eating Disorders (FEDs) comprise a range of psychiatric conditions characterized by persistent disturbances in eating behaviours and weight-control practices that significantly impair physical health and psychosocial functioning. These disorders include anorexia nervosa, bulimia nervosa, and binge-eating disorder, alongside newer diagnostic categories such as avoidant/restrictive food intake disorder, pica, and rumination disorder, traditionally associated with childhood [1].

FEDs primarily affect adolescents and young adults, with markedly lower prevalence in older populations, and are among the psychiatric conditions with the highest mortality rates, particularly anorexia nervosa [2,3].

Despite their severe implications, many individuals affected by FEDs do not access care, often due to stigma, limited treatment availability, or lack of awareness [4]. The development and maintenance of these disorders are shaped by a complex interplay of psychological, social, and environmental factors. A key challenge in treatment is the egosyntonic nature of FEDs, wherein the symptoms are perceived as congruent with the individual's identity, thus diminishing motivation for change [5]. Central to their psychopathology is body dissatisfaction, reinforced by pervasive societal ideals and cultural pressures [6].

In recent years, social media has emerged as a significant environmental influence in the development and trajectory of FEDs [7-9]. These platforms can exert both harmful and beneficial effects. On one hand, social media fosters unrealistic beauty standards, encourages body comparison, and promotes disordered eating behaviours [10]. On the other hand, it can also provide a space for peer support and pro-recovery communities that encourage help-seeking and resilience [11,12]. Although many platforms have censored explicit pro-anorexia (pro-ana) content, it continues to circulate in more subtle forms, such as hashtags, coded language, and implicit messages [10,13,14]. Among the various platforms, TikTok plays a distinctive role due to its widespread popularity, especially among adolescents and young adults [15]. Unlike traditional social media, TikTok curates content primarily through an algorithm-driven personalized feed, which amplifies content based on user behaviour [16]. Recent research has shown that this algorithm may inadvertently expose vulnerable users to harmful content, such as dieting or pro-ana material, even in the absence of direct search behaviour [17]. Although TikTok has implemented restrictions on pro-ana content, certain videos continue to circumvent moderation efforts. In parallel, anti-pro-ana material has become increasingly visible, benefiting from fewer limitations and broader dissemination [18]. Nonetheless, content moderation on the platform might be influenced by corporate priorities, often privileging highly engaging content over the consistent removal of harmful material [19]. Moreover, the moderation of video-based content presents greater challenges than that of text or static images, due to its dynamic and multimodal nature [20].

This study explores the complex role of TikTok in shaping narratives around FEDs. Through an exploratory analysis, it investigates user engagement with various types of FED-related content. It hypothesizes that creators with larger audiences receive higher engagement, and that videos promoting disordered behaviours may be shared widely due to both identification and critical dissemination. Conversely, recovery-focused and informational videos are expected to foster supportive interactions. Another factor examined was the perceived body weight of individuals in the videos, which was hypothesized to influence engagement levels, as body-related content might provoke stronger reactions or debates.

The study also considered the role of informational credibility, predicting that videos offering evidence-based information or referencing healthcare professionals would be more widely shared. Emotional self-disclosure and humour are also analysed for their influence on engagement, as both are known to affect viewer response. Ultimately, this study seeks to understand how TikTok's algorithm, content features, and user interactions contribute to the broader discourse on eating disorders.

Materials and Methods

Methodology and Tools

This study aimed to explore the impact of TikTok short videos on FEDs through an exploratory research approach, analysing how different types of content influence user engagement. Inspired by the work of Lookingbill et al. [2], a double-blind observational research design was adopted.

A new TikTok profile was created exclusively for this study, using a randomly generated username. To minimize algorithm influence, all settings related to advertisements, sponsored content, and targeted suggestions were disabled. The selection process for Italian hashtags related to feeding and eating disorders was informed by the methodology outlined in Lookingbill et al.'s study[2] and initially guided by popularity rankings retrieved from Best-Hashtags.com [21]. A detailed overview of the process is provided in Figure 1.

These methodological choices were deliberate scope decisions. First, we relied on Best-Hashtags.com to identify relevant hashtags because it provides a transparent and replicable procedure, even though this approach may privilege more popular or easily discoverable content. Second, we restricted the analysis to Italian-language hashtags to capture the cultural and linguistic specificity of the Italian TikTok landscape. Finally, we used a newly created account to minimize prior algorithmic influences. While this protocol reduces

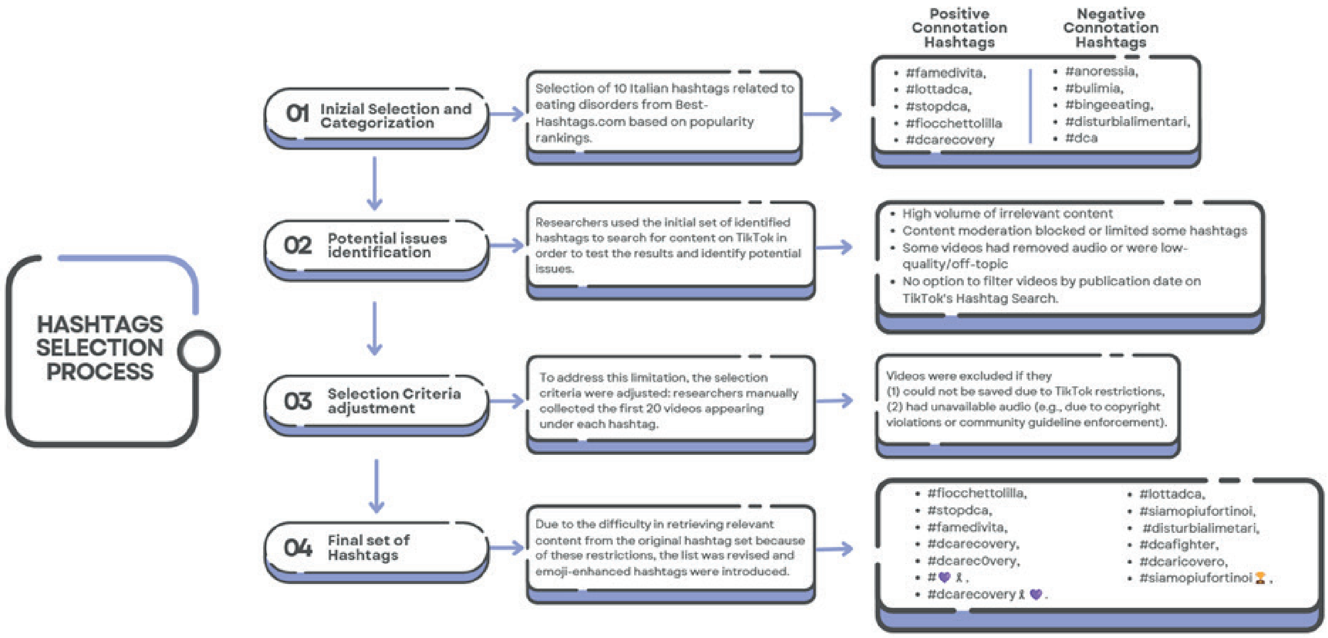

FIGURE 1. *Hashtag identification process flowchart.*

ecological validity compared to real user experiences, it allowed us to maintain internal consistency and control across the data collection process. Given the inherent complexity of TikTok's algorithmic curation, we acknowledge that a single new account and a short harvesting window cannot fully neutralize personalization effects or capture the platform's dynamics over time. Therefore, our dataset should be interpreted as an exploratory snapshot of the Italian TikTok landscape at the time of collection, rather than as a platform-level estimate.

Sample and data collection

The initially expected sample consisted of 260 videos (13 hashtags × 20 videos per hashtag). Exclusion criteria for videos were as follows: (1) videos that could not be downloaded due to TikTok platform restrictions (*e.g.*, content removal or privacy settings), and (2) videos with unavailable audio, such as those muted due to copyright claims or community guideline enforcement. A total of 58 videos (22.3% of the initially expected 260) were excluded for these reasons. Although these exclusions were necessary to ensure analyzable material, they may have disproportionately removed content that violated community guidelines or was otherwise subject to platform moderation. This exclusion could bias the sample toward content that passed moderation filters, an issue directly relevant to the research question. Where possible, we compared available metadata (e.g., hashtag, posting date, number of likes at exclusion) between excluded and included items; however, TikTok's interface limited systematic retrieval of these data. Video collection was conducted between April 8 and April 21, 2024, using the 13 selected hashtags.

A structured database was used to organize and analyse the data. Each video was assigned a unique identification code and evaluated based on both objective and subjective variables. Objective variables included the total number of posts under each hashtag, the video's publication date, and the download date for research purposes. Engagement indicators, such as number of views, likes, comments, shares, and saves, were recorded, along with information about the creator's profile (follower count and total profile likes).

Content Coding and Categorization

Subjective content variables were extracted independently by two primary researchers (L.B. and S.T.) based on a classification framework adapted from Lookingbill et al. (2023). The researchers analysed the videos separately and blindly, without knowledge of each other's coding. A third senior researcher (S.C.) reviewed both datasets to ensure consistency and resolve any discrepancies. Each video was coded for the presence of individuals (e.g., number of people, gender, apparent weight) and for specific content elements such as food, text, music, recognizable backgrounds, and filters. Videos were also classified by their informative value into three categories: (1) informative (e.g., a video explaining the diagnostic criteria for anorexia nervosa based on the "Diagnostic and Statistical manual of Mental disorders – 5 (DSM-5)", or discussing evidence-based treatment options), (2) misleading (*e.g.*, a video promoting extreme dietary restrictions as a healthy lifestyle or romanticizing visible signs of malnutrition), and (3) other (e.g., content using relevant hashtags but unrelated to eating disorders, such as humorous or dance videos).

Following the approach by Lookingbill et al. [2], videos were further grouped into four thematic categories: (1) pro-ana (e.g., a video encouraging food avoidance or showing extreme thinness with captions like "thinspiration"), (2) anti-pro-ana (e.g., a video debunking myth about eating disorders or criticizing toxic body ideals), (3) pro-recovery (e.g., a personal story of progress in recovery, showing support for therapy or healthy eating habits), (4) other (e.g., general wellness content, lifestyle vlogs, or motivational posts unrelated to eating disorder narratives).

These categories (pro-ana, anti-pro-ana, pro-recovery, other), along with analytically derived subgroups (*e.g.*, weight-loss content within the pro-ana category), were consistently used in all subsequent analyses.

Within the pro-ana category, a specific subcategory labelled 'weight-loss content' was defined a priori. This subcategory included videos explicitly encouraging or normalizing weight-loss behaviours, such as calorie counting, dieting, WIEIAD ('What I Eat in a Day'), or exercise aimed at weight reduction, regardless of whether these behaviours were framed as wellness, lifestyle, or motivational content. Videos classified as weight-loss content therefore represent a subset of pro-ana content, not an independent thematic category.

An open field was included for any additional qualitative observations. A detailed overview of video themes and subthemes is provided in Table I. A detailed codebook with operational definitions and illustrative examples for key subjective variables is provided in Appendix A. Information accuracy was assessed by comparing the content of each video against established clinical knowledge on eating disorders, distinguishing between accurate, misleading, and non-applicable information, as detailed in the Codebook (Appendix A).

Data Analysis

Once data collection and categorization were completed, all information was entered into SPSS - Statistical Package for Social Science for statistical analysis [22]. The initial analyses focused on summarizing key findings related to hashtags and videos. Descriptive statistics, including means and standard deviations for quantitative variables, and medians and percentages for qualitative variables, were used to summarize key characteristics of the videos, user engagement, and content types.

To evaluate the reliability of the categorization process, inter-rater agreement was assessed using Cohen's Kappa coefficient, a standard statistical measure of agreement between evaluators. The interpretation of Kappa values follows conventional thresholds: values close to 0 indicate no agreement, while scores between 0.01 and 0.20 reflect poor agreement. Fair agreement is observed between 0.21 to 0.40, with moderate agreement falling within the range of 0.41 to 0.60. Scores from 0.61 to 0.80 suggest substantial agreement, and values above 0.81 indicate almost perfect agreement.

Inter-rater agreement for the identification of weight-loss content within the pro-ana category was almost perfect (Cohen's $\kappa = 1.00$).

Statistical significance was assessed using multiple statistical tests. Spearman's Rho coefficient was applied to measure association between ranked data, while Kendall's Tau-b was used as a non-parametric correlation

TABLE I. *Themes and subthemes in TikTok videos related to eating disorders.*

Theme	Subtheme
Encouraging the development or support of eating disorders (EDs): creators promote EDs as a lifestyle, ask other creators to support their ED behaviours, or actively encourage other users to develop or sustain an ED.	Promoting thinness as an ideal, with or without subtle language; Eating with an ED; Calorie counting; Dieting; Food-related guilt; WIEIAD ("What I Eat in a Day"); Losing weight to reach a predetermined weight; Exercising to reach a predetermined weight.
Sharing physical/psychological symptoms of EDs: creators share their experiences with EDs to raise awareness or educate other users about EDs. This includes recounting how their ED developed and the associated symptoms.	Best advice on talking to someone with an ED; Discussing myths or misconceptions about EDs; Revealing the "less glamorous" side of EDs; Fighting pro-ana content; Personifying EDs; Talking about the onset of EDs; Using humour.
Sharing recovery stories: creators express their experiences by sharing advice, words of encouragement, and challenges encountered with other users.	Engaging with healthcare professionals; Talking about recovery; Celebrating recovery; Eating during recovery; Fighting for recovery.
Social support: creators provide, seek, or discuss the support they receive online and offline.	Providing social support; Receiving social support; Seeking social support.

measure for ordinal variables. Additionally, the Mann-Whitney U test was employed for non-parametric comparison between independent samples.

To quantify linear associations between variables, Pearson's correlation coefficient was calculated. Results were interpreted based on p-values. Findings with $p \geq 0.05$ were considered not statistically significant, while values between 0.01 and 0.05 indicated statistical significance. Results within the 0.001 to 0.01 range were regarded as highly significant, whereas findings with $p < 0.001$ were interpreted as very highly significant, reflecting a minimal margin of error.

In addition to p-values, effect size measures appropriate to non-parametric analyses were considered to aid interpretation of results. For Mann–Whitney U tests, effect sizes were estimated using rank-biserial correlations, while correlation coefficients were reported for rank-based association analyses. Given the exploratory nature of the study, these effect sizes were interpreted descriptively rather than as confirmatory estimates.

Given the large variance in the number of days videos had been online (mean ≈ 530 days, SD ≈ 343), engagement metrics were normalized by video age. Specifically, we divided each engagement variable (views, likes, comments, shares, saves) by the number of days each video had been online, obtaining per-day rates (*e.g.*, views/day). All analyses involving engagement were repeated using these normalized values to control for potential inflation of engagement counts in older videos. The consistency between normalized and raw analyses confirmed the robustness of the findings.

Given the exploratory nature of the study and the highly skewed distribution of engagement metrics, non-parametric statistical tests were selected as an initial analytical approach. Although engagement outcomes are count variables potentially subject to zero inflation and multiple confounding factors, the sample size and study design did not allow for stable multivariable generalized linear models. Therefore, the analyses were intended to identify descriptive patterns and hypothesis-generating associations rather than causal estimates.

Ethical considerations

This study was conducted in accordance with established ethical standards for research using publicly available online data. All analysed TikTok videos were publicly accessible at the time of data collection, and no interaction with users or content creators occurred. Data collection and analysis complied with TikTok's Terms of Service, and no attempts were made to access private, restricted, or deleted content.

No personal identifiers were collected, stored, or reported, and all results are presented in aggregate form to minimize the risk of indirect identification. Given the sensitive nature of eating disorder–related content, researchers involved in coding were trained to recognize potentially distressing material and conducted analyses in a controlled academic setting, with the possibility of pausing or discontinuing coding if needed. These safeguards were adopted to reduce potential psychological burden associated with exposure to triggering content.

Results

Following the download of the videos, the analysis and selection process was carried out by the reviewers, resulting in a final dataset of 202 videos. The selection process results are summarized in the flowchart (Fig. 2). Following the analysis of the complete sample of 202 TikTok short videos, the data presented in Table II were obtained.

The analysis revealed that, for most hashtags, the number of identified videos met the initial target of 20 videos. An exception was observed for the hashtag #lottadca, from which less than 20 videos were identified. Despite this, the total number of posts under this hashtag was 93, one of the lowest counts recorded within its category.

The descriptive analysis reveals that the average duration of online availability for the analysed videos is 530 days, with a standard deviation of 343.04 days. Additionally, in videos featuring individuals, the number of people ranges from one to three.

Furthermore, statistics on absolute and percentage frequencies for the analysed categories are reported in the following table (Tab. III) for the entire sample of 202 videos. Of the 202 analysed videos, 42 were classified as pro-recovery, 7 as anti-pro-ana, 21 as pro-ana, and 135 as other. Within the pro-ana category (n=21), 13 videos (61.9%) explicitly promoted weight-loss behaviours and were therefore classified as weight-loss content, while the remaining 8 videos (38.1%) conveyed pro-ana messages without explicit encouragement of weight loss.

In this version, engagement metrics (views, likes, comments, saves, and shares) were normalized by the number of days each video had been online, resulting in per-day average values (*e.g.*, views/day).

Finer numerical intervals were used for the "comments," "saves," and "shares" metrics to capture small variations in low-frequency interactions. Moreover, in all sections, the first categorical interval consistently corresponds to the lowest video frequency.

The profiles from which the videos were taken were also analysed, resulting in a total of 122 profiles (Tab. IV). The categories are characterized by broad intervals defined by high-order numbers. For instance, the total number of likes refers to all the videos of a specific profile.

Moreover, the agreement level, quantified using Cohen's kappa coefficient (κ) to indicate the degree of consistency beyond chance, was calculated. Table V the inter-rater agreement between the two evaluators for each subjective assessment item.

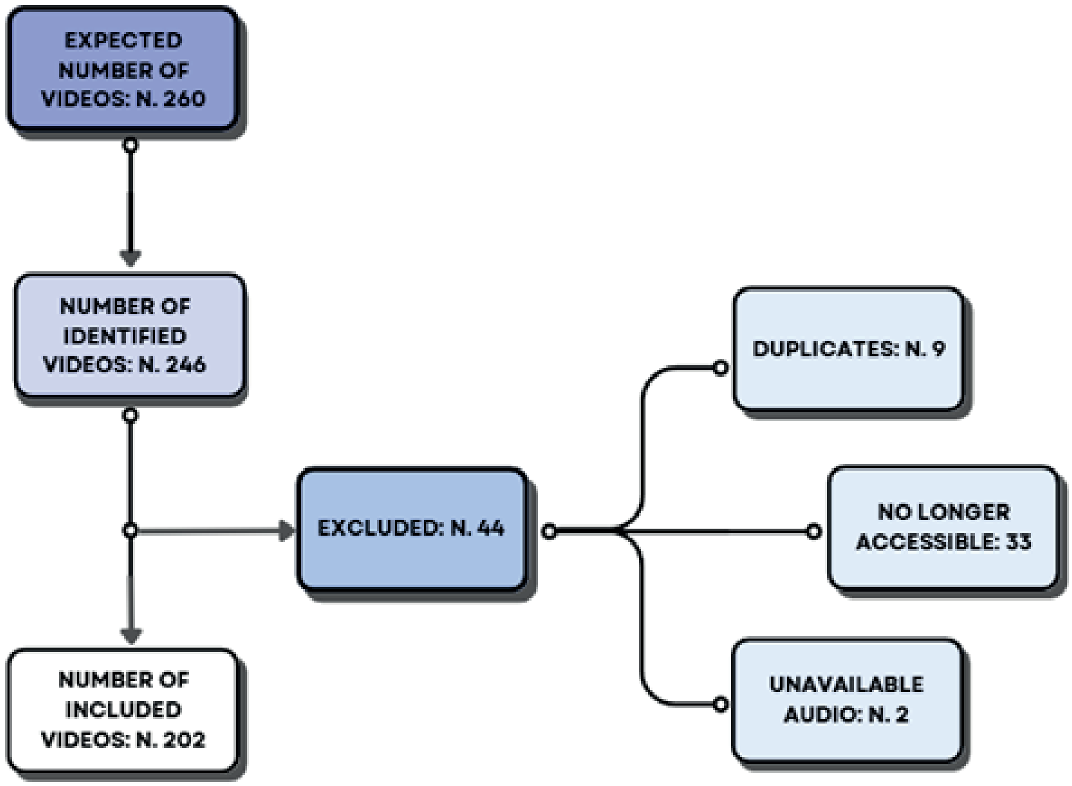

FIGURE 2. *Selection process flowchart.*

TABLE II. *Summary of video analysis results.*

Hashtag	Number of extracted videos	Number of posts per hashtag as of 08/04/2024	Category
#disturbialimentary	19	392	0-1000
#💜🎗	18	32.6K	10001-100000
#dcarecovery🎗💜	10	4342	1001-10000
#ricoverodca	15	484	0-1000
#siamopiufortinoi🏆	16	26.5K	10001-100000
#dcafighter	18	5767	1001-10000
#dcarecovery	18	37.7K	10001-100000
#dcaricovero	15	55	0-1000
#disturbialimetari	17	9476	1001-10000
#fiocchettolilla	19	14.3K	10001-100000
#lottadca	6	93	0-1000
#siamopiufortinoi	14	1398	1001-10000
#stopdca	17	65	0-1000

TABLE III. *Video distribution by views, likes, comments, saves, and shares normalized* by the number of days each video had been online.*

	Category	N	%
Views	≤1 0	67	33.2
	11 - 50	51	25.2
	51 - 100	20	9.9
	101 - 200	18	8.9
	201 - 500	17	8.4
	501 - 1000	14	6.9
	1001 - 2000	3	1.5
	2001 - 5000	9	4.5
	> 5000	3	1.5
Likes	0	17	8.4
	1	58	28.7
	2 - 5	52	25.7
	6 - 10	21	10.4
	11 - 20	15	7.4
	21 - 50	15	7.4
	51 - 100	8	4
	101 - 500	9	4.5
	> 500	7	3.5
Comments	< 1	184	91.1
	1 - 2	8	4
	3 - 5	7	3.5
	> 5	3	1.5
Saves	< 1	165	81.7
	1 - 2	11	5.4
	3 - 5	11	5.4
	> 5	15	7.4
Shares	< 1	188	93.1
	1 - 2	5	2.5
	3 - 5	6	3
	> 5	3	1.5

** All engagement metrics (views, likes, comments, saves, shares) averages were computed as mean daily values, obtained by dividing the total count by the number of days each video had been online (e.g., views/day).*

TABLE IV. *Profile distribution by number of followers and total likes.*

	Category	N	%
Total Profiles		**122**	**100**
Number of Followers	0-1000	60	29.7
	1001-10000	53	26.2
	10001-100000	61	**30.2**
	100001-5000000	28	13.9
Total Likes	0-10000	52	25.7
	10001-1000000	82	**40.6**
	1000001-30000000	68	33.7

Additionally, the correlation results between the objective and subjective data of the hypotheses and observations were calculated. The analyses revealed several findings related to the formulated hypotheses. Regarding the correlation between the number of followers and video interactions, a significant positive relationship was observed. Kendall's Tau-b coefficient was 0.310 ($p < .001$), and Spearman's Rho reached 0.609 ($p < .001$) for the number of shares. A significant correlation was also found for views (Tau-b=0.517, $p < .001$) and likes (Tau-b=0.548, $p < .001$), confirming that a larger follower base is associated with higher levels of engagement. For the hypothesis suggesting that videos in which the creator promotes eating disorders as a lifestyle would generate more shares compared to those that do not address this topic, the Mann–Whitney U test did not indicate a higher number of shares for lifestyle-promoting content (p=.397). Given the interpretative nature of this construct, this result is further discussed in light of inter-rater reliability in the Discussion.

Similarly, the hypothesis that the apparent body weight of people in the video would influence the number of likes, comments, and shares was not confirmed, as the correlation results were not significant (Kendall's Tau-b=0.123, p=.122 for shares; 0.033, p=.675 for comments; 0.085, p=.248 for likes). An interesting result emerged from the analysis of videos promoting recovery from eating disorders: those that do not celebrate recovery mostly convey pro-recovery messages (56.5%), followed by other messages (19.4%), anti-pro-ana messages (12.5%), and a small percentage of pro-ana messages (1.4%). In contrast, videos that celebrate recovery predominantly convey pro-recovery messages (97.4%), with only 2.6% featuring anti-pro-ana messages, while no pro-ana or other messages are present. The chi-square test revealed a statistically significant difference distribution of message categories between videos that celebrate recovery and those that do not (χ^2=13.615, p=.003), indicating greater content diversity and interaction in videos related to recovery. However, there was no significant difference in the number of supportive comments between videos celebrating recovery and pro-ana videos promoting thinness as an ideal (p=.529). The analysis of videos in which the creator

TABLE V. *Inter-rater agreement for subjective assessment items.*

Item	Cohen's κa	Standard Error of κb	T approx.c	Approximate Significancec
Are there people in the video?	1.00	.00	14.21	< .001
If there are people in the video, how many appear?	1.00	.00	19.16	< .001
If there is only one person in the video, what is their gender?	1.00	.00	12.25	< .001
If there are multiple people in the video, what is their gender?	1.00	.00	5.57	< .001
If there is only one person in the video, what is their apparent weight?	1.00	.00	14.32	<.001
If there are multiple people in the video, what is their apparent weight?	1.00	.00	10.25	< .001
Is food shown in the video?	1.00	.00	14.21	< .001
Is there text in the video?	1.00	.00	14.21	< .001
Is there music in the video?	1.00	.00	14.21	< .001
Is there a recognizable background in the video?	0.97	.03	13.83	< .001
Are filters used in the video?	1.00	.00	14.21	< .001
Does the creator promote the disorder as a lifestyle?	0.51	.11	7.40	< .001
If yes, do they promote thinness as an ideal?	1.0	.00	3.00	.003
If yes, do they encourage weight loss?	1.0	.00	3.00	.003
If yes, do they suggest ways to favor ED through diet (calorie counting, WIEIAD, etc.)?	1.0	.00	3.00	.003
If yes, do they discuss how to lose weight?	[d]	-	-	-
If yes, do they talk about exercise as a way to lose weight?	1.0	.00	3.00	.003
Does the creator share their physical/emotional experience with ED?	0.78	.05	11.20	< .001
If yes, do they give advice on how to talk to someone with an ED?	0.89	.05	9.74	< .001
If yes, do they discuss myths or misconceptions about EDs?	0.92	.04	9.91	< .001
If yes, do they describe ED symptoms (physical or psychological)?	0.93	.04	10.07	< .001
If yes, do they openly fight pro-ana content?	0.76	.14	8.20	< .001
If yes, do they personify the ED?	1.0	.00	10.82	< .001
If yes, do they tell the story of the ED onset?	1.0	.00	10.82	< .001
If yes, do they use humor?	0.91	.05	9.81	< .001
Does the creator share their recovery experience?	0.85	.04	12.11	< .001
If yes, do they describe experiences with professionals?	1.0	.00	10.00	< .001
If yes, do they explain what helped in their recovery process?	0.83	.07	8.46	< .001
If yes, do they celebrate recovery?	0.93	.04	9.36	< .001
If yes, do they share what they eat during recovery?	1.0	.00	10.00	< .001
If yes, do they discuss the difficulties of recovery?	0.94	.03	9.39	< .001
Does the creator talk about social support?	0.84	.04	12.02	< .001
If yes, do they promote/provide support?	1.0	.00	6.63	< .001
If yes, do they talk about the support they received?	1.0	.00	6.63	< .001
If yes, do they ask for support?	1.0	.00	6.63	< .001
How accurate is the video?	0.60	.06	11.21	< .001
What type of message does the video convey?	0.54	.05	12.07	< .001

a. Kappa values indicate the level of agreement: ≤ 0 (no agreement), 0.01-0.20 (poor), 0.21-0.40 (fair), 0.41-0.60 (moderate), 0.61-0.80 (substantial), and 0.81-1.00 (almost perfect); b. The null hypothesis is not assumed; c. The asymptotic standard error is used, assuming the null hypothesis; d. The agreement between the two evaluators regarding whether the creator discusses how to lose weight cannot be calculated due to constant values observed; e. Statistically significant value (≤ 0.05) discusses the challenges of recovery did not show significant differences in the number of shares compared to videos that do not address this theme (p=.733). Similarly, videos considered more accurate from an informational perspective did not receive significantly more shares compared to less accurate videos (p=.171). Importantly, the absence of higher sharing rates for more accurate videos suggests that information accuracy alone may not be a primary driver of content diffusion on TikTok. However, this finding should be interpreted cautiously, given the subjective nature of accuracy coding and the moderate inter-rater agreement observed for this variable.

Findings related to videos in which the creator shares emotional or physical experiences related to eating disorders showed an association with a higher number of comments compared to videos that did not feature such experiences (U=3413.5, p=.007). Conversely, videos that describe interactions with professionals or discuss myths about eating disorders did not show significant differences in the number of shares or comments (p=.898 and p=.619, respectively). Finally, the hypothesis that using humour in videos discussing eating disorders might generate more likes than videos that address the topic seriously was not supported by the data (p=.365).

Discussion

This study explored the influence of TikTok short videos on users affected by FEDs, focusing on the nature of the content, user engagement, and the balance between recovery-oriented and potentially harmful messages. The findings underscore the complex and dual nature of social media, where messages supporting recovery coexist with content that promotes unhealthy behaviours or reinforces harmful ideas.

Social media platforms enable the rapid global dissemination of health-related information, bypassing traditional communication channels. While they can promote positive messages and foster supportive communities, they also pose risks, particularly to adolescents, by exposing them to harmful content that can negatively affect mental health and encourage disordered eating behaviours [23]. Rapid and widespread exposure to such content may contribute to shaping social norms, increasing anxiety, and influencing users' body image and eating patterns [24].

Although social media platforms can empower individuals to share recovery experiences and offer peer support, they can also serve as a space for the spread of disordered behaviours. Previous research has shown that media often reinforce idealized beauty standards, which increases exposure to thinness norms and body dissatisfaction [25]. Interestingly, in the present study, most individuals featured in the analysed videos appeared to be of average weight, and no statistically significant associations were observed between perceived body weight cues and levels of engagement (likes, comments, shares).

Interpretations related to perceived body weight cues should be considered in light of the coding procedure, which relied on visual assessment and yielded varying levels of inter-rater agreement; accordingly, these findings reflect patterns of association rather than robust indicators of causal influence.

It is important to highlight the growing dissemination of messages in recent years aligned with the "body-positive" movement, which aims to promote body diversity, self-acceptance, and a healthier relationship with one's body, challenging traditional beauty standards [11]. Body positivity content seems to be a valuable tool in eating disorder treatment, as exposure to such material may help reduce body dissatisfaction and negative emotions [26]. However, critics argue that even body-positive content often retains a focus on physical appearance, potentially perpetuating the emphasis on the body rather than truly shifting the narrative [11].

A particularly concerning trend is the rise of online communities that normalize and promote eating disorders [27]. Pro-eating disorder (pro-ED) groups, such as pro-ana communities, frame FEDs as lifestyle choices, encourage dangerous behaviours, and discourage recovery efforts [16,24,27,28]. These messages are especially harmful to vulnerable young users [16]. Although platforms like TikTok have taken steps to moderate such content, pro-ED creators often adapt by using alternative spellings and coded language to bypass moderation [10,16]. In our study, 1.4% of non-recovery videos contained explicit pro-ana messages. However, determining whether a creator was promoting the disorder as a lifestyle yielded only moderate inter-rater agreement, highlighting the interpretive complexity of this type of content. Accordingly, results involving this variable-particularly null findings-should be interpreted with caution, as lifestyle promotion often relies on implicit, contextual cues rather than explicit statements.

The study also confirmed the presence of anti-pro-ana content, which aims to raise awareness of the risks associated with eating disorders and has gained increasing popularity on social media platforms [18,29]. Such videos accounted for 12.5% of the non-recovery-focused content. Additionally, most recovery-oriented videos (97.4%) contained explicitly positive and hopeful narratives, emphasizing personal progress and transformation. These videos elicited high levels of engagement, often in the form of supportive comments, indicating that recovery content fosters a sense of community and emotional resonance. Recovery-focused videos gener-

ated significantly more engagement compared to pro-ana videos explicitly promoting weight-loss behaviours, a subgroup of content encouraging disordered eating.
We also examined whether videos promoting thinness or eating disorders as lifestyle choices received more shares than other videos. Contrary to expectations, descriptive analyses did not reveal higher engagement. Given the relatively small number of pro-ana videos in the sample, comparisons involving this category may be underpowered. Therefore, the absence of statistically significant differences should not be interpreted as evidence of equivalence between content types. This aligns with some literature reporting no significant differences in engagement across pro-ED, anti-ED, and recovery content[2]. However, other studies have found that pro-ana content can attract more user interaction than educational or supportive videos[30].
Videos featuring emotional or physical experiences related to FEDs received significantly more comments than those without emotional disclosure (p=.007).
Emotional expression was associated with higher levels of commenting, suggesting that emotionally salient content may elicit greater audience interaction. However, this association was observed in unadjusted analyses and may be influenced by exposure, creator reach, and platform-level dynamics [31].
Importantly, these associations should not be interpreted as evidence that emotional expression independently increases engagement, as the present analyses did not adjust for exposure (*e.g.*, views), creator popularity, or other correlated content features. Future studies using multivariable models are needed to assess whether these relationships remain significant after appropriate statistical controls.
Furthermore, creator popularity emerged as a significant factor in engagement metrics. Videos from creators with more followers consistently received more views, likes, and shares (p < .001). This finding aligns with prior research showing that audience size influences content visibility and interaction rates [2,32,33]. However, some studies suggest that smaller accounts can generate deeper engagement due to more intimate creator–follower relationships [34,35]. Interestingly, prior literature also indicates that on TikTok, algorithmic restrictions may minimize the differences in engagement between creators of pro-recovery and pro-ED content [2]. Future research should consider a more controlled design, holding content type and follower count constant, to better understand their specific effects on engagement.
This study has several limitations. The sample was not randomized, and the evolving nature of TikTok's algorithm and moderation strategies may limit the generalizability of findings over time. The analysis was confined to the TikTok platform, preventing cross-platform comparisons. Data collection was also shaped by specific scope choices.
Our reliance on Best-Hashtags.com for hashtag identification may have favoured the inclusion of more visible or trending content, potentially underrepresenting less popular or niche communities. Similarly, limiting the analysis to Italian-language hashtags constrains the generalizability of our findings to international contexts but aligns with our objective of examining the Italian TikTok discourse. Finally, the use of a newly created TikTok account may not fully reproduce the experience of typical users, since prior interaction history strongly influences algorithmic recommendations. However, this strategy minimized uncontrolled biases from previous activity and ensured a standardized observation protocol. These methodological decisions reflect deliberate trade-offs between ecological validity and internal consistency and should therefore be considered when interpreting the findings. Moreover, the reliance on one newly created account and a limited data collection window means that our dataset reflects a partial and time-bounded perspective. While this approach supports internal consistency, it does not fully account for TikTok's history- and context-dependent recommendation system. As such, the study should be understood as an exploratory snapshot of FED-related discourse on Italian TikTok, which can inform future research employing multiple accounts, randomized collection times, and longitudinal designs. Additionally, the exclusion of undownloadable or muted videos may have biased the dataset toward content that remained accessible and compliant with TikTok's moderation systems. Since videos removed for community guideline violations are directly relevant to understanding how harmful content circulates and is regulated, their absence represents an important limitation. Future research could address this by developing strategies to capture and archive metadata from excluded videos in real time, allowing for more comprehensive comparisons. Although this approach cannot fully account for TikTok's nonlinear visibility patterns–where engagement often peaks shortly after publication–it provides a reasonable adjustment for time-related bias.
In addition, given the large variance in the number of days videos had been online, we normalized all engagement metrics by video age to control for potential inflation of interaction counts in older posts. From an analytical perspective, engagement metrics on TikTok represent skewed count data influenced by multiple factors, including creator popularity, exposure time, and algorithmic amplification. While non-parametric tests were appropriate for the exploratory aims of this study, more advanced modelling approaches–such as negative binomial or zero-inflated regression models

incorporating multiple covariates and clustering at the creator level–would allow for more robust effect estimation. Future studies with larger samples and longitudinal designs should adopt such models to disentangle the relative contribution of content features, creator characteristics, and platform dynamics.

In addition, views may be considered an exposure variable for other engagement outcomes (*e.g.*, likes, comments, shares, and saves). While normalization by video age partially accounts for differential exposure over time, the present analyses do not explicitly model engagement as a function of views (*e.g.*, rates per 1,000 views or models including log(views) as an offset). Future research should address this aspect by adopting rate-based outcomes or generalized linear models incorporating exposure offsets. Finally, given the exploratory design and the number of statistical tests performed, no formal correction for multiple comparisons was applied. Accordingly, p-values should be interpreted cautiously and in conjunction with effect size estimates, with an increased focus on the direction and relative magnitude of observed associations rather than strict thresholds of statistical significance. Future studies should adopt preregistered analytic plans and confirmatory modelling strategies, including appropriate corrections for multiple testing, to mitigate the risk of Type I error.

Although inter-rater reliability was generally high, subjective coding–especially regarding emotional tone and lifestyle promotion–introduces potential bias. Lastly, while we analysed comment quantity, we did not assess their content, which could provide deeper insights into user reactions.

Indeed, comment counts represent a blunt proxy for community response, as comments may vary widely in tone and function, ranging from supportive and recovery-oriented messages to neutral, critical, or potentially harmful interactions. Future research should incorporate qualitative or automated sentiment and toxicity analyses–either on full datasets or well-defined subsamples–to better characterize the nature of audience engagement and distinguish supportive discourse from adverse or triggering interactions.

Despite these limitations, our study highlights TikTok's dual role in eating disorders, where recovery-focused content fosters engagement and support, but harmful narratives persist. Recovery-oriented videos were found in greater numbers, emphasizing social media's potential in promoting positive mental health messages. However, the presence of pro-ana content, though limited, underscores the need for continuous content moderation. Emotional appeal and creator influence significantly impact user interaction, suggesting that engagement is shaped by multiple factors. Future research should explore cross-platform comparisons and algorithmic influences to enhance digital health interventions and create safer online spaces.

Conclusions

The findings provide valuable insights into TikTok's dual role serving both as a risk and a resource in the context of eating disorders. While recovery-oriented content appears to foster engagement and create supportive communities, harmful narratives persist, highlighting the challenges of content moderation and the platform's influence on user's eating behaviours. The significant engagement with recovery-focused videos underscores the potential of social media in promoting positive mental health messages and encouraging community support.

However, the presence of pro-ana content, even in a minority of cases, reinforces the need for continuous monitoring and intervention strategies to mitigate the spread of harmful material. Future research should explore the mechanisms driving user engagement across various content types, particularly by considering the interplay between emotional appeal, creator influence, and TikTok's algorithmic recommendations. Additionally, cross-platform comparisons could provide a more comprehensive understanding of how social media platforms collectively shape public discourse on eating disorders. Addressing these gaps will be crucial in developing more effective digital health interventions and improving the safety of online environments for vulnerable users.

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Conflict of interest

The authors declare no relevant conflicts of interest or financial ties with organizations or entities discussed in this work. This includes (but is not limited to) consultancy, honoraria, stock ownership, or other benefits that could adversely affect the objectivity of the research. The authors emphasize that the research was conducted ethically and without influence from any conflicts of interest in the design, conduct, or presentation of the results. This research did not receive any specific grant from funding agencies in the public, commercial or not-for-profit sectors.

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Author's contributions

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cifically, S.C. and L.P. were responsible for the conceptualization of the study. S.C., L.B., S.T., and L.P. developed the methodology, and L.P. carried out the formal analysis. The investigation was conducted by L.B. and S.C. The original draft was prepared by E.D.M., G.P., and L.B., with critical review and editing by G.M.G., M.M., and L.P. L.P. provided supervision throughout the study. All authors contributed to drafting or critically revising the manuscript for important intellectual content, approved the final version for submission, and agreed to be accountable for all aspects of the work, ensuring that any issues related to accuracy or integrity are thoroughly investigated and resolved.

References

1 Treasure J, Duarte TA, Schmidt U. Eating disorders. The Lancet 2020;395:899-911. https://doi.org/10.1016/S0140-6736(20)30059-3

2 Lookingbill V, Mohammadi E, Cai Y. Assessment of Accuracy, User Engagement, and Themes of Eating Disorder Content in Social Media Short Videos. JAMA Netw Open 2023;6:e238897. https://doi.org/10.1001/jamanetworkopen.2023.8897

3 Uniacke B, Walsh BT. Eating Disorders. Ann Intern Med 2022;175:ITC113-ITC128. https://doi.org/10.7326/AITC202208160

4 Lee N, Buchanan K, Yu M. Each post matters: a content analysis of #mentalhealth images on Instagram. Journal of Visual Communication in Medicine 2020;43:128-138. https://doi.org/10.1080/17453054.2020.1781535

5 Jones ME, Salafia EHB, Leonard KC. Users' perceptions of how an unmoderated eating disorder community may benefit or harm their recovery. J Eat Disord 2022;10:129. https://doi.org/10.1186/s40337-022-00653-3

6 Uchôa FNM, Uchôa NM, Daniele TM da C, et al. Influence of the Mass Media and Body Dissatisfaction on the Risk in Adolescents of Developing Eating Disorders. Int J Environ Res Public Health 2019;16:1508. https://doi.org/10.3390/ijerph16091508

7 J Devoe D, Han A, Anderson A, et al. The impact of the COVID-19 pandemic on eating disorders: A systematic review. Int J Eat Disord 2023;56:5-25. https://doi.org/10.1002/eat.23704

8 Bonfanti RC, Melchiori F, Teti A, et al. The association between social comparison in social media, body image concerns and eating disorder symptoms: A systematic review and meta-analysis. Body Image 2025;52:101841. https://doi.org/10.1016/j.bodyim.2024.101841

9 McCashin D, Murphy CM. Using TikTok for public and youth mental health – A systematic review and content analysis. Clin Child Psychol Psychiatry 2023;28:279-306. https://doi.org/10.1177/13591045221106608

10 Herrick SSC, Hallward L, Duncan LR. "This is just how I cope": An inductive thematic analysis of eating disorder recovery content created and shared on TikTok using # EDrecovery. Intl J Eating Disorders 2021;54:516-526. https://doi.org/10.1002/eat.23463

11 Cohen R, Irwin L, Newton-John T, et al. #bodypositivity: A content analysis of body positive accounts on Instagram. Body Image 2019;29:47-57. https://doi.org/10.1016/j.bodyim.2019.02.007

12 Tiggemann M, Anderberg I, Brown Z. #Loveyourbody: The effect of body positive Instagram captions on women's body image. Body Image 2020;33:129-136. https://doi.org/10.1016/j.bodyim.2020.02.015

13 Au ES, Cosh SM. Social media and eating disorder recovery: An exploration of Instagram recovery community users and their reasons for engagement. Eating Behaviors 2022;46:101651. https://doi.org/10.1016/j.eatbeh.2022.101651

14 Goh AQY, Lo NYW, Davis C, et al. #EatingDisorderRecovery: a qualitative content analysis of eating disorder recovery-related posts on Instagram. Eat Weight Disor 2022;27:1535-1545. https://doi.org/10.1007/s40519-021-01279-1

15 Social media: TikTok users in Italy. Statista. Avaiable at: https://www.statista.com/study/73539/social-media-tiktok-users-in-italy/. (Accessed on: 08/03/2025).

16 Pruccoli J, De Rosa M, Chiasso L, et al. The use of TikTok among children and adolescents with Eating Disorders: experience in a third-level public Italian center during the SARS-CoV-2 pandemic. Ital J Pediatr 2022;48:138. https://doi.org/10.1186/s13052-022-01308-4

17 Griffiths S, Whitehead G, Angelopoulos F, et al. Corrigendum to "Does TikTok contribute to eating disorders? A comparison of the TikTok algorithms belonging to individuals with eating disorders versus healthy controls" [Body Image 51 (2024) 101807]. Body Image 2025;52:101834. https://doi.org/10.1016/j.bodyim.2024.101834

18 Logrieco G, Marchili MR, Roversi M, et al. The Paradox of Tik Tok Anti-Pro-Anorexia Videos: How Social Media Can Promote Non-Suicidal Self-Injury and Anorexia. IJERPH 2021;18:1041. https://doi.org/10.3390/ijerph18031041

19 Wismashanti RA. Social Media Content Moderation Challenges for Vulnerable Groups: A Case Study on Tiktok Indonesia. Eduvest 2023;3:1449-1464. https://doi.org/10.59188/eduvest.v3i8.893

20 Zeng J, Kaye DBV. From content moderation to visibility moderation: A case study of platform governance on TikTok. Policy & Internet 2022;14:79-95. https://doi.org/10.1002/poi3.287

21 best-Hashtag.com. https://best-hashtags.com/

22 IBM Corp. Released 2021. IBM SPSS Statistics for Windows, Version 28.0.

23 Khalaf AM, Alubied AA, Khalaf AM, et al. The Impact of Social Media on the Mental Health of Adolescents and Young Adults: A Systematic Review. Cureus 2023;15: e42990. https://doi.org/10.7759/cureus.42990

24 Chung A, Vieira D, Donley T, et al. Adolescent Peer Influence on Eating Behaviors via Social Media: Scoping Review. J Med Internet Res 2021;23:e19697. https://doi.org/10.2196/19697

25 Aparicio-Martinez P, Perea-Moreno AJ, Martinez-Jimenez MP, et al. Social Media, Thin-Ideal, Body Dissatisfaction and Disordered Eating Attitudes: An Exploratory Analysis. IJERPH 2019;16:4177. https://doi.org/10.3390/ijerph16214177

26 Ladwig G, Tanck JA, Quittkat HL, et al. Risks and benefits of social media trends: The influence of "fitspiration", "body positivity", and text-based "body neutrality" on body dissatisfaction and affect in women with and without eating disorders. Body Image 2024;50:101749. https://doi.org/10.1016/j.bodyim.2024.101749

27 Branley DB, Covey J. Pro-ana versus Pro-recovery: A Content Analytic Comparison of Social Media Users' Communication about Eating Disorders on Twitter and Tumblr. Front Psychol 2017;8:1356. https://doi.org/10.3389/fpsyg.2017.01356

28 Bond E. Virtually Anorexic – Where's the Harm? Uno Studio Di Ricerca Sui Rischi

Dei Siti Web pro-Anoressia; 2012.

29 Oksanen A, Garcia D, Sirola A, et al. Pro-Anorexia and Anti-Pro-Anorexia Videos on YouTube: Sentiment Analysis of User Responses. J Med Internet Res 2015;17:e256. https://doi.org/10.2196/jmir.5007

30 Sjöström DK, De Mendonca Lindström T, et al. Helpful or Not? A Qualitative Study on Female Adolescents' Experience of TikTok When Recovering From Anorexia Nervosa. Intl J Eating Disorders 2024;57:2217-2227. https://doi.org/10.1002/eat.24265

31 Dong X, Liu H, Xi N, et al. Short video marketing: what, when and how short-branded videos facilitate consumer engagement. INTR 2024;34:1104-1128. https://doi.org/10.1108/INTR-02-2022-0121

32 Jaakonmäki R, Müller O, Vom Brocke J. The Impact of Content, Context, and Creator on User Engagement in Social Media Marketing; 2017.

33 Suh B, Hong L, Pirolli P, Chi EH. Want to be Retweeted? Large Scale Analytics on Factors Impacting Retweet in Twitter Network. In: 2010 IEEE Second International Conference on Social Computing. IEEE 2010;2010:177-184. https://doi.org/10.1109/SocialCom.2010.33

34 Conde R, Casais B. Micro, macro and mega-influencers on instagram: The power of persuasion via the parasocial relationship. J Bus Res 2023;158:113708. https://doi.org/10.1016/j.jbusres.2023.113708

35 Borges-Tiago MT, Santiago J, Tiago F. Mega or macro social media influencers: Who endorses brands better? J Bus. Res 2023;157:113606. https://doi.org/10.1016/j.jbusres.2022.113606

APPENDIX A

Codebook for subjective content variables

Emotional expression
Definition: Presence of explicit verbal or non-verbal emotional expression related to eating disorder experiences.
Inclusion criteria: crying, laughing, visible distress or joy; explicit statements of emotional states (e.g., fear, hope, shame)
Exclusion criteria: neutral narration without affective cues
Example: A creator crying while describing a relapse or smiling while celebrating recovery milestones.

Promotion of eating disorders as a lifestyle
Definition: Content framing eating disorders as desirable, normalized, or compatible with a chosen lifestyle.
Inclusion criteria: encouragement of food restriction or weight loss; romanticization of thinness or ED behaviours; discouragement of recovery
Exclusion criteria: critical discussion of Eds; recovery-oriented narratives
Example: A video presenting extreme calorie restriction as “discipline” or “self-control”.

Information accuracy
Definition: Degree to which the video content aligns with evidence-based clinical knowledge on eating disorders.
Categories: accurate; misleading; other / not applicable
Example (accurate): Reference to DSM-5 criteria or evidence-based treatment.
Example (misleading): Promoting extreme dieting as a healthy lifestyle.

Perceived body weight
Definition: Visual perception of the creator’s body weight based on appearance alone.
Categories: underweight; average weight; overweight; not assessable

Note: This variable reflects perceived appearance, not clinical diagnosis.