

When Scrolling Becomes Risk: Problematic Social Media Navigation and Eating Disorders on TikTok

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Chapter 1

Introduction

Social media platforms have spread quickly over the past years, weaving right into the pulse of everyday life. They are no longer just simple communication tools for interacting, but serve as pervasive digital environments in which identities are constantly constructed and validated. Especially among passive social media users, this can lead to isolation and social comparison that affect personal well-being, rather than generating connections (Clark et al., 2018; Quiroz & Mickelson, 2021). Within these algorithmically curated apps, the user experience is never neutral. Those clever algorithms decide what pops up, what echoes back, and what gains traction, subtly filtering and reinforcing certain types of content over others, and creating feedback loops that can influence emotions and actions in cumulative ways (Griffiths et al., 2024). Their popularity has attracted increasing attention from scholars and decision-makers, particularly regarding their potential influence on users' behaviors and mental well-being (Longobardi et al., 2020).

The evolution of this field has occurred together with the diffusion of highly visual social media (HVSM) platforms, which have recently gained significant popularity, especially among younger users (Dane & Bhatia, 2023). These apps focus on sharing visual content like images and short-form videos which can be easily filtered and edited (Cheng, 2024). Researchers have found that the use of HVSM leads to greater body image concerns and dissatisfaction for users (Marengo et al., 2017). HVSMs rely on algorithmic recommendation systems that continuously adapt content streams based on subtle users' behavioral signals such as how long they watch, where they stop, how they click or scroll (Griffiths et al., 2024).

People dealing with eating disorders seem particularly exposed to these dynamics. Eating disorders (EDs) are complex mental conditions characterized by abnormalities in eating behaviors, distorted body image, and extreme sensitivity to appearance assessment.

Research has consistently shown that being exposed to idealized body norms can contribute to body dissatisfaction and thin-ideal internalization. These mechanisms might be exacerbated in digital spaces where content focused on physical appearance is widely shared and often promoted by algorithms, leading to the creation of harmful echo chambers (Merino et al., 2024; Griffiths et al., 2024). Furthermore, eating disorders are frequently ego-syntonic, meaning that beliefs and actions related to the condition may be seen as consistent with one's identity or aspirations (Williams & Reid, 2010). In such conditions, where individuals may be motivated to maintain their toxic behaviors, either active or passive involvement with specific content online can further reinforce their maintenance tendencies.

Multiple research studies link social media to eating disorders, but significant gaps still exist. Psychological studies have examined eating disorder mechanisms such as social comparison or thin-ideal, identifying individual vulnerability factors activated within digital environments. Computational and data-driven approaches have focused on detecting eating disorder signals within large-scale social media datasets, treating risk primarily as a content-level or text-based phenomenon. However, less attention has been devoted to understanding how everyday navigation patterns and differentiated interaction behaviors within highly visual platforms may contribute to vulnerability. Limited research has sorted out specific or ambiguous categories despite their potentially distinct psychological implications. Finally, few studies adopt a context-sensitive approach, even though algorithmic ecosystems may vary across countries.

This work fills these gaps focusing on the role of ED maintenance specifically in the Italian context, through the adoption of an approach centered on navigation within TikTok. By combining a systematic review and an empirical investigation of Italian users, the research examines how problematic social network use (PSNU), interaction patterns, exposure to different content, and perceived psychological impact intersect. In this study, risk is framed as a dynamic process emerging from the interaction between individual behaviors and platforms' algorithmic setups rather than a static consequence of exposure. It also aims to contribute to the development of targeted and context-sensitive digital support strategies capable of identifying early vulnerability signals within highly personalized online spaces.

Chapter 2

Theoretical Background

2.1 Eating disorders

Eating disorders (EDs) are a broad category of severe conditions that include significant disturbances in eating behavior, distortions in body image, and marked psychological and medical consequences (Schmidt et al., 2016). High levels of anxiety, low self-esteem, and obsessive-compulsive behaviors are frequently linked to these disorders, which contribute to their clinical complexity and chronicity. Eating disorders are seen not only as medical illnesses, but also as conditions influenced by social environments and pressures. In this context, social media platforms where unrealistic ideals of thinness and physical perfection are disseminated become risk factors as vulnerable individuals are more likely to internalize these artificial standards and perceive them as the only socially accepted norms (Saunders et al., 2018; Pérez-Jiménez et al., 2025). What makes some eating disorders distinct is their ego-syntonic nature, that is, the fact that disturbed cognitions and behaviors are seen as congruent with the self and its goals (Williams & Reid, 2010). This trait has long been acknowledged as a significant barrier to seeking help, frequently postponing activities that require treatment and making therapeutic interventions more difficult (Mazzeo et al., 2024; Zhou et al., 2020; Ramírez-Cifuentes et al., 2021).

2.2 Social Media

Social media have evolved into holistic and immersive digital environments where users are continuously exposed to personalized, algorithmically curated streams of information. Through the extraction and processing of behavioral data, including browsing duration, search history, and interaction patterns, these platforms are able to customize content in order to optimize user engagement dynamically (Griffiths et al., 2024). A substantial body of literature has consistently documented associations between social media use and

negative body image outcomes, as well as disordered eating behaviors, particularly among adolescents (Dahlgren et al., 2024; Vandenbosch et al., 2022; Marks et al., 2020). These associations are largely mediated by social comparison based on physical appearance in turn intensified by repeated exposure to idealized and seemingly authentic representations of bodies online (Kraymer et al., 2008; Merino et al., 2024). Continuous exposure to tailored material streams over time contributes to the internalization of unrealistic standards of thinness subconsciously (Marks et al., 2020). Such dynamics are especially pronounced within highly visual social media (HVSM) apps centered on image and video sharing that enable editing and aesthetic optimization (Merino et al., 2024). Within these environments, visual self-presentation and social feedback mechanisms amplify pressure on physical appearance and vulnerability to body dissatisfaction and disordered eating behaviors (Rodgers et al., 2020; Sharma & Vidal, 2023).

2.3 TikTok as a case study

In the highly visual social media landscape, TikTok is a crucial case due to the central role of its algorithmic recommendation system and its popularity among adolescent and young adult users. Its structure differs from previous platforms, which were based on networks of friends. Within this app, videos are selected by the algorithm and shown to users via the For You page, an endless stream of short clips that fill the screen, designed more to capture attention than to create connections (Griffiths et al., 2024; Herrman, 2024). TikTok's algorithm relies on silent signals, such as viewing time and those brief pauses before scrolling away, allowing for rapid adjustments even in the absence of intentional engagement (Wall Street Journal, 2021; Chayka, 2024). When it comes to body concerns and eating disorders, such features carry special weight. A large-scale observational study analyzing over one million TikTok videos showed that users with eating disorders were disproportionately exposed to content focused on physical appearance, dieting, fitness, and toxic eating disorders, with algorithmic distribution channelling all of this in their direction, without solely relying on what their taps and likes might suggest (Griffiths et al., 2024). Furthermore, stronger algorithmic biases toward these content categories were linked to greater severity of ED symptoms, indicating the formation of self-reinforcing exposure patterns or “echo chambers” that may intensify

vulnerability over time (Merino et al., 2024; Griffiths et al., 2024). These loops are not merely activated by time spent online, but shaped by the type of content users encountered and how they engaged with it, positioning TikTok as a key example for understanding the function of highly visual social media in intensifying appearance pressures and the risk of eating disorders.

Chapter 3

Literature Review

3.1 Framework Design

This study delineates its review approach around the model proposed by Tranfield et al. (2003), which provides a three-phase methodological and transparent structure for organizing and synthesizing prior research.

The model helps spotlight patterns, trends, and gaps in the existing literature relevant to eating disorder risks within social media networks.

The phases of the review process are outlined as follows:

- Phase I – Planning the Review:

This stage establishes the foundation of the review by defining the research question and aims, and by developing a structured review protocol that outlines the search strategy, inclusion requirements, and scope of the analysis

- Phase II – Conducting the Review:

This phase explains the procedures used for selecting relevant studies. It is implemented through a structured screening process involving identification, exclusion, and selection of the final set of studies to be included.

- Phase III – Corpus Analysis and Findings:

The final phase focuses on analyzing the 29 selected studies through a combination of qualitative thematic analysis and topic modeling using Latent Dirichlet Allocation in KNIME Analytics Platform.

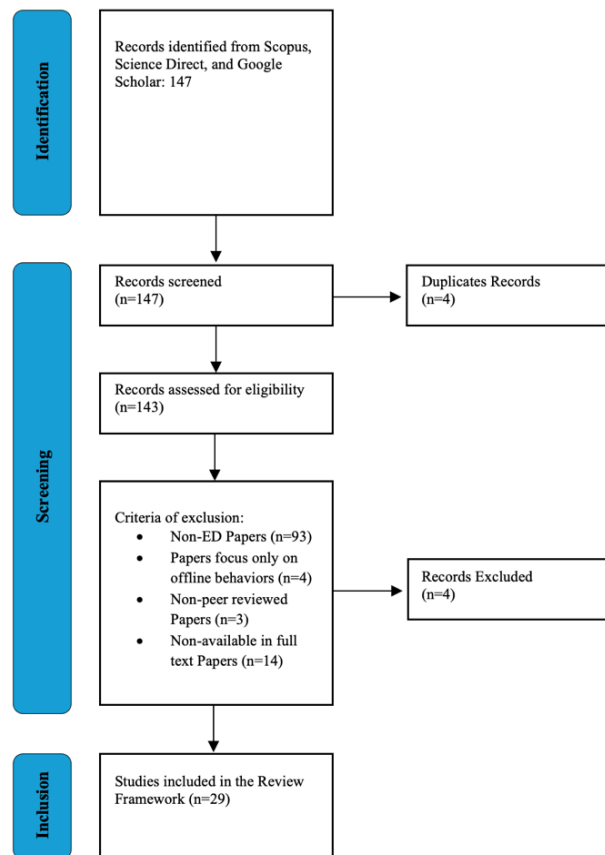


Fig. 1. Review Methodology (adopted from PRISMA).

3.2 Phase I - Planning the Review

a) Research Focus and Research Aims

Following the principles of Tranfield et al. (2003) and Kitchenham and Charters (2007), this study defines a clear review focus, a set of research aims, and a methodological protocol for selecting and analyzing relevant academic sources. This review is conducted to identify key research themes and trends and those that remain unexplored within the literature examining the risks associated with eating disorders in social media.

To ensure conceptual clarity, the PICO framework was applied to guide the analytical scope of the review:

- *Population*: Individuals affected by or at risk of developing eating disorders
- *Phenomenon of Interest*: Spotting and framing risk signs tied to eating disorders
- *Context*: Online social networks

b) Review Protocol

The design of the systematic collection of relevant literature for this review was based on a rigorous protocol to ensure the quality, consistency, and relevance of the sources.

The following primary requirements were applied:

- *Requirement I* - The review was conducted between August and September 2025 through systematic searches in three scholarly databases: Scopus, ScienceDirect, and Google Scholar. Such platforms were selected for their extensive coverage of peer-reviewed articles in data science, psychology, and digital health, making them relevant to the research area.
- *Requirement II* - To ensure thematic consistency and conceptual alignment, articles were selected based on the presence of relevant keywords in their title or abstract, and were reviewed in light of the research objectives.
- *Requirement III* - Only peer-reviewed articles in English and published after 2020 were included in the review in order to reflect the quick evolution of social media platforms and big data tools, ensuring the relevance of the findings.
- *Requirement IV* – According to the multidisciplinary nature of the research question, the review incorporated a variety of empirical approaches, including computational studies, text and image analysis, NLP-based classification, quantitative models, and systematic reviews.
- *Requirement V* - As a final quality assessment step, all selected studies underwent a full-text analysis to confirm their alignment with the inclusion requirements and their contribution to the research topic.

3.3 Phase II - Conducting the Review

The literature selection process was carried out in three structured stages:

Stage I – Identification

The identification stage involved a systematic search across three academic databases: Scopus, ScienceDirect, and Google Scholar (Requirement I). Scopus and ScienceDirect were chosen for their relevance to the topic and their broad coverage of peer-reviewed literature in fields such as psychology and digital health. Google Scholar was additionally included to expand the breadth of the search; for this platform, the Boolean search string was adapted and applied using the advanced search interface to better target scientific literature.

All collected records were entered into Rayyan, a tool built especially for systematic reviews, to speed up the screening process. Before being uploaded to Rayyan, the application Zotero was used to make it easier to export and arrange the articles found using Google Scholar.

The search was carried out using the following Boolean query:

("eating disorders" OR anorexia OR bulimia) AND ("social media" OR Instagram OR TikTok) AND ("big data" OR "machine learning" OR "natural language processing")

As a result of this identification process, a total of 147 publications were retrieved: 55 from Scopus, 68 from ScienceDirect, and 24 from Google Scholar.

Stage II – Screening and Exclusion Criteria

In this second stage, an exploratory screening process was carried out based on the analysis of titles, abstracts, and keywords to ensure that all selected articles aligned with the research scope and aims defined in the review protocol.

As a preliminary step, duplicate records identified across the three databases were removed (n = 4).

Then, a series of exclusion criteria was applied. Studies focusing exclusively on offline behavioral contexts were excluded (n = 4), as they fell outside the digital side this review

targets. Articles that did not examine eating disorders or related psychopathological outcomes were removed (n = 93), including studies centered on general concepts like body image or wellness without a clinical focus on disordered eating. In accordance with Requirement III, non-peer-reviewed materials were excluded from the dataset (n = 3), as they do not meet the criteria for scholarly validation required by the review protocol. Additionally, articles that were not available in full-text format (n = 14) were excluded, as their content could not be subjected to a complete quality assessment (Requirement V). After this screening process, a total of 29 articles were retained for full-text review.

Stage III – Inclusion

The final corpus of studies (n = 29) was examined in full to establish a solid conceptual base for this systematic review and to shape the analysis ahead. This process facilitated the identification of dominant themes, recurring methodological approaches, and key areas of focus across the selected works.

3.4 Phase III – Corpus Analysis and Text Analytics

The chosen corpus is characterized by a predominantly recent body of literature. The distribution of publications over time reveals growing academic curiosity about social media ties to eating disorder risks, reflecting the growing relevance of this topic within both psychological and data-driven research.

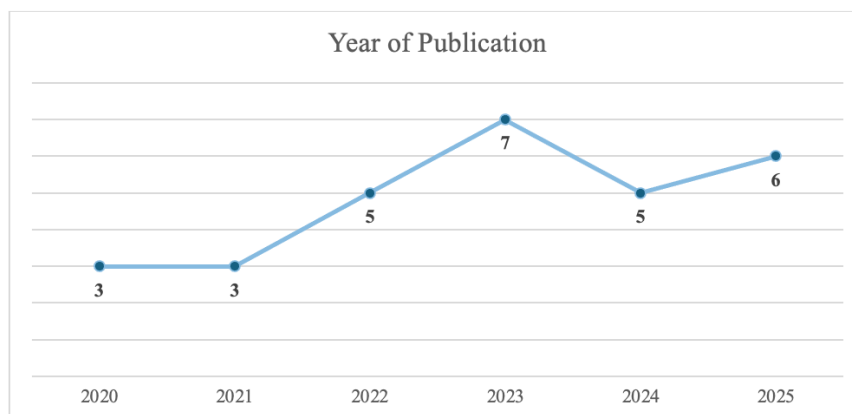


Fig. 2. Paper distribution across years

Building on the selected corpus, the final phase of the methodology was structured into two complementary sub-phases: (1) an automated text mining process applied to the abstracts of the selected papers, handled in KNIME Analytics Platform, and (2) a full-text reading of all papers aimed at refining, validating, and expanding the computational results through qualitative analysis.

This two-step approach allows the integration of data-driven exploration with human interpretation. While the automated analysis enabled the identification of latent thematic patterns across the corpus, the qualitative phase supported a deeper synthesis anchored in full-text evidence.

3.4.1 Automated Abstract Analysis and Topic Modelling in KNIME

This text mining process in KNIME focused on analyzing the abstracts of the 29 selected articles to uncover underlying research themes, commonly used methodologies, and frequently studied platforms. To achieve this, the workflow incorporated techniques from Natural Language Processing (NLP) and Latent Dirichlet Allocation (LDA) topic modeling, enabling a structured and data-driven exploration of the literature.

Dataset Structure

The dataset used for the automated analysis was organized in tabular format, with one row corresponding to each article. The dataset included four columns:

- Paper_ID: a unique numeric identifier assigned to each article;
- Title: the full title of the publication;
- Year: the year of publication;
- Abstract: the abstract text, used as the primary textual input for the analysis.

The dataset was loaded into KNIME using the *Excel Reader* node where the Abstract column served as the core input for the text mining pipeline.

Text Preprocessing

A series of transformations was applied to the textual data of the Abstract column following the pipeline to ensure the text was clean and ready for the analysis:

- Strings to Document (Convert Abstract to Documents): Converted the raw text into a KNIME-compatible document format;
- Case Converter (Convert to LowerCase): Standardized all text to lowercase;
- Punctuation Erasure (Remove Punctuation): Removed punctuation characters;
- Number Filter (Remove Numbers): Removed numerical values;
- Stop Word Filter (Remove Stop Words): Eliminated common stop words that carry limited semantic value (e.g., "the", "and", "in").

Vocabulary Reduction using Entropy

After preprocessing, a Bag-of-Words model was created using the Bag of Words Creator (Create Bag of Words) node, which computed word frequencies across documents. To retain only the most informative terms, the Term Document Entropy node (Calculate Term Entropy) was applied. Using the Row Filter node (Select Entropy > 0.2 Terms), all terms with entropy ≤ 0.2 were removed. This significantly improved the semantic clarity of the resulting topics. The Term Frequency node (Calculate Term Frequency) was then used to finalize the word frequency calculations based on the filtered terms.

Topic Modeling with LDA

With the cleaned vocabulary, the Topic Extractor (Parallel LDA) node (LDA Topic Modeling) was used to perform Latent Dirichlet Allocation (LDA). The number of topics was set to five, as this provided a balance between granularity and interpretability.

The output assigned each document a distribution across the five latent topics and extracted a list of representative keywords for each.

Topic-Level Visualization and Article Mapping

For a detailed exploration of the semantic content of the topics, the output of the LDA model was merged with the filtered term frequency data using a Joiner node in order to identify the most representative terms associated with each topic. Topic-specific keyword sets were isolated using Row Filter nodes and visualized through Tag Cloud nodes, where word size reflected term importance. These visualizations provided an intuitive overview of the thematic focus of each topic and

supported the exploratory interpretation of the results. Finally, GroupBy nodes were used to summarize the distribution of studies across the identified topics and to maintain a link between topic assignments and the corresponding articles.



Fig. 3. Tag Cloud – Topic 0



Fig. 4. Tag Cloud – Topic



Fig. 5. Tag Cloud – Topic 2

Both Topic 0 and Topic 4 deal with recent and converging developments in the study of eating disorders within digital environments, so they have been combined. They differ in methodological focus, but share a common emphasis on the experience of social media use, the role of engagement patterns and platform affordances, and the growing relevance of highly visual social media in shaping risk and vulnerability. Together, they reflect a shift in the literature from exposure-based models toward approaches that consider how users interact with, navigate, and experience social media platforms (Fig. 3 and Fig. 7).

In a similar manner, Topic 1 and Topic 2 were merged, as both focus on computational approaches to eating disorder research on social media. Topic 1 addresses model development independently of platform, while Topic 2 applies detection techniques to specific platforms such as Twitter and blogs. While they differ in platform specificity, both frame eating disorders as text-based digital patterns, putting emphasis on sorting them out rather than on how people navigate sites. On this basis, these topics were integrated into a single thematic cluster centered on computational detection approaches (Fig. 4 and Fig. 5).

Topic 3 was retained as a standalone cluster, as it focuses primarily on psychological and developmental mechanisms linking social media use to body image concerns and eating disorder psychopathology, rather than on detection (Fig. 6).

On the basis of this qualitative synthesis, those initial five exploratory topics were consolidated into three main thematic groups.

Thematic Clusters

Cluster 1: User Experience and Navigation Patterns

Within this first cluster, there are studies that examine risks for eating disorders within social media environments, focusing on user actions online, the content they come across, and how algorithms boost specific items on highly visual platforms. This body of literature shows how eating-related distress becomes visible in digital contexts through recurrent forms of interaction, content production, and community response.

Engagement with visual content focused on body shape, weight, dieting, and exercise is consistently associated with body dissatisfaction, thin-ideal internalization, and disordered eating behaviors. Highly visual social media platforms facilitate social comparison and self-objectification processes by encouraging users to evaluate their bodies through external, socially mediated cues. These effects are primarily related to the type of content and mode of engagement, rather than overall time staring at screens (Marks et al., 2020).

Research in this field also emphasizes the way algorithmic recommendation systems shape the content that reaches users. A study of the TikTok algorithm reveals that users dealing with eating disorders encounter more content related to appearance, diet routines, fitness, and explicitly toxic ED content, with exposure intensity increasing alongside symptom severity. In this context, personalization through algorithms traps individuals in self-reinforcing loops (Griffiths et al., 2024).

In addition, studies examining large-scale social media data have identified recurrent macro-level online behavioral patterns associated with eating-related distress. Hwang et al. (2020) break them into groups such as emotional expression, sharing of physical changes, dietary information seeking, and sharing of dietary strategies.

Finally, recent work points to how these patterns rooted in actions could guide the creation of online help tools. D'Adamo et al. (2025) highlight the value of pairing social media-based detection of ED-related signals with context-sensitive digital interventions, such as delivering focused help or encouraging words right at moments when danger peaks.

Cluster 2: Analytical and Computational Approaches

Cluster 2 collects research that explore eating disorders in social media settings using analysis and computational methods, primarily relying on machine learning and natural language processing techniques applied to content that users create online (Zhou et al., 2020; Benítez-Andrades et al., 2022; HaCohen-Kerner et al., 2022). Social media sites are viewed here as large-scale sources of data where signs of eating disorders can be automatically extracted, classified, and monitored (Zhou et al., 2020).

Across studies, eating disorders are treated as recognizable configurations embedded in digital traces, such as posts, comments, or user profiles. Risks are defined by linguistic, semantic, or stylistic features, enabling the distinction between eating disorder-related and unrelated content or users (Abuhassan et al., 2023; HaCohen-Kerner et al., 2022). This approach emphasizes scalability, efficiency, and predictive performance, making it particularly suitable for population-level monitoring and early identification (Benítez-Andrades et al., 2022).

From a methodological point of view, the cluster is characterized by the use of supervised classification, feature engineering, and model comparison procedures. Studies compare traditional machine learning algorithms with deep learning and transformer-based models, such as BERT, highlighting improvements in performance when contextual semantic information is incorporated (Benítez-Andrades et al., 2022; López-Úbeda et al., 2021).

As a result of this methodological focus, eating disorders are largely conceptualized as content-level or text-based phenomena, abstracted from users' lived experience and everyday engagement with social media platforms (Abuhassan et al., 2023; HaCohen-Kerner et al., 2022). While computational approaches provide valuable tools for automated monitoring and early detection, they offer limited insight into how individuals navigate platforms or the ways digital routines sustain symptoms over time (Benítez-Andrades et al., 2022; Naseriparsa et al., 2025; D'Adamo et al., 2025).

Cluster 3: Psychological Mechanisms and Individual Traits

This cluster looks at social media habits and eating disorders from a psychosocial lens, emphasizing mechanisms of individual vulnerability rather than technological or platform-specific features. In these studies, appearance-based social comparison, thin-ideal internalization, body dissatisfaction, and negative affect consistently emerge as central pathways linking social media engagement to eating disorder symptomatology (Aranha-de-Macedo et al., 2022; Padín et al., 2021; Dane & Bhatia, 2023).

Facing idealized body content on social media pushes internal beauty norms and intensifies self-objectification processes, all of which are predictive of compulsive

exercise, binge-purge behaviors, and restrictive eating (Rizwan et al., 2022; Suhag et al., 2024). These effects appear stronger on image-centered platforms and are amplified during a vulnerable development stage marked by identity formation and growing peer comparison (Mazzeo et al., 2024; Naji et al., 2025).

Within this framework, social media is not conceptualized as a direct causal agent, but as a contextual risk factor that interacts with pre-existing psychological traits such as perfectionism, low self-esteem, emotion regulation difficulties, anxiety, and obsessive-compulsive tendencies (Padín et al., 2021; Aggarwal, 2023). People with these characteristics are more prone to engage in comparison processes and interpret social media content in a self-critical or ruminative manner, increasing their vulnerability to eating disorder onset and symptom escalation (Aranha-de-Macedo et al., 2022; Rizwan et al., 2022).

While this body of work provides robust evidence regarding vulnerability profiles and pathways to symptom emergence, it offers more limited insight into everyday navigation behaviors or into the mechanisms through which social media use may support symptom maintenance over time, rather than initial onset.

Table 1
Overview of identified literature thematic clusters, their primary focus, and underlying conceptualizations of eating disorder vulnerability in social media contexts.

Cluster	Main Focus	How EDs are conceptualized
Cluster 1 User Experience and Navigation Patterns	User experience, engagement patterns, and platform affordances	Eating disorder vulnerability emerges from dynamic interactions between user behavior, algorithmic processes, and highly visual digital environments
Cluster 2 Analytical and Computational Approaches	Machine learning and NLP-based detection of eating disorder-related signals	Eating disorders are treated as identifiable patterns within digital traces, primarily textual in nature
Cluster 3 Psychosocial Mechanisms and Individual Traits	Psychological and developmental mechanisms linking social media use to eating disorders	Eating disorder risk arises from psychosocial vulnerability factors activated by social media use

How studies spread out among those three thematic groups points up the imbalanced development in current research areas (Table 1). Cluster 3, focused on psychosocial mechanisms and individual vulnerability, includes the largest number of studies, reflecting a well-established psychological research tradition. Cluster 2 also shows

substantial coverage, indicating growing interest in computational and detection-oriented approaches. By contrast, Cluster 1, the one digging into user experience, navigation patterns, and highly visual platforms, holds fewer works.

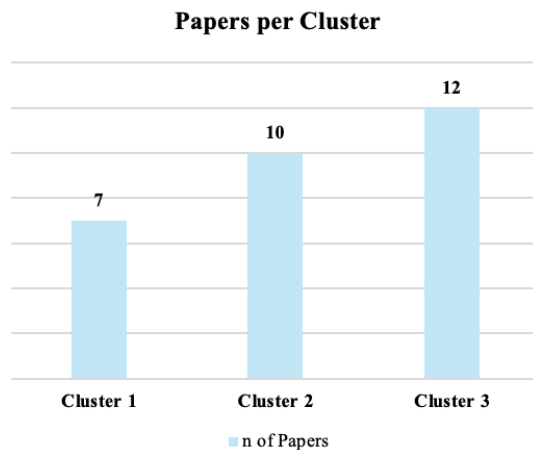


Fig. 8. Papers within each cluster

Such a gap highlights the novelty of this perspective by implying that studies around visual and algorithm-driven spaces that tie risk to how people move through them, stand as newer territory.

3.5 Findings

Cluster 1: User Experience and Navigation Patterns

From Time of Use to Type of Navigation: Problematic Social Network Use (PSNU)

Across studies in Cluster 1, a consistent finding is that time-based measures of social media use are not enough to account for eating disorder vulnerability. Risk seems to be more closely linked to platform navigation than to the amount of time spent online, particularly when it comes to compulsivity, lack of self-control, and emotional dependence (Sharma & Vidal, 2023; Lo Coco & Rodgers, 2025).

A trend that is reflected in the way Problematic Social Network Use (PSNU) is gaining ground as a crucial pattern characterized by compulsive checking, difficulty disengaging, and persistent use despite negative emotional repercussions (Andreassen et al., 2015; Lo Coco & Rodgers, 2025). Problematic use is connected with greater levels of body

dissatisfaction and disordered eating even when usage time does not differ among users (Sharma & Vidal, 2023).

Within this framework, eating-related vulnerability manifests through distinct macro-patterns of online navigation. Hwang et al. (2020) identify recurrent categories of behavior associated with emotional eating and linked to different community feedback configurations, suggesting that engagement styles are embedded in interactive social dynamics that can differentially reinforce disordered behaviors. Overall, these findings support a shift toward the analysis of navigation patterns as the real measure for spotting threats.

Highly Visual Social Media and Algorithmic Amplification of Risk

A second core finding concerns the role of highly visual social media platforms (HVSM), which intensify eating disorder-related vulnerability through visual salience and algorithmic content delivery, reporting stronger associations compared to text-based social media (Marks et al., 2020; Sharma & Vidal, 2023). It is important to underline that recent empirical evidence shows that SM algorithms directly affect exposure patterns. In a large-scale observational study, Griffiths et al. (2024) demonstrate that users with eating disorders are disproportionately exposed to specific types of TikTok content compared to the general population, a pattern only partially explained by explicit engagement behaviors such as likes, indicating that algorithmic personalization alone can lead people deeper into trouble, targeting them with feeds that echo their struggles.

These findings support the presence of algorithmically reinforced feedback loops, in which users' existing vulnerabilities interact with tailored suggestions to produce increasingly homogeneous and risky environments, potentially limiting exposure to alternative content (Griffiths et al., 2024).

Ambiguous, Wellness, and Sensitization Content

The literature indicates that eating disorder-related risk does not originate exclusively from explicitly pro-eating disorder material. Weight-centric narratives framed as health-promoting—such as *fitspiration* or *clean eating*—may reinforce body surveillance,

dietary restraint, and control-oriented behaviors, particularly among users already at risk (Marks et al., 2020; Sharma & Vidal, 2023). Similarly, recovery- or awareness-oriented content may produce heterogeneous effects. While such content can be supportive for some individuals, it may inadvertently trigger comparison processes or reinforce disorder-focused identities in others, depending on users' interpretation, stage of vulnerability, and navigation patterns (D'Adamo et al., 2025). These findings highlight the importance of evaluating content not solely on explicit intent, but in relation to users' paths through it, how they frame and blend it into their daily habits.

Linking Analytical Approach and User Experience (Cluster 2 and 1)

From Detection to Understanding Maintenance Processes and Digital Support Opportunities

Studies relying on analytical and computational approaches often paint eating disorder risks on social media as items detectable via automated detection of linguistic and behavioral signals embedded in digital content (Zhou et al., 2020; Benítez-Andrades et al., 2022; HaCohen-Kerner et al., 2022). Focusing on supervised classification and scalability, within this corpus eating disorders are recognizable patterns in posts, comments, or users' profiles (Abuhassan et al., 2023; López-Úbeda et al., 2021).

Several contributions within Cluster 2 recognize the limits of detection-oriented models in capturing the dynamics through which eating disorder risk develops over time (Benítez-Andrades et al., 2022; Naseriparsa et al., 2025). While they are effective in identifying risk-related signals, these approaches rely on static units of analysis and generally do not incorporate users' engagement styles or navigation dynamics (Abuhassan et al., 2023; HaCohen-Kerner et al., 2022).

These studies also highlight the limited contributions of detection approaches in capturing sustaining factors, particularly those fueled by repeated exposure and algorithmic personalization (D'Adamo et al., 2025). In algorithmically curated environments, users may be repeatedly exposed to disorder-congruent content even without explicit

endorsement or active searching, a dynamic that detection models alone are not designed to capture (Rodgers et al., 2025; Griffiths et al., 2024).

Importantly, this cluster underlines the possibility of leveraging detection outputs beyond classification, proposing their application as the basis for digital support mechanisms such as early warning systems, targeted psychoeducational resources, or referrals to care triggered by identified risk patterns (Benítez-Andrades et al., 2022; D'Adamo et al., 2025). The effectiveness of such approaches appears to depend on their alignment with the specific behavioral signals identified by analytical models, rather than on generic strategies, making distinctions between different modes of online behavior particularly relevant (Zhou et al., 2020; Hwang et al., 2020).

Cluster 3: Psychological Mechanisms and Individual Traits

From Population-Level Associations to Individual Vulnerability
Findings highlight the limits of population-level analyses in capturing heterogeneous trajectories of individual vulnerability. Although robust associations between social media use and eating disorder outcomes are consistently reported at the group level, individuals differ substantially in how they dive into platforms and react to appearance-centered material (Dane & Bhatia, 2023; Padín et al., 2021).

Evidence indicates that demographic and psychosocial factors like gender or developmental stage shape both exposure and psychological impact. It has been found that adolescent and young adult females appear particularly susceptible to social comparison and body dissatisfaction processes, reflecting heightened sensitivity to peer evaluation and sociocultural pressures (Aranha-de-Macedo et al., 2022; Rizwan et al., 2022; Suhag et al., 2024).

Engagement type further differentiates risk trajectories. Passive consumption of appearance content has been consistently associated with greater body dissatisfaction, negative affect, and disordered eating symptoms compared to more expressive forms of interaction (Mazzeo et al., 2024; Aggarwal, 2023). Overall, these findings challenge approaches that assess risk based simply on exposure, pointing instead to engagement style as a pivotal mechanism through which social media contributes to ED vulnerability.

Synthesis of Findings

Across the three clusters, eating disorder–related risk on social media emerges as a dynamic and cumulative process, shaped by the interaction between individual risk factors, patterns of navigation, and algorithmically curated environments (Marks et al., 2020; Dane & Bhatia, 2023).

Research focused on psychological mechanisms highlights population-level associations between social media use, appearance-based social comparison, body dissatisfaction, and negative affect, identifying vulnerability factors rather than deterministic risk profiles (*Cluster 3*) (Marks et al., 2020; Suhag et al., 2024).

Studies centered on user experience and navigation uncover that compulsive engagement, passive consumption, and algorithmically reinforced exposure loops play a central role in sustaining risk over time, particularly within highly visual platforms (*Cluster 1*) (Sharma & Vidal, 2023; Griffiths et al., 2024).

Analytical approaches demonstrate that risk signals can be detected at scale, but broadly conceptualize risk as static and content-level, offering limited insight into lived experience and maintenance processes (*Cluster 2*) (Zhou et al., 2020; Benítez-Andrades et al., 2022).

3.6 Research Gap and Implications

Research Gap

Despite extensive evidence linking social media use to eating disorder–related outcomes, important gaps remain in how risk is conceptualized and measured. Across reviews and empirical studies, time-based indicators of use consistently emerge as insufficient, while the qualitative nature of engagement and navigation remains underexplored (Padín et al., 2021; Dane & Bhatia, 2023; D’Adamo et al., 2025). Although constructs such as Problematic Social Network Use (PSNU) have been proposed to capture compulsive and emotionally driven engagement, they are rarely examined in relation to concrete, platform-specific navigation behaviors, particularly within algorithmically curated environments such as TikTok (Lo Coco & Rodgers, 2025; Fioravanti et al., 2024).

Much of the existing literature prioritizes risky content detection over user experience, treating risk as a static property of content exposure rather than as a dynamic process shaped by interaction, consumption, and algorithmic feedback loops (Benítez-Andrades et al., 2022; D'Adamo et al., 2025). Evidence regarding the impact of ambiguous or apparently healthy content remains fragmented, despite indications that such content may reinforce control-oriented behaviors in vulnerable users (Marks et al., 2020; Dane & Bhatia, 2023; Cardoza et al., 2022).

Finally, while population-level associations between social media use and eating disorder symptoms are well established, there is limited empirical work addressing individual-level vulnerability as it emerges through everyday navigation patterns (Suhag et al., 2024; Solans Noguero et al., 2023; Sharma & Vidal, 2023). This limitation is further compounded by the lack of validated assessment frameworks tailored to specific cultural contexts, including young Italian populations, despite evidence that algorithms and what shows up varies across countries.

Taken together, these gaps highlight the need for a navigation-centered and context-sensitive framework capable of linking PSNU, engagement behaviors, content exposure, and subjective experience within platforms driven by visuals and algorithms. Addressing this gap requires moving beyond time-based metrics and content-level detection toward an exploratory assessment of everyday navigation patterns, particularly within specific cultural contexts such as TikTok use in Italy.

Research Questions

In response to these gaps, the present study addresses the following research questions:

RQ1: Do individuals with an eating disorder diagnosis differ from healthy individuals in their patterns of TikTok navigation and interaction?

RQ2: How are these differences reflected in problematic social network use, exposure to content linked to eating disorders, and perceived psychological impact?

Chapter 4

Questionnaire Design

4.1 Research Design and Objectives

The present study relied on a cross-sectional, questionnaire-based design to investigate patterns of TikTok use among Italian users and their potential associations with body image, eating behaviors, and psychological well-being. Participation was anonymous, and all data were collected and analyzed exclusively for research purposes.

4.2 Questionnaire Structure and Data Collection

The questionnaire was developed by adapting measures from prior studies on TikTok and risks tied to eating disorders, drawing especially from Griffiths et al. (2024), and refining it on the basis of the findings emerging from the review of existing literature. The selection of content- and impact-related questionnaire items was informed by topic domains identified in prior data-driven analyses of eating disorder–related social media discourse (Zhou et al., 2020).

The questionnaire was administered online and consisted of several self-report sections designed to assess TikTok use and eating disorder–related variables. Participants were recruited through multiple channels. Specifically, the survey was disseminated on TikTok through study-related posts, relevant hashtags, and thematic content to reach users engaged with eating disorder–related material, with a particular focus on the Italian ED-related community. In addition, the questionnaire was shared through university networks and academic communities to facilitate the inclusion of participants from the general population.

Inclusion criteria required participants to report using TikTok at least once per week. Individuals who did not meet this criterion were automatically excluded, and the

questionnaire terminated for these respondents. In addition, the analytical sample was further limited to individuals residing in Italy.

The questionnaire comprised the following sections.

First, socio-demographic information was collected, including age, gender, and country of residence. Eating disorder (ED) status was assessed through a self-report item distinguishing between current diagnosis, past diagnosis, no diagnosis, suspected but non-diagnosed ED, and preference not to answer.

General TikTok habits were tracked by measuring frequency of use and average daily minutes spent on the platform. Problematic Social Network Use (PSNU) was measured through items capturing core dimensions of dysregulated social media engagement and rated on a five-point Likert scale, assessing difficulty disengaging from TikTok, emotional use of the platform, loss of time awareness, and continued use despite negative consequences (Lo Coco & Rodgers, 2025). How users engage with TikTok content was evaluated via items about viewing full videos, reading and spending time in comment sections, liking videos, saving content, and commenting on videos.

Finally, participants reported their perceived exposure to specific categories of TikTok content, including body image and appearance, diet, fitness, pro-eating disorder content, eating disorder-related experiences, and eating disorder awareness or sensitization. The questionnaire also assessed the perceived psychological effect across multiple domains, namely body image and social comparison, negative affect and emotion regulation, normalization and reinforcement of dysfunctional behaviors, behavioral effects, and awareness of cumulative exposure over time (Zhou et al., 2020).

4.3 Sample Description

For analytical purposes, several exclusion criteria were applied. In line with the study's inclusion rules, only participants residing in Italy were retained. Responses from participants not identifying as either female or male were excluded from gender-related analyses due to the very limited number of non-binary or undisclosed responses.

Respondents who selected “prefer not to answer” as regards their eating disorder condition were excluded from analyses as ED status serves as a key factor.

After applying inclusion criteria and data screening procedures, the final analytical sample comprised 1,054 participants. Age of participants ranged from 11 to 52 years ($M = 24.04$, $SD = 5.21$). The sample was predominantly female (92.8%), with 7.2% identifying as male.

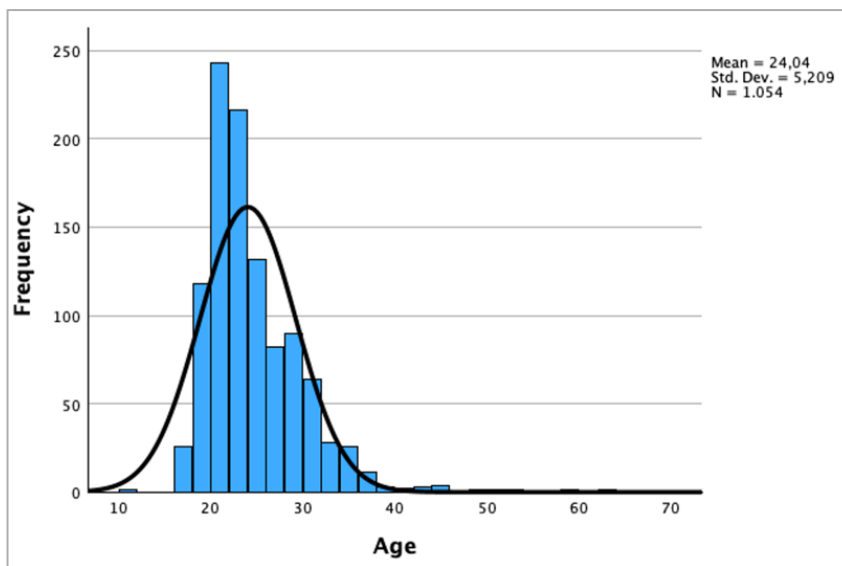


Fig 9. Age frequency distribution across the sample

Eating disorder condition was recoded into a new variable called ED status comprising three categories: *Diagnosed ED* (current or past formal diagnosis), *Healthy* (no history of eating disorders), and *Suspected ED* (no formal diagnosis but suspected experience of an eating disorder). In the final sample, 29.9% of participants were classified as Diagnosed ED, 23.1% as Healthy, and 47.1% as Suspected ED.

Chapter 5

Results

5.1 Between-Group Differences

5.1.1 Descriptive Analyses

In this phase, individuals classified as Suspected ED were excluded in order to ensure a clear and analytically distinct comparison between participants with a formal diagnosis and healthy individuals. Restricting the analysis to these two groups allows for a more interpretable assessment of between-group differences, minimizing ambiguity.

Descriptive analyses were conducted to explore differences between participants with an eating disorder diagnosis and healthy individuals across general TikTok habits, problematic social network use (PSNU), interaction styles, and perceived exposure to specific content categories. This initial stage aims to assess whether ED status is associated with distinct engagement characteristics.

General TikTok Use

TikTok use seemed highly integrated into daily routines across both groups; however, descriptive analyses stratified by eating disorder (ED) status revealed marked differences in the intensity of platform use.

Regarding frequency of use, the vast majority of participants with a diagnosed ED reported using TikTok multiple times per day (88.3%), compared to a lower proportion among healthy participants (73.1%). Using TikTok at least once per day was reported by a similar proportion of participants in both groups (ED: 9.7%; Healthy: 8.3%).

The average time per day mirrors this pattern: 58.8% of ED users reported spending at least an hour per day on the platform compared to 42.6% among healthy users.

Problematic Social Network Use (PSNU)

At the descriptive level, participants with a diagnosed eating disorder (ED) consistently scored higher on troublesome TikTok habits across PSNU dimensions. Emotional use and reduced self-control showed the most pronounced differences between groups: high levels of using TikTok to manage negative emotions were reported by 36.8% of individuals with ED compared to 17.5% of healthy participants, while continuing to use TikTok despite negative effects was reported by 43.4% of the ED group versus 20.6% of healthy users.

Difficulties related to control and disengagement were also more frequent among participants with ED. High levels of difficulty stopping TikTok use once started were reported by 34.2% of individuals with ED compared to 29.4% of healthy participants, whereas using TikTok longer than intended was highly prevalent in both groups but more pronounced among those with ED (67.5% vs. 60.5%).

Finally, temporal dysregulation emerged as a common feature across the sample, with loss of time awareness at high levels reported by 59.5% of participants with ED and 54.8% of healthy participants, indicating a shared but more intense experience among individuals with ED.

Perceived Exposure to TikTok Content

Splitting by eating disorder status, descriptive statistics uncover wide gaps in perceived exposure across every content type.

Exposure to body image and appearance-related content was markedly higher among participants with a diagnosed ED, with 60.4% reporting that many or almost all of videos belonged to this category, compared to 39.7% of healthy participants (Fig. 10). A similar pattern emerged for diet-related content, where over half of individuals with ED (50.6%) reported moderate to high exposure, compared to only 20.7% of healthy respondents (Fig. 11).

Fitness videos highlighted the most subtle difference between ED and healthy participants: 38.9% of subjects diagnosed with ED and 27.5% of healthy participants reported moderate to high exposure levels (Fig. 12).

The biggest gaps came with eating disorder content, specifically 32.2% of individuals with ED reported that many or almost all of videos in their feeds are about pro-eating

disorder content while only 7.2% of healthy users reported the same (Fig. 13). Similarly, exposure to ED narratives was reported at moderate to high levels by 58.4% of participants with ED, compared to 9.5% of healthy participants (Fig. 14).

Finally, 38.9% of respondents with ED reported moderate to high exposure to awareness content, whereas only 10.0% of healthy participants perceived the same exposure (Fig.15).

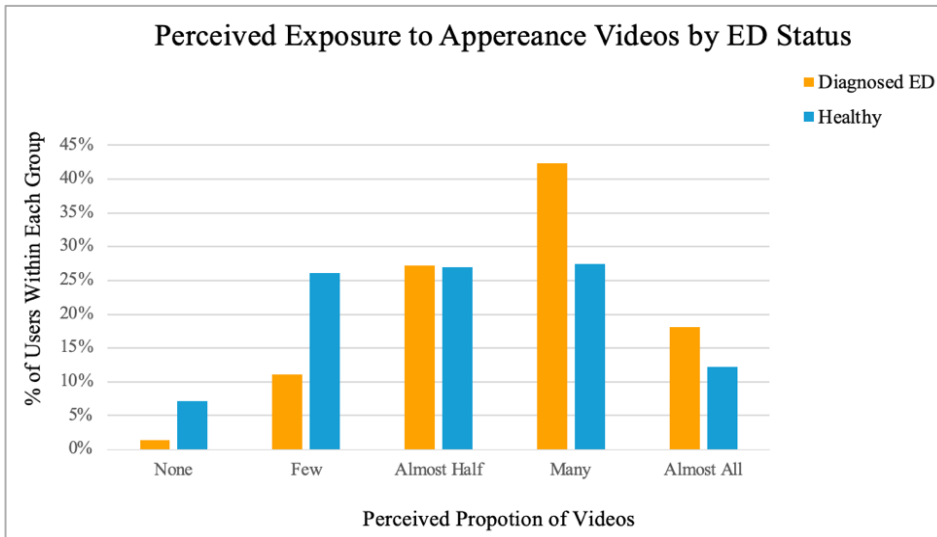


Fig. 10. Perceived exposure to Appearance-related content by ED status

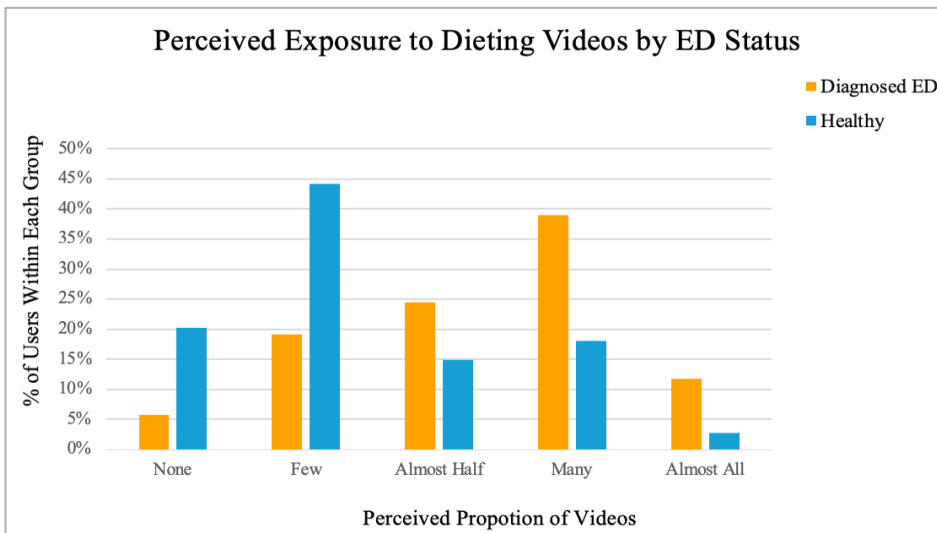


Fig. 11. Perceived exposure to Dieting content by ED status

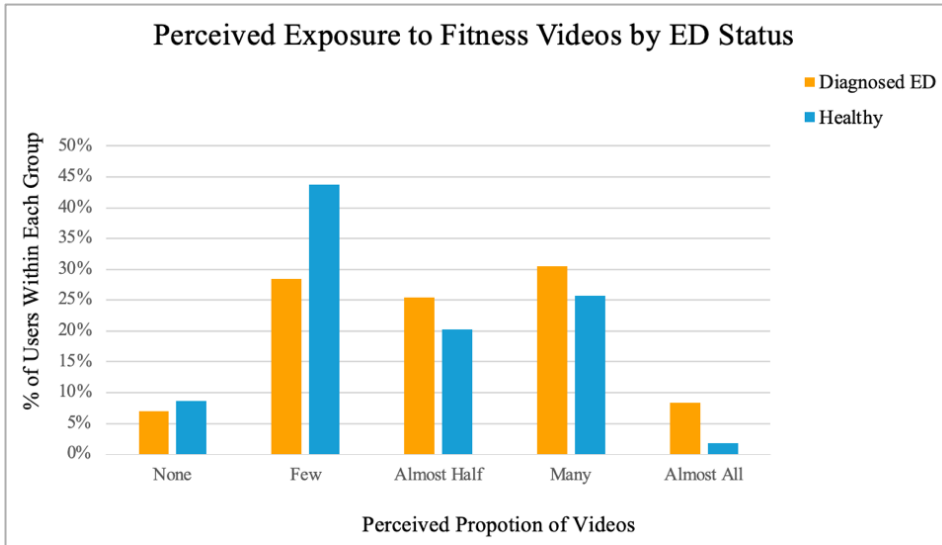


Fig. 12. Perceived exposure to Fitness content by ED status

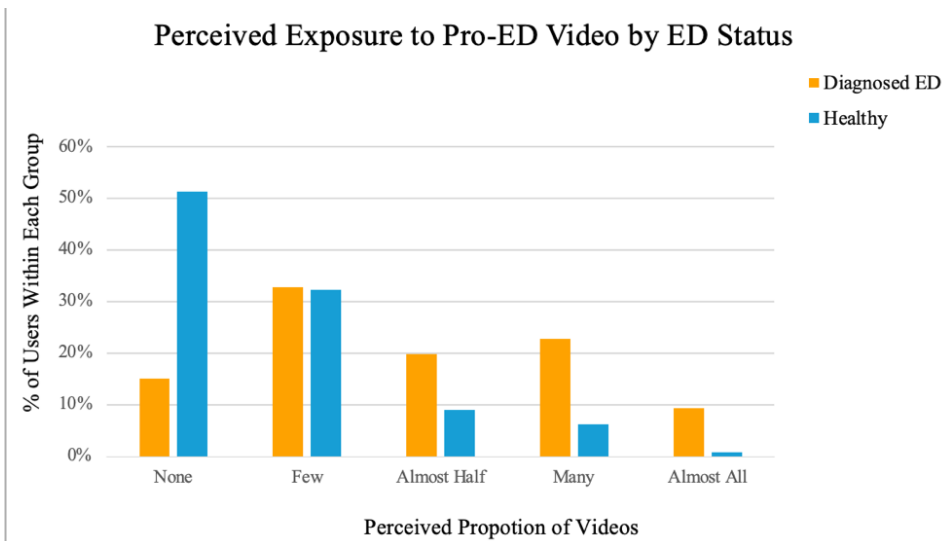


Fig. 13. Perceived exposure to Pro-ED content by ED status

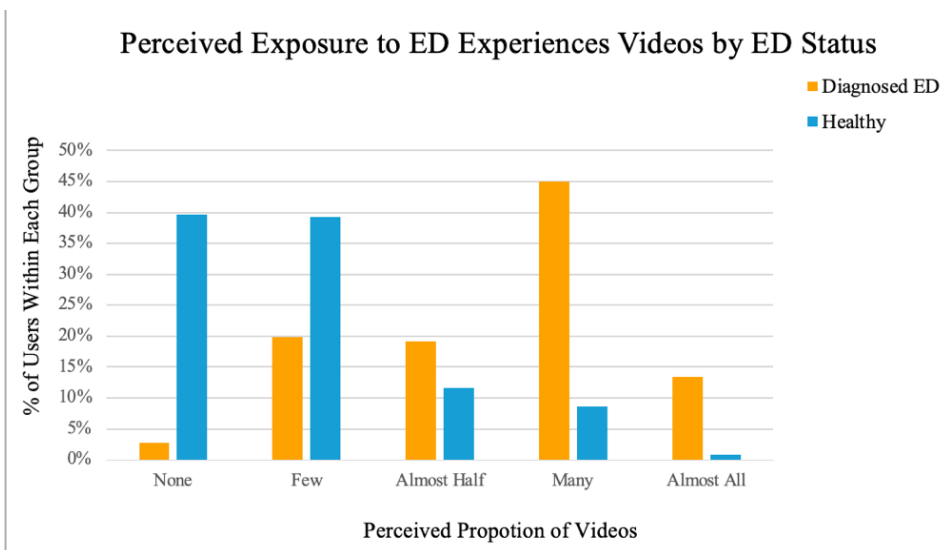


Fig. 14. Perceived exposure to ED Experiences content by ED status

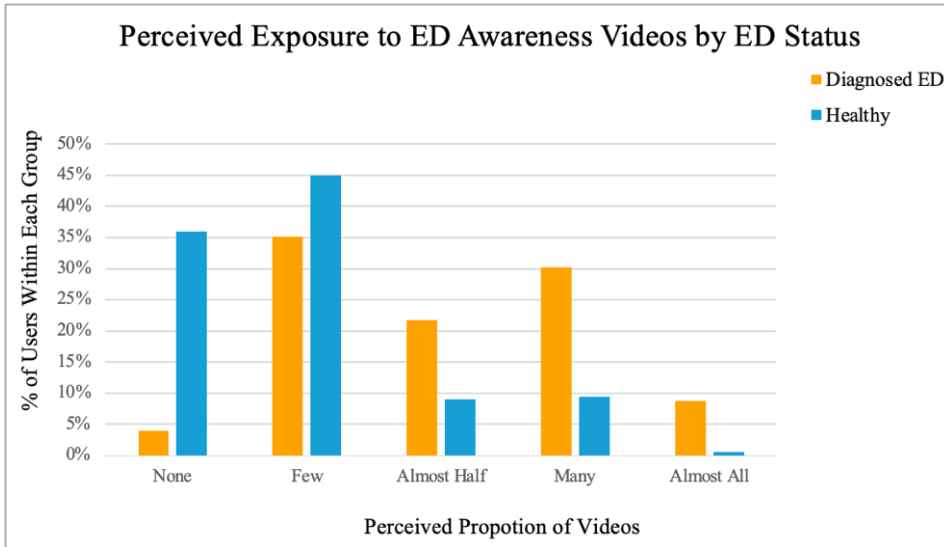


Fig. 15. Perceived exposure to ED Awareness content by ED status

5.1.2 Inferential Analyses

Inferential analyses examined differences between participants with a diagnosed eating disorder (ED) and healthy participants across multiple domains of TikTok use, including general platform engagement, problematic social network use, interaction patterns, and perceived exposure to ED-related content. In line with the predefined analytical strategy, people suspected of having an ED were excluded from this phase to ensure a clear and interpretable comparison between groups.

For each domain, group differences were first estimated by using independent-samples t-tests for the unadjusted models, then analyses of covariance (ANCOVAs) were conducted including age and gender as covariates to check if those differences stuck around after accounting for demographics. Results from both models are reported to evaluate the robustness of effects.

General TikTok Use, Problematic Use, and Interaction Patterns

With regard to general TikTok use, the group difference observed in the unadjusted analysis vanished after adjusting for age and gender, $F(1, 528) = 0.19, p = .660, \eta^2p < .001$.

In the domain of problematic social network use, several indicators showed group differences in the unadjusted analyses; however, not all remained statistically significant after demographic adjustment. Significant differences persisted for using TikTok to regulate negative emotions, $F(1, 528) = 6.21, p = .013, \eta^2p = .012$, continuing to use the

platform despite knowing it made them feel worse, $F(1, 528) = 7.44, p = .007, \eta^2p = .014$, and using TikTok longer than intended, $F(1, 528) = 4.92, p = .027, \eta^2p = .009$. Other indicators of problematic use were no longer statistically significant after controlling for age and gender.

Interaction pattern differences were also selective. Only a few behaviors remained significant after adjustment: reading comments under videos remained significantly higher among participants with a diagnosed ED, $F(1, 528) = 4.42, p = .036, \eta^2p = .008$, as did spending more time in the comment section than watching the video itself, $F(1, 528) = 14.49, p < .001, \eta^2p = .027$, and saving videos to rewatch later, $F(1, 528) = 9.28, p = .002, \eta^2p = .017$.

In contrast, liking videos, which had shown group differences in the unadjusted analyses, did not remain statistically significant after adjustment, $F(1, 528) = 0.19, p = .667$, as did watching videos until completion, $F(1, 528) = 0.12, p = .732$.

Conversely, commenting on videos, which was not statistically significant in the unadjusted model, gained significance once age and gender enter the picture, $F(1, 528) = 4.70, p = .031, \eta^2p = .009$.

Table 2

Statistics for the Independent Samples t-test and Ancova F-tests comparing general TikTok use, problematic social network use, and interaction patterns between Diagnosed ED and Healthy individuals.

Area	Item	Between-groups significance test									
		Unadjusted					Adjusted for age and gender				
		MP	SE	t (df)	p	d	MP	SE	F (adjusted)	P	η^2p
General TikTok Use	Daily Time Spect	0.42	0.09	4.83 (479.44)	< .001	0.42	0.05	0.09	0.19	.660	<.001
	Difficulty stopping TikTok use once started	0.06	0.09	0.66 (530)	.509	0.06	-0.01	0.06	0.01	.936	<.001
	Using TikTok to regulate negative emotions	0.44	0.11	3.98 (528)	< .001	0.38	0.29	0.12	6.21	.013	.012
	Continuing to use TikTok despite knowing it makes me feel worse	0.48	0.12	4.01 (528)	< .001	0.39	0.33	0.12	7.44	.007	.014
	Losing track of time while using TikTok	0.31	0.09	3.44 (528)	.001	0.32	0.21	0.11	3.85	.050	.007
Problematic Social Network Use (PSNU)	Using TikTok longer than intended	0.36	0.10	3.62 (528)	< .001	0.34	0.24	0.11	4.92	.027	.009
	Watching videos until the end	-0.09	0.08	-1.07 (528)	.284	-0.09	-0.04	0.08	0.12	.732	<.001
	Reading comments under videos	0.30	0.09	3.12 (454.80)	.002	0.28	0.20	0.10	4.42	.036	.008
	Spending more time in the comment section than watching the video itself	0.50	0.10	4.83 (511.66)	< .001	0.42	0.39	0.10	14.49	<.001	.027
	Liking videos	0.24	0.10	2.41 (528)	.016	0.21	0.05	0.10	0.19	.667	<.001
	Saving videos to rewatch later	0.50	0.11	4.67 (499.67)	< .001	0.41	0.31	0.10	9.28	.002	.017
	Commenting on videos	0.09	0.06	1.44 (500.41)	.151	0.13	0.16	0.07	4.70	.031	.009

Perceived Content Exposure by ED Status

People with an eating disorder noted higher exposure to each type of content compared to healthy controls, and these differences persisted in every domain even after demographic adjustment.

The strongest group difference was observed for exposure to ED-related experiences, $F(1, 518) = 77.73$, $p < .001$, $\eta^2p = .140$. Diet-focused content came next with the second-largest effect size, $F(1, 518) = 65.44$, $p < .001$, $\eta^2p = .120$, followed by ED awareness content, $F(1, 506.87) = 53.66$, $p < .001$, $\eta^2p = .100$.

Fitness content revealed milder effects, $F(1, 518) = 49.21$, $p < .001$, $\eta^2p = .090$. The smallest effect sizes were found for pro-eating disorder material, $F(1, 517.74) = 32.74$, $p < .001$, $\eta^2p = .060$, and body image/appearance content, $F(1, 422.68) = 30.20$, $p < .001$, $\eta^2p = .060$.

Table 3

Statistics for the Independent Samples t-test and Ancova F-tests comparing exposure to TikTok content types between Diagnosed ED and Healthy individuals.

Area	Item	Between-groups significance test									
		Unadjusted					Adjusted for age and gender				
		MP	SE	t (df)	p	d	MP	SE	F (adjusted)	P	η^2p
Content Type	Body Image / Appearance	0.54	0.09	5.68 (422.68)	<.001	0.52	0.59	0.11	30.20	<.001	.060
	Diet	0.93	0.10	9.69 (518)	<.001	0.86	0.86	0.11	65.44	<.001	.120
	Fitness	0.37	0.10	3.85 (518)	<.001	0.34	0.80	0.12	49.21	<.001	.090
	Pro-ED Content	1.06	0.10	11.17 (517.74)	<.001	0.95	0.67	0.12	32.74	<.001	.060
	ED Experiences	1.55	0.09	17.31 (518)	<.001	1.54	1.02	0.12	77.73	<.001	.140
	ED Awareness	1.11	0.09	12.56 (506.87)	<.001	1.09	0.87	0.12	53.66	<.001	.100

Psychological Impact of TikTok Content: Unadjusted and Adjusted Models

Across all psychological domains, both unadjusted analyses and models adjusted for age and gender were conducted and significant between-group differences emerged (all $ps < .001$), with effect sizes ranging from moderate to large. Importantly, results remained virtually unchanged after adjustment, indicating that differences in perceived psychological impact were robust and largely independent of age and gender (Table 4).

Table 4

Statistics for the Independent Samples t-test and Ancova F-tests comparing self-reported Psychological Impacts of Diagnosed ED versus Healthy.

Area	Item	Between-groups significance test									
		Unadjusted					Adjusted for age and gender				
		M ^D	SE	t (df)	p	d	M ^D	SE	F (adjusted)	P	η ² p
Body Image and Social Comparison	The content I see on TikTok influences the way I perceive my body	1.02	0.11	9.70 (388.47)	< .001	0.92	0.59	0.11	30.20	<.001	0.06
	The content I see on TikTok influences my relationship with food or eating	1.26	0.10	12.35 (427.53)	< .001	1.15	0.86	0.11	65.44	<.001	0.12
	After viewing content on TikTok, I engage more frequently in comparisons with other people's physical appearance.	1.25	0.11	11.09 (376.10)	< .001	1.06	0.80	0.12	49.21	<.001	0.09
	Content on TikTok makes me feel less satisfied with my physical appearance	1.19	0.12	10.29 (387.61)	< .001	0.98	0.67	0.12	32.74	<.001	0.06
Negative Affect and Emotion Regulation	Some content on TikTok makes me feel guilty about what I eat.	1.35	0.12	11.33 (423.49)	< .001	1.05	0.85	0.12	46.79	<.001	0.09
	Some content on TikTok increases my body- or food-related anxiety.	1.47	0.11	13.01 (395.72)	< .001	1.23	1.02	0.12	77.73	<.001	0.14
	After viewing certain content on TikTok, I tend to ruminate about my body or my eating habits.	1.30	0.11	11.45 (399.64)	< .001	1.08	0.87	0.12	53.66	<.001	0.10
	Some content on TikTok makes very rigid or extreme eating behaviors seem "normal."	0.84	0.10	8.27 (399.05)	< .001	0.78	0.60	0.11	29.90	<.001	0.06
Dysfunctional Behaviors Normalization	Content on TikTok can make me feel justified in exerting greater control over food or my body.	1.05	0.10	10.44 (448.34)	< .001	0.96	0.75	0.11	46.95	<.001	0.09
	After viewing some content on TikTok, I feel the need to change my habits (diet and/or physical exercise).	0.99	0.11	9.08 (434.16)	< .001	0.84	0.64	0.12	30.03	<.001	0.06
Behavioral Effects	Even if they seem harmless when taken individually, over time these contents affect my well-being.	0.95	0.10	9.55 (420.34)	< .001	0.89	0.70	0.11	41.90	<.001	0.08
	Repeated exposure to this type of content has a greater impact than isolated individual videos.	0.67	0.10	6.60 (395.79)	< .001	0.62	0.57	0.11	26.48	<.001	0.05

Body image concerns and social comparison processes showed the strongest links, the most substantial effects were observed for items reflecting disruptions in eating-related self-evaluation and comparison-based processes. In particular, the items “*The content I see on TikTok influences my relationship with food or eating*” ($\eta^2p \approx .12$) and “*After viewing content on TikTok, I engage more frequently in comparisons with other people's physical appearance*” ($\eta^2p \approx .09$) showed the strongest effects within this domain, indicating heightened sensitivity to appearance-based evaluation among individuals with a diagnosed eating disorder.

Negative affect and emotion regulation emerged as the domain most strongly affected by TikTok content. The largest proportions of explained variance were observed for the items “*Some content on TikTok increases my body- or food-related anxiety*” ($\eta^2p \approx .14$) and “*After viewing certain content on TikTok, I tend to ruminate about my body or my eating habits*” ($\eta^2p \approx .10$). These findings indicate that exposure to TikTok content is closely associated with emotional activation and repetitive negative thinking, with markedly stronger effects among individuals with ED.

With respect to the normalization of toxic behaviors, the item “*Content on TikTok can make me feel justified in exerting greater control over food or my body*” demonstrated a statistically significant adjusted effect ($\eta^2p \approx .09$), suggesting that exposure may legitimize rigid or extreme control-oriented behaviors. Behavioral activation was similarly reflected in the item “*After viewing some content on TikTok, I feel the need to change my habits (diet and/or physical exercise)*”, with a smaller but significant adjusted effect ($\eta^2p \approx .06$). Although internalization was stronger among individuals with ED, mean levels of both items across groups reflect that TikTok content serves as a behavioral trigger in general.

Even after controlling for demographics, between-group differences in the cumulative impact awareness remained significant; however, effect size differed among questions. The item “*Even if they seem harmless when taken individually, over time this content affect my well-being*” showed a moderate adjusted effect ($\eta^2p \approx .08$), together with relatively high adjusted mean scores in both groups, indicating a shared recognition of cumulative impact with stronger perceived effects among individuals with a diagnosed eating disorder. By contrast, the item “*Repeated exposure to this type of content has a greater impact than isolated individual videos*” exhibited a smaller adjusted effect size ($\eta^2p \approx .05$), explaining a smaller percentage of variance.

The psychological impact of TikTok content systematically involves eating-related self-evaluation, emotional responses, and behavioral processes. Exposure appears to activate mental schemas centered on comparison, control, and dissatisfaction, with consistently greater levels of anxiety, rumination, and perceived behavioral influence among

individuals with eating disorders. Although awareness of cumulative exposure effects was relatively high across participants, cognitive recognition alone did not correspond to reduced psychological vulnerability, as individuals with ED still report elevated perceived impact despite levels of awareness comparable to those of healthy participants.

5.3 Vulnerability-Related Navigation Dynamics

In this stage, the focus shifts from group comparison (ED vs. Healthy) to patterns connected straight to vulnerability. Participants classified as Suspected ED were included in order to capture a broader population dealing with raised eating disorder concerns, regardless of formal diagnostic status. By looking at diagnosed and suspected individuals, the analyses aim to identify behavioral, interactional, and exposure patterns within a population defined by increased psychological vulnerability in the context of TikTok use.

5.3.1 Correlation Analyses

Problematic TikTok Use and Interaction Patterns

Correlational analyses examined associations between indicators of problematic TikTok use and interaction behaviors.

Problematic use signals were not significantly linked with automatic viewing behaviors such as watching videos until the end. This suggests that simple content consumption is unrelated to problematic engagement.

In contrast, significant positive associations emerged for interaction behaviors characterized by attentional involvement like reading comments, spending more time reading comments than viewing the video, and saving videos. Reading comments under videos was strongly associated with losing track of time while using TikTok ($r = .13, p < .001$), using TikTok longer than intended ($r = .14, p < .001$), and continuing to use TikTok despite feeling worse ($r = .12, p < .001$). Spending more time in the comment section than watching the video itself was also significantly associated with losing track of time ($r = .16, p < .001$), using TikTok longer than intended ($r = .18, p < .001$), and continued use despite negative emotional consequences ($r = .18, p < .001$).

Saving videos for later viewing was significantly related to using TikTok longer than intended ($r = .13, p < .001$) and continuing to use TikTok despite feeling worse ($r = .12, p < .001$).

By contrast, active behaviors such as commenting on videos showed non-systematic associations with PSNU indicators, reaching significance for a limited subset of items such as emotional regulation ($r = .11, p < .001$) and continued use despite negative consequences ($r = .10, p < .001$), while remaining non-significant for the other dimensions.

Table 5

Pearson correlation coefficients between interaction types on TikTok and problematic social networking use (PSNU) items.

		PSNU Items				
Interaction Type		Difficulty stopping TikTok use once started	Using TikTok to regulate negative emotions	Continuing to use TikTok despite knowing it makes me feel worse	Losing track of time while using TikTok	Using TikTok longer than intended
Watching videos until the end	Pearson Correlation	.034	-.049	.008	.034	.005
Reading comments under videos	Pearson Correlation	.097**	.118**	.115**	.135**	.143**
Spending more time in the comment section than watching the video itself	Pearson Correlation	.115**	.157**	.183**	.160**	.177**
Liking videos	Pearson Correlation	.039	.065	.71*	.080*	.040
Saving videos to rewatch later	Pearson Correlation	.086*	.126**	.116**	.066	.071*
Commenting on videos	Pearson Correlation	.061	.109**	.095**	.012	-.027

* Correlation is significant at the 0.01 level (2-tailed)

** Correlation is significant at the 0.05 level (2-tailed)

Interaction Patterns and Content Types

Associations between how people interact online and perceived content exposure were then examined.

Watching videos until completion showed no significant associations with any content category, meaning that simple viewing completion does not differentiate exposure profiles. Likewise, liking behaviors were largely non-significant or trivial in magnitude. In contrast, passive and prolonged ways of engaging showed selective associations with ED content categories. Reading comments under videos was most strongly associated with ED experience content ($r = .157, p < .001$) and body image-focused material ($r = .143, p < .001$), followed by pro-eating disorder content ($r = .135, p < .001$).

For the behavior of spending more time reading comments than viewing the video, the largest associations were with body image content ($r = .167, p < .001$) and ED experience content ($r = .133, p < .001$).

Saving videos for later viewing emerged as the most relevant interaction behavior and it showed the strongest associations with ED experience content ($r = .190, p < .001$) and diet-related material ($r = .183, p < .001$), followed by body image-focused content ($r = .155, p < .001$).

These findings indicate that exposure to certain content is selectively structured by deep-divide interactions more than obvious social engagement.

Table 6

Pearson correlation coefficients between self-reported exposure to TikTok content and interaction types.

		Content Type					
Interaction Type		Body Image / Appearance	Diet	Fitness	Pro-ED Content	ED-related experiences	ED Awareness
Watching videos until the end	Pearson Correlation	.008	.048	-.002	.061	.080*	.054
Reading comments under videos	Pearson Correlation	.143*	.073*	.034	.135**	.157**	.084*
Spending more time in the comment section than watching the video itself	Pearson Correlation	.167**	.087*	.053	.122**	.133**	.067
Liking videos	Pearson Correlation	.088*	.042	.009	.090*	.067	.048
Saving videos to rewatch later	Pearson Correlation	.155**	.183**	.155**	.149**	.190**	.126**
Commenting on videos	Pearson Correlation	.087*	.026	.005	.105**	.102**	.080**

* Correlation is significant at the 0.01 level (2-tailed)

** Correlation is significant at the 0.05 level (2-tailed)

Content Types and Psychological Impact

The last set of correlational analyses examined associations between perceived exposure to different TikTok content categories and self-reported psychological impact dimensions.

Seeing more appearance-driven content showed the widest links across impact domains. Within the body image and social comparison domain, the strongest correlations emerged for “*The content I see on TikTok influences my body perception*” ($r = .453, p < .001$) and “*The content I see on TikTok influences my relationship with food or eating*” ($r = .449, p < .001$).

Negative affect and emotion regulation indicators, such as “*After viewing certain content on TikTok, I tend to ruminate about my body or my eating habits*” ($r = .426, p < .001$) and “*Some content on TikTok increases my body- or food-related anxiety*” ($r = .402, p < .001$), were strongly associated with greater perceived exposure to body image content. This suggests a strong link between exposure intensity and both cognitive and emotional vulnerability.

Self-reported exposure to dieting videos showed moderate but consistent links, particularly with “*I feel guilty about eating after viewing certain content*” ($r = .352, p < .001$), “*Some content increases my body- or food-related anxiety*” ($r = .342, p < .001$), and “*After viewing some content on TikTok, I feel the need to change my habits (diet and/or physical exercise)*” ($r = .359, p < .001$).

A similar pattern emerged for reported exposure to pro-eating disorder and ED experience videos, which exhibited highly similar impact profiles. Greater exposure to pro-ED material was strongly associated with “*Some content increases my body- or food-related anxiety*” ($r = .348, p < .001$), “*After viewing certain content, I tend to ruminate about my body or eating habits*” ($r = .339, p < .001$), “*Content can make me feel justified in exerting greater control over food or my body*” ($r = .310, p < .001$), and “*I feel the need to change my habits*” ($r = .381, p < .001$).

Reported exposure to ED narratives showed similarly strong associations with rumination ($r = .315, p < .001$). Notably, for this kind of content, higher exposure levels were particularly associated with cumulative impact awareness, especially “*Repeated exposure to this type of content has a greater impact than isolated individual videos*” ($r = .281, p < .001$).

In contrast, there were relatively weaker correlations across psychological domains for perceived exposure to fitness-related and ED awareness content. However, exercise videos were most strongly associated with “*I feel the need to change my habits*” ($r = .255, p < .001$) and rumination ($r = .243, p < .001$). By contrast, exposure to ED awareness content showed its strongest correlations with anxiety ($r = .202, p < .001$) and cumulative impact awareness ($r = .218, p < .001$), suggesting greater cognitive recognition of potential harm rather than pronounced affective or behavioral activation.

Table 7

Pearson correlation coefficients between self-reported exposure to TikTok content and psychological impacts.

Area	Item		Content Type					ED Awareness
			Body Image / Appearance	Diet	Fitness	Pro-ED Content	ED-related experiences	
Body Image and Social Comparison	The content I see on TikTok influences the way I perceive my body	Pearson Correlation	.453**	.274**	.200**	.309**	.279**	.150**
	The content I see on TikTok influences my relationship with food or eating	Pearson Correlation	.449**	.385**	.264**	.431**	.353**	.176**
	After viewing content on TikTok, I engage more frequently in comparisons with other people's physical appearance.	Pearson Correlation	.448**	.282**	.198**	.309**	.258**	.131**
	Content on TikTok makes me feel less satisfied with my physical appearance	Pearson Correlation	.427**	.285**	.189**	.295**	.239**	.117**
Negative Affect and Emotion Regulation	Some content on TikTok makes me feel guilty about what I eat.	Pearson Correlation	.401**	.352**	.218**	.328**	.293**	.178**
	Some content on TikTok increases my body- or food-related anxiety.	Pearson Correlation	.402**	.342**	.216**	.348**	.307**	.202**
	After viewing certain content on TikTok, I tend to ruminate about my body or my eating habits.	Pearson Correlation	.426**	.350**	.243**	.339**	.315**	.210**
Dysfunctional Behaviors Normalization	Some content on TikTok makes very rigid or extreme eating behaviors seem "normal."	Pearson Correlation	.214**	.226**	.139**	.310**	.265*	.188**
	Content on TikTok can make me feel justified in exerting greater control over food or my body.	Pearson Correlation	.359**	.330**	.228**	.378**	.344**	.241**
Behavioral Effects	After viewing some content on TikTok, I feel the need to change my habits (diet and/or physical exercise).	Pearson Correlation	.392**	.359**	.255*	.381**	.280**	.149**
Cumulative Impact Awareness	Even if they seem harmless when taken individually, over time these contents affect my well-being.	Pearson Correlation	.336**	.272**	.207**	.312**	.311**	.218**
	Repeated exposure to this type of content has a greater impact than isolated individual videos.	Pearson Correlation	.302**	.249**	.174**	.264**	.281**	.199**

* Correlation is significant at the 0.01 level (2-tailed)

** Correlation is significant at the 0.05 level (2-tailed)

5.3.2. Integrated Pattern of Vulnerability

Overall, the correlational analyses delineate a coherent pattern of TikTok use tied to vulnerability emerging through interconnected layers of engagement. Problematic TikTok use showed no real tie to general time spent on the app or overt social interaction, but rather with passive and cognitively immersive interaction patterns, particularly engagement with comment sections and selective content retention. Such approaches connected directly to higher contact with ED-relevant content categories, most notably appearance-focused material, pro-eating disorder content, and personal stories about those struggles. Exposure to these content types, in turn, showed the strongest associations with psychological impact across emotional, cognitive, and behavioral domains, especially ruminative processes, anxiety, and feelings-related vulnerability. Notably, this pattern emerged within a population defined not only by an eating disorder diagnosis but also by elevated vulnerability, indicating that dynamics around risk might build up well ahead of any clinical diagnosis showing up.

5.3.3. Multivariate predictors of perceived psychological impact

A hierarchical multiple regression analysis was conducted to examine predictors of self-reported psychological impact, the scale of which demonstrated excellent internal consistency (Cronbach's $\alpha = .946$), indicating that the twelve items reliably measured, from slightly different perspectives, the same underlying construct.

So, a composite perceived impact index was computed by averaging its twelve items and used as the dependent variable in the following analysis.

As regards demographics, age was significantly negatively associated with psychological impact ($\beta = -.16$, $p < .001$), indicating higher impact among younger participants, whereas gender was not statistically significant in the final model ($p = .090$).

With healthy participants serving as the reference category, both diagnosed ED status ($\beta = .20$, $p < .001$) and suspected cases ($\beta = .19$, $p < .001$) were independently associated with higher psychological impact.

With engagement variables entered into the model, overall time spent on TikTok did not retain statistical significance ($\beta = -.04$, $p = .060$). In contrast, problematic social network use (PSNU) emerged as the strongest predictor ($\beta = .30$, $p < .001$), indicating that

dysregulated engagement, rather than exposure duration alone, is centrally related to psychological impact.

Upon inclusion of perceived content exposure variables, several content categories demonstrated additional independent associations. Exposure to appearance-focused content ($\beta = .20$, $p < .001$), pro-eating disorder content ($\beta = .16$, $p < .001$), ED-related experience content ($\beta = .12$, $p = .002$), and diet-related content ($\beta = .10$, $p = .002$) remained significant predictors. Conversely, fitness-related content ($\beta = .00$, $p = .941$) and ED awareness content ($\beta = -.05$, $p = .145$) were not significantly associated with psychological impact once other variables were held constant.

Overall, the final model explained a substantial proportion of variance in perceived psychological impact ($R^2 = .602$; adjusted $R^2 = .596$). Taken together, the findings indicate that psychological impact is most strongly associated with problematic engagement patterns and selective exposure to appearance- and ED-related content, while overall time spent on the platform does not independently predict impact when these factors are simultaneously considered.

Table 8

Summary statistics for the multivariate regression models with perceived psychological impact as the dependent variable and healthy participants reference category for ED status

Predictor	B	SE	β	p
Age	-0.030	0.005	-0.16	< .001
Gender	0.151	0.089	0.05	.090
ED Status (ref. = Healthy)				
Diagnosed ED	0.407	0.063	0.20	< .001
Suspected ED	0.360	0.058	0.19	< .001
Time spent on TikTok	-0.042	0.026	-0.04	.060
PSNU index	0.339	0.028	.0.30	< .001
Perceived Content Exposure				
Body image / appearance content	0.166	0.027	0.20	< .001
Diet-related content	0.096	0.030	0.10	.002
Fitness content	0.002	0.024	0.00	.941
Pro-ED content	0.134	0.022	0.16	< .001
ED Experience content	0.118	0.038	0.12	.002
ED Awareness content	-0.041	0.028	-0.05	.145
R²	.602			
Adjusted R²	.596			
N	1054			

5.3 Identification of Risk-Related Navigation Patterns

Through this study's descriptive, inferential, correlational, and multivariate analyses, a structured configuration of vulnerability emerged.

The findings delineate a cumulative process in which engagement styles, exposure patterns, and psychological responses are interwoven within the broader dynamics of platform navigation.

Splitting by group, individuals with a diagnosed eating disorder exhibited selective patterns of differentiated engagement. Overall time spent on TikTok did not remain statistically significant after controlling for age and gender. Certain types of problematic engagement, specifically emotion regulation through platform use, continued use despite negative emotional consequences, and use beyond intention, remained robustly associated with ED status even after controlling for covariates. Differences also emerged in immersive interaction behaviors, including sustained engagement with comment sections, content saving, and commenting activity. In parallel, participants with ED reported significantly greater exposure across all the content categories selected, with the strongest effects observed for ED-related experiences, diet-related material, and ED awareness content. Participants with ED also reported higher levels of anxiety, rumination, social comparison, and behavioral activation. Together, these patterns indicate that vulnerability is reflected less in overall usage intensity and more in the qualitative structure of platform engagement.

Switching the focus on the vulnerable side, which included both diagnosed and suspected individuals, indicators of problematic engagement, such as loss of time awareness and continued use despite negative emotional consequences, co-occurred with immersive interaction styles, particularly prolonged immersion with comment sections and repeated content saving.

At the content level, exposure to appearance-focused, pro-eating disorder, and ED experience material demonstrated the strongest and most consistent associations with psychological impact across affective, cognitive, and behavioral domains. Diet-related content showed more moderate associations, whereas fitness-oriented and awareness-

focused material exhibited weaker and less consistent effects. The multivariate model further clarified this configuration: when demographic factors, ED status, engagement indicators, and content exposure were considered simultaneously, psychological impact was independently predicted by PSNU and selective exposure to appearance- and ED-related content, whereas overall time spent on the platform did not retain significance.

Taken together, the results suggest that risk on TikTok unfolds as a self-reinforcing process embedded within patterns of navigation. Dysregulated engagement, immersive interaction styles, and selective exposure to high-risk content appear to operate simultaneously, consolidating emotional activation and comparison over time. Within this framework, vulnerability is not reducible to screen time or to the presence of specific content alone, but reflects the stabilization of engagement patterns that intensify psychological sensitivity within the platform environment. Such dynamics may precede formal diagnosis and extend beyond explicit pro-eating disorder intent, positioning navigation style as a potential behavioral marker of emerging vulnerability.

Chapter 6

Framework

6.1 Rationale and Objectives

This framework integrates findings from both the systematic review and the empirical analyses, translating the identified risky navigation patterns into an applied self-assessment tool designed to promote user reflection. ED vulnerability on TikTok is not primarily explained by time spent on the platform, but by specific browsing patterns.

Difficulties in disconnecting and continued exposure despite negative emotional effects were consistently associated with greater psychological impact, particularly in relation to social comparison, rumination, and anxiety. Negative psychological outcomes are not only more closely linked to problematic use than to overall usage time (Marciano et al.,

2024), but these effects also tend to accumulate indirectly over time rather than resulting from isolated episodes of exposure, supporting a cumulative understanding of ED digital risk (Marttila et al., 2021; Abiddine et al., 2022; Zhang et al., 2022).

The self-check tool is designed to capture the navigation behaviors that emerged as relevant in the present study. It has a non-diagnostic reflective function and its purpose is to stimulate awareness of engagement dynamics that may reinforce ED-related vulnerability and to offer tailored recommendations.

Translating these insights into a brief digital self-assessment aligns with evidence that digitally delivered screening tools can facilitate early identification of risk (Bryant et al., 2021). When embedded within the environments where users already seek content and support, such tools can increase conscious navigation and encourage help-seeking.

At the same time, recent research on ED detection through social media analytics underscores the importance of pairing detection with scalable digital interventions (D'Adamo et al., 2025). Identifying risk signals alone is insufficient if platforms do not activate supportive responses. From this perspective, social media should not be viewed solely as environments that amplify risk, but also as environments capable of delivering timely support.

Embedding a brief self-assessment directly within the feed, triggered by identified ED-related navigation patterns, represents one possible implementation of this integrated approach. Rather than a standalone screening instrument, it becomes a context-sensitive intervention that transforms moments of algorithmically reinforced immersion into opportunities for reflection and early support.

6.2 Dimensions of the framework

Each self-assessment dimension captures a distinct mechanism repeatedly linked to ED-related vulnerability and negative psychological outcomes in social media environments. Social Comparison captures habits related to appearance- and eating-related comparison processes and subsequent body dissatisfaction during or after platform use (Marciano et al., 2024). The items assess both the tendency to compare oneself to others and the emotional impact of exposure to specific content.

The PSNU dimension focuses on dysregulated engagement, including continued use despite negative mood effects and difficulty disengaging once scrolling begins (Andreassen et al., 2016; Satici & Uysal, 2015). This aligns with evidence that problematic use is more strongly related to negative outcomes than general usage intensity (Marciano et al., 2024).

Content Exposure evaluates self-reported exposure to dieting, fitness, and appearance material, including content framed as “health” or “recovery” when it still produces pressure or distress (Nikolova & LaMarre, 2023). This dimension reflects the idea that apparently innocuous content may remain psychologically activating for vulnerable users (Marks et al., 2020).

The Immersive Engagement dimension captures interaction patterns that extend beyond passive viewing, such as prolonged attention to comment sections and saving/revisiting content. These behaviors represent deeper cognitive involvement and generate signals that shape subsequent content delivery in algorithmically curated environments (Griffiths et al., 2024).

Finally, the Navigation Awareness and Cumulative Exposure dimension assesses recognition of recurring content themes and reflection on the effects of repeated exposure over time, within a feed shaped by recommendation dynamics (Griffiths et al., 2024).

6.3 Self-Assessment Items

Based on the previous dimensions, the framework was operationalized through a brief self-administered assessment consisting of ten items evaluated using a five-point Likert scale. Response options (1= very rarely; 5= very often) indicate the frequency with which each statement reflects the respondent’s typical experience when using social media platforms (Andreassen et al., 2016; Zarate et al., 2023). Each item reflects a specific navigation-related signal that has been found to be significant in the online context of eating disorders. The items are formulated using neutral language to facilitate self-reflection and are summarized in Table 6, which maps each item to its corresponding framework dimension. Collectively, the ten items provide an integrated operationalization of the framework and constitute the basis for the subsequent scoring procedure and interpretative feedback, in line with a harm reduction perspective.

Table 9

Self-assessment items grouped by conceptual dimension

Dimension	Item	Statement
Social Comparison	Q1	While using TikTok, I find myself comparing my body, eating habits, or lifestyle to those of others
	Q2	After viewing certain content on TikTok, I feel more dissatisfied with my body or myself.
Problematic Social Network Use (PSNU)	Q3	I continue scrolling even when I notice that the content is negatively affecting my mood.
	Q4	I find it difficult to stop using TikTok once I have started, especially when similar content keeps appearing.
Content Exposure	Q5	I am frequently exposed to content related to food, dieting, fitness, or body shape while using TikTok
	Q6	Some content that appears to promote health or recovery still makes me feel pressured about food or my body.
Immersive Engagement	Q7	I spend a considerable amount of time reading comments under videos related to food, body, or appearance.
	Q8	I find myself repeatedly thinking about certain content, which leads me to save videos and revisit them later.
Navigation Awareness and Cumulative Exposure	Q9	I notice that certain types of content tend to appear repeatedly in my feed, even when I did not actively search for them.
	Q10	I reflect on how repeated exposure to certain content affects my thoughts or feelings over time.

6.4 Self-assessment

The self-assessment tool is designed to be navigation-sensitive, reacting to how users move through the app and integrated directly into the social media environment rather than administered as an external questionnaire. The tool is meant to be conditionally triggered, in response to specific user navigation patterns, signals of immersive engagement or cumulative exposure. Such patterns include, but are not limited to, prolonged interaction with food- and body-related content, extended engagement with comment sections, and repeated saving or revisiting of videos over time.

Designed in a familiar format, in line with its non-diagnostic orientation, the self-assessment is integrated into the feed and framed as a brief reflective prompt rather than a formal evaluative instrument.

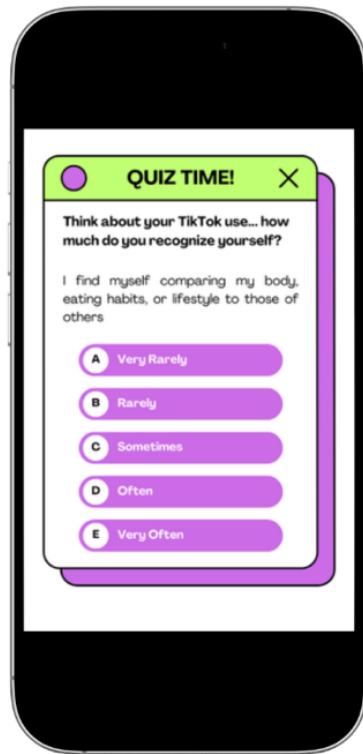


Fig 16. In-feed Self Assessment Prompt

6.5 Output Score and Interpretative Feedback

Following completion of the self-assessment, an output score will be generated, reflecting the frequency of risk signals identified.

Rather than a categorical or diagnostic classification, the score is conceived as a continuous indicator of navigation-related vulnerability. This conceptualization is consistent with research on problematic social media use, which frames digital risk along a continuum of engagement behaviors instead of discrete diagnostic thresholds (Andreassen et al., 2016). Psychometric evidence further supports the use of brief self-report instruments for the identification of elevated levels of problematic engagement, particularly in contexts focused on early risk detection and the delivery of tailored feedback rather than on clinical diagnosis (Zarate et al., 2023). Within this perspective,

the primary function of the score is to facilitate self-awareness and reflective interpretation of navigation patterns.

The composite score is derived from the aggregation of ten items rated on a five-point Likert scale, resulting in a total score ranging from 10 to 50. Each item contributes equally to the overall score (five points per item) and captures the frequency of specific navigation experiences. The composite score generated represents the cumulative frequency and co-occurrence of online risk signals. Higher scores indicate a greater concentration of such patterns, whereas lower scores reflect more regulated navigation practices.

To support interpretability and feedback delivery, the continuous score is organized into four qualitative ranges corresponding to increasing levels of eating disorder-relevant navigation experiences. These ranges are labeled as regulated navigation (10–20), intensive navigation (21–30), problematic navigation (31–40), and highly problematic navigation (41–50). The introduction of qualitative labels is intended to facilitate intuitive understanding of score levels and to provide behaviorally grounded recommendations. These interpretative ranges do not imply diagnostic classifications, but function as a mechanism for translating a continuous score into user-oriented feedback aligned with reported navigation experiences. Feedback associated with each range is framed in experiential and navigational terms and is explicitly oriented toward self-regulation and increased awareness of cumulative exposure effects, in line with the applied and non-diagnostic aims of the proposed framework.

To illustrate how such feedback may be communicated in practice, the following examples present short, navigation-aware prompts tailored to each interpretative range.

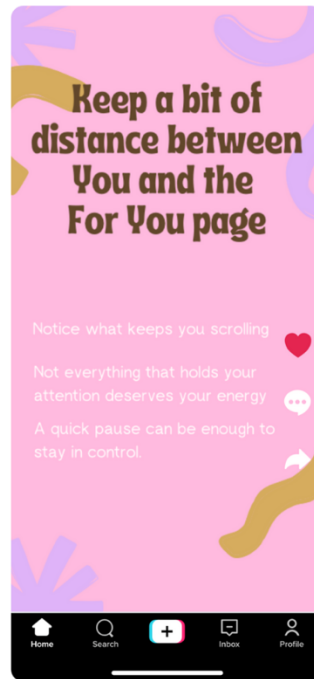
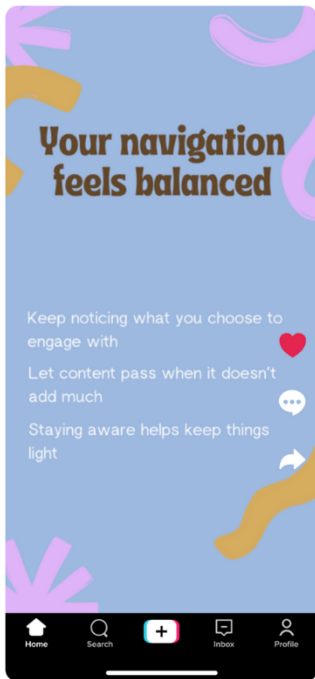


Fig 17. Navigation-based Reco – Regulated Navigation. **Fig 18.** Navigation-based Reco – Intensive Navigation.

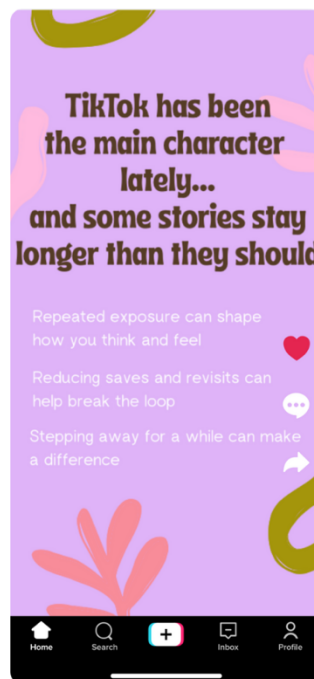
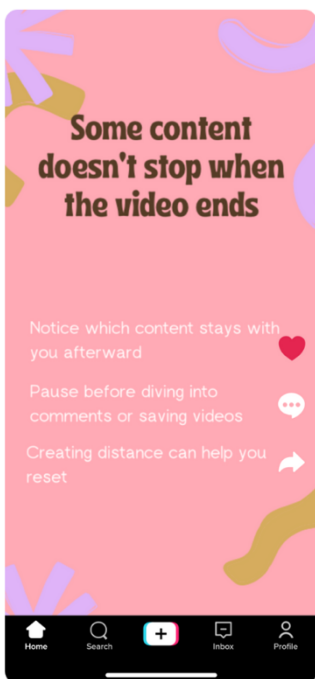


Fig 19. Navigation-based Reco – Problematic Navigation. **Fig 20.** Navigation-based Reco – Highly Problematic Navigation.

Chapter 7

Discussion

7.1 Contribution

7.1.1 Theoretical Implications

The findings of this thesis reshape the role of social media in eating disorders. Risk does not emerge as a linear function of time spent on the platform, nor as a simple effect of generic exposure to problematic content, but appears to be structured around specific navigation patterns that favour immersion, repetition, and content retention.

Once engagement modalities and selective exposure are taken into account, time of use does not influence perceived emotional impact. This shifts the focus from “how much” to “how.” EDs do not arise exclusively from linguistic traits or exposure to specific content, but from interaction styles characterized by perseveration, emotional involvement, and difficulty disengaging.

From this perspective, social media function not merely as a primary trigger of vulnerability onset but also as space of maintenance. The observed patterns like prolonged engagement in comment sections, saving content, and repeated return to similar materials, are consistent with maintenance models. The algorithm does not necessarily introduce new vulnerabilities; rather, it may stabilize the exposure to content that aligns with pre-existing cognitive and identity schemas.

A theoretically crucial element concerns ED-related content. Psychological impact appears more strongly associated with appearance-focused content and content directly connected to ED experience. Even categories that are seemingly “positive,” such as sharing of ED experiences or awareness-raising content, show meaningful associations with psychological impact. ED narratives content, in fact, may also contribute to sustaining identification with the symptomatology, in light of the ego-syntonic nature of EDs for which such content may be perceived as confirmatory. From a maintenance

perspective, repeated exposure can reinforce the centrality of the disorder within self-representation, making the identity configuration linked to EDs more stable and resistant to change.

7.1.2 Empirical Implications

At the empirical level, the analyses converge on a clear point: variables capturing cognitive immersion assume a more central role than general interactions. Practices involving content retention and prolonged engagement in discursive spaces are associated with both problematic use and selective exposure to ED-related material. This does not reflect undifferentiated passive consumption, but rather an immersive and repetitive mode of navigation. Moreover, psychological impact is more closely linked to appearance-focused and ED-experience content, whereas more generic content types show weaker associations. This suggests that the effect depends on the interaction between individual vulnerability, engagement style, and content type. Dysregulated engagement emerges as a central driver of psychological harm, while time of use appears less relevant, meaning that ED digital risk is qualitative before it is quantitative.

7.1.3 Practical Implications

The practical implications of these findings extend beyond risk reduction and call for an integrated approach that combines early detection with digital intervention. If ED-related vulnerability is embedded in navigation patterns and reinforced through recursive exposure, then prevention cannot rely solely on limiting screen time. There is a need to identify behavioral markers within the platform that signal sustained immersion in ED-related trajectories and to pair such detection mechanisms with context-sensitive interventions. Social media should not be framed exclusively as environments of risk, but also as potential infrastructures for support. The same algorithmic systems that personalize exposure could be leveraged to introduce adaptive prompts, reflective pauses, or supportive resources when navigation patterns indicate persistent engagement with dangerous content for vulnerable users.

The proposed self-assessment framework aligns with this logic. It is conceptually designed to be embedded within the user experience, integrated directly into the feed.

This approach moves beyond passive risk identification. It is the representation of a model in which detection of maintenance-relevant navigation patterns is paired with digital micro-interventions aimed at increasing awareness, disrupting automaticity, and potentially redirecting exposure. In doing so, social media platforms could evolve from merely amplifying vulnerability to actively participating in early-stage support.

7.2 Limitations of the Study

Several limitations should be considered when interpreting these findings. First, the sample was not representative of the broader population of TikTok users due to strong gender imbalance and the recruitment procedures, which likely attracted participants who were already sensitive to ED-related topics. While this allowed access to high-risk individuals who are often difficult to reach, it limits the generalizability of the results to other contexts and populations.

Second, while the results are consistent with models in which navigation styles contribute to increased exposure and psychological impact, the cross-sectional design of the study precludes causal inference.

Third, all measures relied on self-report data, which may be subject to biased interpretation. In particular, perceived exposure and perceived psychological impact may not fully correspond to objective content consumption or behavioral patterns. Moreover, eating disorder status was self-declared and not clinically verified.

Finally, the navigation framework and self-assessment scoring thresholds proposed in this study are exploratory. They were designed to prioritize interpretability and awareness-raising rather than psychometric rigor, and therefore require systematic validation before being implemented in applied settings.

7.3 Future Research

Future research should extend this work in several directions. Further improvements can be achieved by combining self-report measures with objective behavioral data directly obtained from platforms, such as navigation, interaction, and content exposure metrics. Bringing together subjective experience and digital trace data would provide a more accurate understanding of how engagement patterns evolve over time.

Experimental studies could help clarify how platform design and algorithmic systems reinforce selective exposure and sustained immersion in ED-related content, essential for informing the development of more responsible digital environments.

In addition, future studies should aim to validate the proposed framework and self-assessment tool by testing their factor structure, reliability, and predictive validity, as well as by calibrating scoring thresholds against external criteria. Such validation would support their use in digitally integrated interventions.

Chapter 8

Conclusion

In light of the limitations of the present study and the proposed potential areas to further investigate, this thesis advances a clear position: social media should not only be considered as possible triggers for the onset of eating disorders but also as settings that can contribute to symptom maintenance.

Risk should not be monitored in terms of time spent on the platform because it is embedded into patterns of navigation that make exposure frequent, immersive, and consistent with individual vulnerability.

Videos about appearance, diet, and ED experiences achieve psychological relevance when they are situated within low-control engagement pathways that reinforce their personal meaning.

From this perspective, the role of social media is not linear. HVSMs do not necessarily generate eating disorders, but they may contribute to stabilizing or exacerbating symptomatology through repetition mechanisms and algorithmic reinforcement. This dynamic appears particularly relevant in the presence of an ego-syntonic symptom structure, where ED-related cognitions and behaviors are experienced as coherent with one's identity and value system.

The main contribution of this work is to move the analytical emphasis from simple exposure to immersion and from distinct content encounters to built-up ways of interacting. The study emphasizes the significance of comprehending how patterns of interaction change and become self-reinforcing over time by viewing ED-related digital risk as a process rather than an event.

In this light, ED-related risk in social media environments is not a singular episode of exposure. It is a maintenance process which, once identified and understood, can become target of intervention.

References

- Abiddine, F.Z.E., Aljaberi, M.A., Gadelrab, H.F., Lin, C.-Y., Muhammed, A., 2022. «Mediated effects of insomnia in the association between problematic social media use and subjective well-being among university students during COVID-19 pandemic». *Sleep Epidemiology* 2, 100030.
<https://doi.org/10.1016/j.sleepe.2022.100030>.
- Abuhassan, M., T. Anwar, M. Fuller-Tyszkiewicz, H. K. Jarman, A. Shatte, C. Liu, e S. Sukunesan. 2023. «Classification of Twitter users with eating disorder engagement: Learning from the biographies». *Computers in Human Behavior* 140. doi:10.1016/j.chb.2022.107519.
- Aggarwal, Pragun. 2023. «Impact of Social Media on Anxiety and Eating Disorders». *International Journal of Indian Psychology* 11(3).
<https://ijip.co.in/index.php/ijip/article/view/5796>.
- Andreassen, C. S., Billieux, J., Griffiths, M. D., Kuss, D. J., Demetrovics, Z., Mazzoni, E., & Pallesen, S. 2016. The relationship between addictive use of social media and video games and symptoms of psychiatric disorders: A large-scale cross-sectional study. *Psychological Addictive Behaviors*, 30(2), 252–262.
<https://doi.org/10.1037/adb0000160>
- Andreassen, C. S., S. Pallesen, e M. D. Griffiths. 2017. «The Relationship between Addictive Use of Social Media, Narcissism, and Self-Esteem: Findings from a Large National Survey». *Addictive Behaviors* 64: 287–293.
doi:10.1016/j.addbeh.2016.03.006.
- Aranha-de-Macedo, Patrícia, Nataniel OF, C. F. Paula, R. D. T. de Souza, P. Diogo, e A. Ágata. 2022. «Influence of Social Media on Body Dissatisfaction in Adolescents and Increasing Risk of Developing Eating Disorders: A Systematic Review». *Annals of Clinical Case Reports* 7:2144.
<https://www.anncaserep.com/open-access/influence-of-social-media-on-body-dissatisfaction-in-adolescents-and-8661.pdf>

- Baghi, S., M. H. Ebrahimzadeh, e N. Hedayati. 2021. «Effective factors on eating disorders prevention methods; analysis of food-related data on Twitter». *Health Education and Health Promotion* 9(3):177–84.
- Batista, Amanda, e Deborah Hall. 2024. «Pursuing Perfection or Striving Towards “Superwoman”? Investigating the Roles of Social Media and Individual Differences in Eating Disorders». *Annual Review of Cybertherapy and Telemedicine* 2024:138.
- Benítez-Andrades, J. A., J. M. Alija, M. E. Vidal, R. Pastor-Vargas, e M. T. García-Ordás. 2022. «Traditional Machine Learning Models and Bidirectional Encoder Representations From Transformer (BERT)-Based Automatic Classification of Tweets About Eating Disorders». *JMIR Medical Informatics* 10(2). doi:10.2196/34492.
- Benítez-Andrades, J. A., M. T. García-Ordás, M. Russo, A. Sakor, L. D. Fernandes Rotger, e M. E. Vidal. 2023. «Empowering machine learning models with contextual knowledge for enhancing the detection of eating disorders in social media posts». *Semantic Web* 14(5):873–92. doi:10.3233/SW-223269.
- Bryant, E., J. Miskovic-Wheatley, S. W. Touyz, R. D. Crosby, E. Koreshe, e S. Maguire. 2021. «Identification of High Risk and Early Stage Eating Disorders: First Validation of a Digital Screening Tool». *Journal of Eating Disorders* 9: 109. <https://doi.org/10.1186/s40337-021-00464-y>
- Cardoza, Kristin, Jerilyn Ellis, Samantha Moore, e Samuel Abraham. 2022. «More Than a Picture: The Effects of Educated Social Media Use on People with Eating Disorders». 23:120–34.
- Chayka, K. 2024. *Filterworld: How Algorithms Flattened Culture*. Bonnier. <https://www.booktopia.com.au/filterworldkylechayka/book/9781788706971.htm>
- DataReportal. (2024). *Digital 2024: Global Overview Report*. <https://datareportal.com/reports/digital-2024-global-overview-report>.
- Cheng, I. (2024). The Influence of Highly Visual Social Media Engagement on the Body Image of Cisgender Heterosexual Emerging Adult Men. A Grounded Theory Approach. <https://aura.antioch.edu/etds/1059>
- Cheung, Lauryn Gar-Mun, Pamela Carien Thomas, Eva Brvar, e Sarah Rowe. 2025. «User Experiences of and Preferences for Self-Guided Digital

Interventions for the Treatment of Mild to Moderate Eating Disorders: Systematic Review and Metasynthesis». *JMIR Mental Health* 12. doi:10.2196/57795.

- Clark, J. L., Algoe, S. B., & Green, M. C. 2018. «Social network sites and well-being: The role of social connection». *Current Directions in Psychological Science*, 27(1), 32–37. <http://dx.doi.org/10.1177/0963721417730833>
- Craddock, N., Smith, H. G., Linardon, J., Tylka, T. L., & Diedrichs, P. C. (2026). Existing and future use cases, and safety and ethical considerations for AI in body image, and eating disorder prevention. *Body Image*, 56, 102042.
- D’Adamo, L., J. R. Moussaoui, D. Chu, H. Graver, C. B. Taylor, D. E. Wilfley, S. Sadeh-Sharvit, N. C. Jacobson, P. Cavazos-Rehg, S. M. Manasse, K. Lerman, e E. E. Fitzsimmons-Craft. 2025. «Detecting Eating Disorders From Social Media Content: What Has Been Done and Where Do We Go Next?». *International Journal of Eating Disorders*. doi:10.1002/eat.24565.
- Dahlgren CL, Sundgot-Borgen C, Kvalem IL, Wennersberg AL, Wisting L. «Further evidence of the association between social media use, eating disorder pathology and appearance ideals and pressure: a cross-sectional study in Norwegian adolescents. » *J Eat Disord*. 2024;12(1):34. doi:10.1186/s40337-024-00992-3
- Dane, Alexandra, e Komal Bhatia. 2023. «The social media diet: A scoping review to investigate the association between social media, body image and eating disorders amongst young people». *PLOS Global Public Health* 3(3):e0001091. doi:10.1371/journal.pgph.0001091.
- Dhoke, Rohit, Shaini Suraj, Brij Raj Singh, e Nandkishor Bankar. 2023. «Impact of social media on eating disorders in adolescents and emerging therapies: a review». *Journal of Clinical and Diagnostic Research* 17(4):VE01–3.
- Fioravanti, Giulia, Emanuele Cassioli, Eleonora Rossi, Lorenzo Lucherini Angeletti, Silvia Casale, Valdo Ricca, e Giovanni Castellini. 2024. «The Relationship between Problematic Instagram Use and Eating Disorders Psychopathology: An Explanatory Structural Equation Model». *Social Psychiatry and Psychiatric Epidemiology* 59(9):1617–27. doi:10.1007/s00127-023-02477-1.

- Fueth, M., Schmidt, S. V., Reinkemeier, F., Drysch, M., Steubing, Y., Bausen, S., Puszcz, F., Lehnhardt, M., & Wallner, C. 2025. Social Media Exposure and Muscle Dysmorphia Risk in Young German Athletes: A Cross-Sectional Survey with Machine-Learning Insights Using the MDDI-1. *Healthcare*, 13(14), 1695. <https://doi.org/10.3390/healthcare13141695>
- Ghosh, Sreejita, Pia Burger, M. Simeunovic, Joyce Maas, e M. Petkovic. 2024. «Review of machine learning solutions for eating disorders». *International Journal of Medical Informatics* 105526. doi:10.1016/j.ijmedinf.2024.105526.
- Griffiths, S., E. A. Harris, G. Whitehead, F. Angelopoulos, B. Stone, W. Grey, e S. Dennis. 2024. «Does TikTok contribute to eating disorders? A comparison of the TikTok algorithms belonging to individuals with eating disorders versus healthy controls». *Body Image* 51. doi:10.1016/j.bodyim.2024.101807.
- HaCohen-Kerner, Y., N. Manor, M. Goldmeier, e E. Bachar. 2022. «Detection of Anorexic Girls in Blog Posts Written in Hebrew Using a Combined Heuristic AI and NLP Method». *IEEE Access* 10:34800–814. doi:10.1109/ACCESS.2022.3162685.
- Herrman, J. 2024. «The Secret Weakness of TikTok’s All-Powerful Algorithm». *Intelligencer* (<https://nymag.com/intelligencer/article/the-secret-weakness-of-tiktoks-all-powerful-algorithm.html>)
- Hwang, Y., H. J. Kim, H. J. Choi, e J. Lee. 2020. «Exploring abnormal behavior patterns of online users with emotional eating behavior: Topic modeling study». *Journal of Medical Internet Research* 22(3). doi:10.2196/15700.
- Kitchenham, Barbara, Charters, Stuart, 2007. «Guidelines for performing systematic literature reviews in software engineering version 2.3». *Engineering* 45 (4ve), 1051.
- Kraye A, Ingledew DK, Iphofen R. 2008. «Social comparison and body image in adolescence: a grounded theory approach». *Health Educ Res.* 2008;23(5):892–903. doi:10.1093/her/cym076
- Lo Coco, Gianluca, e Rachel F. Rodgers. 2025. «A proposed model of the maintenance and exacerbation of body image and eating concerns in the context of problematic social network use». *Addictive Behaviors Reports* 22:100623. doi:10.1016/j.abrep.2025.100623.

- Longobardi, C., M. Settanni, M. A. Fabris, e D. Marengo. 2020. «Follow or Be Followed: Exploring the Links between Instagram Popularity, Social Media Addiction, Cyber Victimization, and Subjective Happiness in Italian Adolescents». *Children and Youth Services Review* 113: 104955. <https://doi.org/10.1016/j.chidyouth.2020.104955>
- López-Úbeda, P., F. M. Plaza-del-Arco, M. C. Díaz-Galiano, e M.-T. Martín-Valdivia. 2021. «How Successful Is Transfer Learning for Detecting Anorexia on Social Media?» *Applied Sciences* 11(4):1838. doi:10.3390/app11041838.
- Marciano, L., J. Lin, T. Sato, S. Saboor, e K. Viswanath. 2024. «Does Social Media Use Make Us Happy? A Meta-Analysis on Social Media and Positive Well-Being Outcomes». *SSM - Mental Health* 6: 100331. <https://doi.org/10.1016/j.ssmmh.2024.100331>
- Marengo, D., Longobardi, C., Fabris, M. A., & Settanni, M. 2017. Highly-visual social media and internalizing symptoms in adolescence: The mediating role of body image concerns. *Computers in Human Behavior*, 82, 63-69. doi: 10.1016/j.chb.2018.01.003
- Marks, Rosie Jean, Alexander De Foe, e James Collett. 2020. «The pursuit of wellness: Social media, body image and eating disorders». *Children and Youth Services Review* 119:105659. doi:10.1016/j.chidyouth.2020.105659.
- Marttila, E., A. Koivula, e P. Räsänen. 2021. «Does Excessive Social Media Use Decrease Subjective Well-Being? A Longitudinal Analysis of the Relationship between Problematic Use, Loneliness and Life Satisfaction». *Telematics and Informatics* 59: 101556. <https://doi.org/10.1016/j.tele.2020.101556>
- Mazzeo, Suzanne, Madison Weinstock, Taylor Vashro, Taryn Henning, e Karly Derrigo. 2024. «Mitigating Harms of Social Media for Adolescent Body Image and Eating Disorders: A Review». *Psychology Research and Behavior Management* 17:2587–2601. doi:10.2147/PRBM.S410600.
- Melioli, Tiffany, Stephanie Bauer, Debra L. Franko, Markus Moessner, Fikret Ozer, Henri Chabrol, e Rachel F. Rodgers. 2016. «Reducing Eating Disorder Symptoms and Risk Factors Using the Internet: A Meta-Analytic Review». *International Journal of Eating Disorders* 49(1):19–31. doi:10.1002/eat.22477.

- Merino, M., Tornero-Aguilera, J. F., Rubio-Zarapuz, A., Villanueva-Tobaldo, C. V., Martín-Rodríguez, A., & Clemente-Suárez, V. J. 2024. «Body perceptions and psychological well-being: A review of the impact of social media and physical measurements on self-esteem and mental health with a focus on body image satisfaction and its relationship with cultural and gender factors». *Healthcare*, 12(14), 1396. <https://doi.org/10.3390/healthcare12141396>
- Naji, Basmalah, Mohamed Naji, Salim Fredericks, e Salim Salim Fredericks. 2025. «Investigating the Impact of Social Media on Body Image and Eating Disorders Among Individuals in Arab Countries: A Literature Review». *Cureus* 17(10). <https://www.cureus.com/articles/395015-investigating-the-impact-of-social-media-on-body-image-and-eating-disorders-among-individuals-in-arab-countries-a-literature-review.pdf>
- Naseriparsa, M., S. Sukunesan, Z. Cai, O. AlFarraj, A. Tolba, S. Fathi Rabooki, e F. Xia. 2025. «ED-Filter: dynamic feature filtering for eating disorder classification». *Artificial Intelligence Review* 58(8). doi:10.1007/s10462-025-11244-4.
- Padín, P. F., González-Rodríguez, R., Verde-Diego, C., & Vázquez-Pérez, R. 2021. «Social media and eating disorder psychopathology: A systematic review». *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 15(3), Article 6. <https://doi.org/10.5817/CP2021-3-6>
- Pérez-Jiménez, M., M. D. M. Uclés-Torrente, G. E. Ruiz-Gamarra, M. Álvarez, I. M. Blancas-Sánchez, P. Aparicio-Martínez, e M. Vaquero Abellán. 2025. «Social Media Consumption and Risk of Addiction Associated with Adolescent Disordered Eating Behaviour: An Observational Analysis». *Nutrients* 17(18). doi:10.3390/nu17183017.
- Quiroz, S. I., & Mickelson, K. D. 2021. «Are online behaviors damaging our in-person connections? Passive versus active social media use on romantic relationships». *Cyberpsychology: Journal of Psychosocial Research on Cyberspace*, 15(1), Article 1. <https://doi.org/10.5817/CP2021-1-1>
- Rizwan, Bahisht, Manahil Zaki, Sumaiya Javaid, Zara Jabeen, Minahil Mehmood, Mahesayam Riaz, Laiba Maqbool, e Hamda Omar. 2022. «Increase

in body dysmorphia and eating disorders among adolescents due to social media». *Pakistan BioMedical Journal*:148–52.

- Satici, S. A., e R. Uysal. 2015. «Well-Being and Problematic Facebook Use». *Computers in Human Behavior* 49: 185190.
<https://doi.org/10.1016/j.chb.2015.03.005>
- Saunders, J., e A. Eaton. 2018. «Snaps, Selfies, and Shares: How Three Popular Social Media Platforms Contribute to the Sociocultural Model of Disordered Eating among Young Women». *Cyberpsychology, Behavior, and Social Networking*21(6): 343–354. doi:10.1089/cyber.2017.0713.
- Schmidt, U., Adan, R., Böhm, I., Campbell, I. C., Dingemans, A., Ehrlich, S., Elzakkars, I., Favaro, A., Giel, K., Harrison, A., Himmerich, H., Hoek, H. W., Herpertz-Dahlmann, B., Kas, M. J., Seitz, J., Smeets, P., Sternheim, L., Tenconi, E., van Elburg, A., van Furth, E., ... Zipfel, S. 2016. «Eating disorders: the big issue». *The lancet. Psychiatry*, 3(4), 313–315.
[https://doi.org/10.1016/S2215-0366\(16\)00081-X](https://doi.org/10.1016/S2215-0366(16)00081-X)
- Sharma, Ashley, e Carol Vidal. 2023. «A Scoping Literature Review of the Associations between Highly Visual Social Media Use and Eating Disorders and Disordered Eating: A Changing Landscape». *Journal of Eating Disorders* 11(1):170. doi:10.1186/s40337-023-00898-6.
- Solans, D. S., D. Ramírez-Cifuentes, E. A. Ríssola, e A. Freire. 2023. «Gender Bias When Using Artificial Intelligence to Assess Anorexia Nervosa on Social Media: Data-Driven Study». *Journal of Medical Internet Research* 25.
doi:10.2196/45184.
- Suhag, Khushi, e Shyambabu Rauniyar. 2024. «Social media effects regarding eating disorders and body image in young adolescents». *Cureus* 16(4).
<https://www.cureus.com/articles/184476-social-media-effects-regarding-eating-disorders-and-body-image-in-young-adolescents.pdf>
- Tranfield, David, Denyer, David, Smart, Palminder, 2003. Towards a methodology for developing evidence-informed management knowledge by means of systematic review. *Br. J. Manag.* 14 (3), 207–222.
<https://doi.org/10.1111/1467-8551.00375>

- Vandenbosch L, Fardouly J, Tiggemann M. «Social media and body image: recent trends and future directions». *Curr Opin Psychol.* 2022;45:101289. doi:10.1016/j.copsyc.2021.12.002
- Wall Street Journal. (2021). Inside TikTok's Algorithm: A WSJ Video Investigation. Wall Street Journal. <https://www.wsj.com/articles/tiktok-algorithm-video-investigation-11626877477>
- Williams, S., & Reid, M. 2010. «Understanding the experience of ambivalence in anorexia nervosa: The maintainer's perspective». *Psychology and Health*, 25(5), 551–567. DOI: [10.1080/08870440802617629](https://doi.org/10.1080/08870440802617629)
- Zarate, D., Hobson, B., March, E., Griffiths, M., & Stavropoulos, V. 2023. Psychometric Properties of the Bergen Social Media Addiction Scale: An Analysis Using Item Response Theory. *Addictive Behaviors Reports*, 17, 100473. <https://doi.org/10.1016/j.abrep.2022.100473>
- Zhang, J., C. Marino, N. Canale, L. Charrier, G. Lazzeri, P. Nardone, e A. Vieno. 2022. «The Effect of Problematic Social Media Use on Happiness among Adolescents: The Mediating Role of Lifestyle Habits». *International Journal of Environmental Research and Public Health* 19(5): 2576. <https://doi.org/10.3390/ijerph19052576>
- Zhou, S., Y. Zhao, J. Bian, A. F. Haynos, e R. Zhang. 2020. «Exploring eating disorder topics on Twitter: Machine learning approach». *JMIR Medical Informatics* 8(10). doi:10.2196/18273.