Towards Gaze Tracking on Short Form Videos for Body Image Disturbance-Driven Condition Detection and Self-Monitoring

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Abstract

Individuals with body image disturbance-driven disorders exhibit distinct gaze patterns when viewing images of themselves or others. Engagement with short-form video platforms, such as TikTok, Instagram Reels, or YouTube Shorts often involves prolonged passive scrolling through videos that predominantly feature full or partial views of people's bodies. These platforms present a unique opportunity to explore whether the gaze disparities observed in static images extend to dynamic content. This paper introduces two initial approaches for tracking gaze relative to dynamic bodily areas of interest on short-form video content and a plan for evaluation using directed gaze tasks in an upcoming technical validation study. Participants will view short-form video content on a mobile device that auto-scrolls every few seconds while their gaze is tracked using pupil position estimation from the device's front-facing camera or via a HoloLens 2 mixed reality headset. We will compare the accuracy of the two gaze-tracking methods against each other and adopt the more accurate method for a follow up study which will assess whether significant differences in gaze behavior emerge between individuals with and without BID-driven disorders when viewing dynamic video content featuring human bodies.

Keywords

gaze tracking, body image disturbances, eating disorders, social sensing, social media, short form video platforms

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1 Introduction

Mortality rates for body image disturbance (BID)-driven disorders, such as anorexia nervosa or body dysmorphic disorder, are among the highest associated with any psychiatric condition [42]. These conditions are typically detected and monitored via biophysical indicators, like weight and muscle weakness [30], as well as active self-report methods, like food diaries [44] or survey-based assessments [26, 31, 40]. However, a majority of individuals with these conditions remain undiagnosed and untreated [7]. Body image disturbances (BIDs) are a major factor in the development of conditions associated with restrictive eating or compensatory behaviors [16] and are strongly associated with suicidality [3]. Assessing BIDs themselves largely relies on psychometric and self-report instruments [34, 41], which are prone to self-report bias [27]. Given this, there is a growing need for passive monitoring methods that do not rely on self-reporting.

Although progress has been made in the passive detection and monitoring of BID-driven disorders through physiological and behavioral data from wearable devices [37], broad access to these devices remains a challenge [25]. Alternatively, smartphones, and the widely used social media applications on them, offer a unique opportunity to integrate passive self-monitoring solutions into the places where people already are.

Short form video platforms (SFVPs), are social media platforms which primarily feature short-form video content (such as TikTok, Instagram Reels, and YouTube Shorts). Notably, research suggests that nearly 62% of TikTok users are under the age of 29 [17], transition-age youth (typically aged 16 - 25 years) are disproportionately affected by BID-driven disorders [9], and over half of adolescents diagnosed with an eating disorder use a SFVP as their primary social media platform [28, 35].

Prior work has shown that individuals with BID-driven disorders exhibit distinct gaze patterns when viewing images of themselves or others [4, 14, 19, 33]. Given that engagement with SFVPs often involves prolonged passive scrolling through videos that predominantly feature full or partial views of people's bodies, these platforms present a unique opportunity to explore whether the gaze disparities observed in static images extend to dynamic content. If so, these insights could inform the development of gaze-driven assessment and self-monitoring tools tailored to SFVPs, enhancing strategies for early detection, intervention, and self-regulation. This paper introduces two initial approaches for tracking gaze relative to dynamic bodily areas of interest on short-form video content and a plan for evaluation using directed gaze tasks.

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2 Background

2.1 Body Image Disturbances

Body image disturbances (BIDs) refer to distorted perceptions of and intense preoccupations with one's physical appearance [32], often leading to emotional distress and maladaptive behaviors [18]. Several mental health disorders are associated with such disturbances, including eating disorders (EDs)[42]. Classical examples of BID-driven EDs include anorexia nervosa (AN), characterized by a severely low body mass index (BMI) and restrictive eating or compensatory behaviors, such as vomiting or excessive exercise, and bulimia nervosa (BN), characterized by recurring binge-eating episodes followed by compensatory behaviors [42]. Another related condition, body dysmorphic disorder (BDD), is marked by an obsession with perceived physical flaws, often amplified in the individual's perception [39].

Detection and monitoring of BID-driven eating disorders often relies on regular measurement of biophysical indicators, like weight [30], muscle weakness [30], and other physiological markers [36]. These metrics, however, do not directly assess body image disturbances (BIDs) themselves. Doing this often relies on assessments of perception conducted via validated self-reported instruments [26], such as the Body Image Questionnaire (BIQ, or BIQ-C for youth) [5], the Sick, Control, One, Fat and Food (SCOFF) Questionnaire [31], and the Eating Disorder Diagnostic Scale (EDDS) [40]. However, these tools rely on self-reporting, making them vulnerable to self-report bias.

2.2 Passive Condition Detection

As an alternative to self-report, passive detection methods, which rely on passively-measured signals to make inferences about a person's health [10], are steadily advancing in the ED and BID-driven disorder space. Progress has been made in passive detection of BID-driven disorders, particularly through the development and application of digital phenotypes (passively-detected signals about a person's health based on their interaction with digital technologies [20]) for detecting and monitoring eating disorders [24, 37]. Notable approaches have included leveraging wearable devices to collect physiological and behavioral data, such as heart rate and electrodermal activity, and using this as training data for logistic regression classifiers to predict relevant diagnostic outcomes [37].

In addition to data produced from physical sensors, a large body of work has focused on data extracted from social media and other online platforms where individuals often self-disclose information. These digital platforms enable "social sensing" [21], passively capturing signals that are potentially indicative of certain conditions based on social media usage, often on smartphones. Notably, commercial wearable sensing devices are far less common than smartphones. Globally, while approximately 560 million people own or use a smartwatch [1], nearly 4.8 billion people own a smartphone [15], with a roughly equal number using social media platforms [2]. Given this, social media usage and interaction data could serve as a valuable tool for capturing and measuring behaviors that may act as proxies for clinically maladaptive behaviors, such as those linked to BIDs.

The public health sector regularly leverages social media data for large-scale passive detection, such as tracking outbreaks of influenza [6], COVID-19 [38], and foodborne illnesses [13]; however, the application of these methods for individual mental health condition detection and monitoring has been far less effective. Text-based social media data has demonstrated moderate success in detecting and monitoring specific mental health conditions, such as postpartum depression [12]; nevertheless, key limitations persist. Biases in sampling, data preprocessing, model development, and evaluation metrics have impacted the validity of the models used [8]. A critical gap in the social sensing discipline is the need for more comprehensive data sources, particularly cross-media inputs, such as short-form video content, which is becoming an increasingly prevalent mode of media consumption and engagement [29].

2.3 Short-Form Video Platforms

Short-form video platforms (SFVPs) are social media platforms which primarily feature short-form video content. Popular examples include TikTok, Instagram Reels, and YouTube Shorts. Engagement on SFVPs often consists of rapid consumption of content by scrolling through prolonged video streams. This allows users to quickly browse many videos in a short period of time. Several factors, including the content's brevity, low-barrier access, and engagingness contribute to increased occurrences of events like "binge-scrolling," where users continuously consume content for extended periods of time without actively seeking out specific videos [22, 23]. Recent estimates suggest that users spend an average of 2.5 hours per day scrolling through social media feeds, including SFVPs [11]. While traditional social media research has focused on analyzing text-based contributions, such as posts and comments, the majority of short-form video platform use occurs via screen gaze during prolonged scroll periods. This mode of interaction remains an underexplored area in the context of passive engagement with digital platforms.

2.4 Gaze & BID-Driven Disorders

Early research foundational to the study of passive ED detection, conducted by Freeman et al. in 1991, identified significant differences in the gaze patterns of individuals with and without an ED when viewing images of themselves. Based on these findings, the authors suggested that gaze tracking could eventually be integrated into the assessment and monitoring of eating disorders [14]. Since the Freeman et al. paper, the relationship between a person's gaze and the presence of BID-driven disorders has been supported by several additional studies [4, 19, 33], suggesting that individuals with these conditions exhibit distinct gaze patterns when viewing photos of their own or other people's bodies. These patterns are uniformly characterized by heightened focus on specific body parts or bodily areas compared to individuals without a diagnosed BID-driven disorder. For instance, one study suggests that individuals diagnosed with BID-driven EDs tend to preferentially focus on specific bodily areas, such as the hips and upper legs, as well as on unclothed body parts, compared to those without BID-driven EDs [19]. Additional research indicates that individuals with AN demonstrate prolonged visual attention to bodily areas they perceive as "unattractive" when viewing images of themselves or their peers

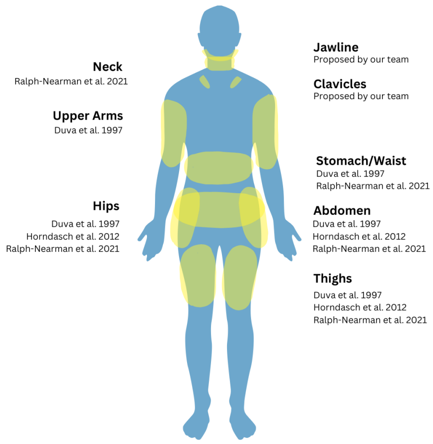

Figure 1: Bodily Areas of Interest Identified in Previous Studies

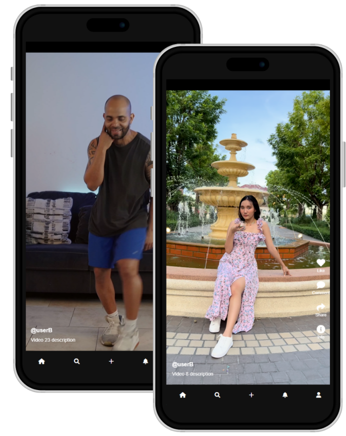

Figure 2: User Interface of Auto-Scrolling Pseudo-Short Form Video Platform (frames adapted from content created by abdel baila baila and Nattanan Suradittanan, YouTube SFV+HDR Dataset, CC BY 4.0)

[4]. We intend to build upon this existing body of work by pursuing research that investigates whether these patterns observed in static image contexts extend to dynamic short form video contexts.

3 Feasibility & Technical Validation Study

Before assessing differences in visual attention on short-form video content between individuals with and without BID-driven disorders, we must first evaluate the feasibility of our approach to gaze tracking. To do so, we developed a feasibility study to validate whether our approach effectively captures area of interest (AOI)-affirmative gaze points during directed gaze tasks. Our primary research question focuses on whether it is possible to reliably measure dynamic AOIs on human bodies in short-form video content presented on mobile devices.

3.1 Characterizing Dynamic Bodily AOIs

Areas of interest (AOIs) refer to specific regions while gazing at a visual stimulus (e.g., an image) that captures visual attention. Dynamic AOIs, in contrast, are regions within dynamic stimuli (e.g., videos) that change over time and correspond to the positions of content of interest (e.g., face). Most research on AOIs involving human bodies has focused on static contexts; however, video-based dynamic AOI research relating to human bodies (dynamic bodily AOIs), particularly in the context of SFVPs remains largely unexplored. Our feasibility study proposes and tests a method for tracking human gaze relative to dynamic AOIs on human bodies in short-form video content. Our goal is to develop a reliable approach for analyzing visual attention in this context, enabling future research to compare gaze patterns across short-form video content.

The study consists of participants viewing short-form video content that auto-scrolls every N seconds on an Android Galaxy A10 mobile device running a JavaScript implementation of a pseudo-SFVP. This implementation replicates key elements of real SFVP user interfaces, including a like button, comment button, and other features. To ensure a diverse sample of videos representing various body presence characteristics (including physical appearance,

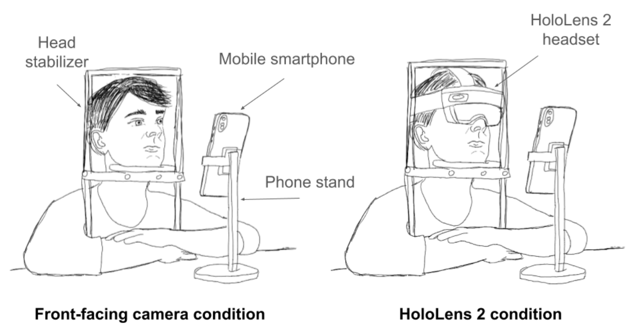

Figure 3: Sketches of Participant & Equipment Configuration

movement pace, etc.), short-form video content will be sourced from the YouTube SFV+HDR dataset, a large-scale dataset containing YouTube Short form and high dynamic range videos intended for use by the wider research community [43].

The mobile device will be mounted on a tabletop stand at eye level, and participants will rest their chin on a 3D printed chin rest to stabilize head movements. During each video, participants will be instructed to fixate on a designated AOI while their gaze is recorded using two distinct gaze-tracking methods, corresponding to two experimental conditions. In one condition, gaze will be recorded using the front-facing mobile phone camera and gaze points will be approximated relative to the SFV content displayed using pupil position estimation. In a second condition, participants will wear a Microsoft HoloLens 2 headset while their gaze is tracked using Microsoft's Mixed Reality Toolkit 3 and a custom eye tracking implementation. In both conditions, gaze points will be recorded as x, y coordinates with corresponding timestamps.

Dynamic bodily AOIs for each short-form video will be manually annotated using Label Studio, where a bounding box will be placed over the bodily AOI in the video at key frames, depending on bodily

Figure 4: Example of SFV AOI annotations using Label Studio (frames adapted from content created by Rashaya Boston, YouTube SFV+HDR Dataset, CC BY 4.0)

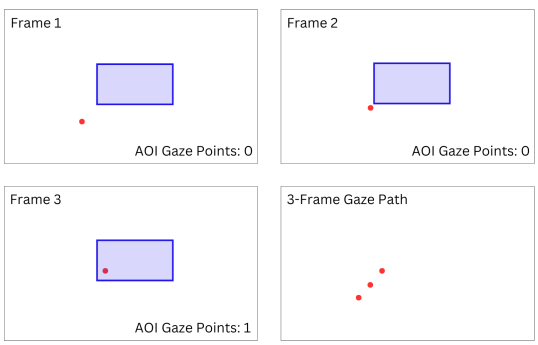

Figure 5: Example of Frame-by-Frame Gaze Point Assessment

motion complexity. Between these frames, the bounding boxes will be linearly interpolated to provide consistent localization across frames. A gaze point will be classified as an affirmative AOI gaze point if its x, y coordinates are contained within the bounding box in a given frame.

We will compare the accuracy of the two gaze-tracking methods against each other and adopt the method that yields affirmative gaze point measurements exceeding 90% across all participants for use in tracking dynamic bodily AOIs in future work. If both methods exceed the 90% threshold, we will adopt the more accurate method. If neither meets this criterion, we will seek improved eye-tracking equipment and revisit our study design.

4 Next Steps

Once high validity is demonstrated in our approach, we will implement this method of measuring dynamic AOIs in a follow-up study. In this next phase, we will examine visual attention on short-form video content among individuals with and without BID-driven disorder diagnoses, using undirected gaze tasks. Our primary goal will be to determine whether, and how, gaze patterns differ between the two groups. We will analyze key metrics such as time to first fixation, fixation duration, dwell time, and transition frequency. These measures will be assessed relative to bodily AOIs previously identified as areas of heightened attention in individuals with BID-driven eating disorders when viewing static images. The central research question driving this study will be whether significant differences in gaze behavior exist between individuals with and without BID-driven disorders when viewing dynamic video content featuring human bodies.

This second study is still in development. Currently, we anticipate recruiting participants with BID-driven disorders through partnerships with care organizations based in New York City; however, other study design decisions remain under consideration. For instance, we are contemplating whether to dichotomize participants by diagnostic status or instead treat BID severity as a continuum to be correlated with gaze behavior. These and other methodological choices will be finalized once we have confirmed the reliability of our gaze tracking approach for short-form video content.

Looking ahead, identifying meaningful differences in undirected gaze behavior between these groups could help characterize distinct gaze patterns linked to BID-driven disorders. In turn, this may guide the development of generalized gaze-tracking methods for short-form videos and pave the way for passive, gaze-based self-monitoring tools to support the detection and management of BID-driven conditions.

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