Title
Social Media’s Mental Health Problem: A Multi-Method Examination of Social Media Mental Health Content and its Impact on Vulnerable Adolescents

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Social Media's Mental Health Problem:
A Multi-Method Examination of Social Media Mental Health Content and its Impact on Vulnerable Adolescents

By

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Abstract

Social media use has become an integral part of adolescents' daily lives and social routines. Along with the rise of social media use, there has also been a concurrent increase in mental health concerns among adolescent populations. Recent research and mainstream media have been concerned with the rise in self-diagnosing and the medicalization of normative behavior on social media sites, which has been of concern for adolescents particularly when the content comes from social media influencers. The current set of studies sought to examine the nature of user-generated content on social media about mental health topics and to investigate the effects of exposure to such content among at-risk adolescent populations who struggle with self-regulation and problematic social media use. Specifically, in Study 1 we conducted a content analysis of YouTube videos from social media influencers on four main mental health concerns among adolescents: attention deficit hyperactivity disorder (ADHD), anxiety, depression, and eating disorders. In Study and Study 3, we conducted national surveys among adolescents ages 14 to 16 to assess their self-regulation skills, problematic social media use, frequency of social media use, exposure to mental health content, and mental health outcomes (i.e., anxiety, depression, and self-reported mental health). To conclude, in Study 4 we experimentally tested through an online survey experiment the immediate effects of exposure to a video on mental health produced by a social media influencer on facets of adolescent mental health. The results of our four studies revealed that adolescents with poor self-regulation and those who have higher rates of problematic social media use are more likely to experience poor mental health outcomes, particularly when they spend more time on social media and follow mental health content. Mental health content on social media tends to be produced by white females, and adolescents

who identified as female demonstrated poorer mental health on all metrics (clinical measures and self-report) across all three samples. Exposure to mental health content was related to higher self-report of mental health conditions, revealing that this content can be particularly suggestive. Overall, the findings in these four studies highlight the need for an increased review process of content on social media sites, as exposure to mental health content from non-professional sources can have serious detrimental effects on adolescents behavior, attitudes, and beliefs. We also identify at-risk groups for mental health struggles that can allow for interventions in a timely and effective manner.

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Introduction

Social media use has become an integral part of adolescents' daily lives, particularly their social lives (Khasawneh et al., 2020), and as a result is now intertwined with key developmental processes that occur during this age range (e.g., self-regulation). Reports estimate that U.S. adolescents are spending more hours with screen media than they are in school, even before the onset of the COVID-19 pandemic (Odgers & Jensen, 2020), and nearly half of adolescents say they are online "almost constantly" (Hynes et al., 2022). National surveys suggest that adolescents spend the majority of their screen media time on social media and viewing online video content (Rideout et al., 2022; Rivas-Lara et al., 2022), with YouTube and TikTok being the top two most used platforms by this age group (Bahorsky, 2022). The most recent Common Sense census states that adolescents ages 13 to 18 years are using screen media for entertainment over eight hours a day, a 17% increase from the daily average reported just two years prior (Rideout et al., 2022). With this increase in screen time, adolescents are also increasing their exposure to social media influencers. This is reflected in recent research that shows that adolescents seek content that is authentic, relatable, and reflects real-life issues (Rivas-Lara et al., 2022). In fact, adolescents make up the largest proportion of viewers for social media influencers (Dopson, 2022).

With such high rates of use, researchers, educators, and policymakers are increasingly interested in the relationship between social media use and mental health, particularly among adolescents, as many studies have linked increases in screen time to the rise in mental health problems in this population (e.g., Fernandes et al., 2020; Odgers & Jensen, 2020; Twenge et al., 2018). Social media use in particular has received the most attention and blame in relation to mental health as use is linked with lack of real in-person contact and increased bullying (Hynes et al., 2022; Twenge, 2020) to name a few. Mental health is one of the top public health concerns globally (Rutter et al., 2023) and recent studies estimate that approximately half of adolescents ages 13 to 18 years in the United States experience some form of mental health condition (National Institute of Mental Health, 2023). Approximately 50% of all lifelong mental health issues onset by age 14 (National Alliance on Mental Illness, 2022) and suicide is the second leading cause of death among young adolescents (Center for Disease Control, 2020), with rates of depression and suicide increasing at an alarming rate (Odgers & Jensen, 2020). In addition to clinical diagnoses of mental health conditions, overall well-being fluctuates the most during adolescence (Valkenburg et al., 2022), as self-regulation is in flux and risk-taking behavior and internalizing problems increase (Burnell & Odgers, 2023; Steinberg et al., 2018). Adolescents are also experiencing significant physical (i.e. puberty), cognitive (i.e., brain growth and emotional reactivity), and social (i.e., new dynamics in parental and peer relationships) changes, which they often struggle to cope with due to heightened emotional reactivity and a still-developing decision-making system (Limone & Toto, 2021; Pitt et al., 2021). Therefore, adolescents are particularly vulnerable to experiencing mental health struggles.

Though this topic has garnered significant research attention, there is little consensus on the overall effect that social media use has on adolescent mental health, with some studies showing positive effects and some showing negative effects (Limone & Toto, 2021; Odgers & Jensen, 2020). As cumulative effects are little to null, researchers have begun to take a person-specific approach (Valkenburg et al., 2022). Specifically, this paradigm refers to studying social media effects at the individual level. Sometimes this employs a methodological design of $N = 1$ to assess within-person fluctuations of social media use and resulting well-being, rather than differences between subjects. Another approach is the concept of individual susceptibility, which refers to risk and resilience factors at the individual level that may influence social media use and subsequent effects (Valkenburg & Peter, 2013). Introduced in 2013, the Differential Susceptibility to Media Effects Model (DSMM; Valkenburg & Peter, 2013) was an innovative way to view the individual differences that influence the media effects process, as well as the transactional relationships that occur in media use.

There are several variables to consider in understanding the complex relationship between social media use and mental health outcomes. First, individual susceptibility characteristics, such as age, gender, social influences, and developmental stage, greatly influence social media use (Valkenburg & Peter, 2013). Recent research has identified self-regulation as a key developmental susceptibility factor influencing social media use and subsequent effects (Valkenburg et al., 2022). Self-regulation refers to a set of top-down cognitive processes that help an individual regulate their thoughts, emotions, and behaviors in service of their long-term goals (Karoly, 1993; Siebers et al., 2021). Individuals with poor self-regulation skills tend to use social media more frequently (Coyne et al., 2019) and in more problematic ways (Arness & Ollis, 2022). Problematic media use (PMU), also commonly referred to as media addiction or dependence, is a growing concern among adolescents (Burnell et al., 2022). PMU is like an addiction as it is characterized by uncontrolled and excessive use of media in a way that leads to harmful consequences on the user's functioning and mental health (Arness & Ollis, 2022; Lopes et al., 2022). Therefore, self-regulation and PMU are individual risk factors that influence *how* media is consumed and its subsequent effects on mental health.

In addition to these individual susceptibility factors, specific content is also necessary to consider in the process of social media use and mental health outcomes. It is now widely accepted that it is not just the frequency of social media use that leads to negative effects, but what adolescents are spending their screen time doing (Odgers & Jensen, 2020). There has been a rapid increase in the amount of user-generated content (UGC) on health topics (Fergie et al., 2016), in particular, mental health, which raises concern as this content is not necessarily well-sourced or factual (Gaus et al., 2021). Though research has begun to consider the potential of social media for disseminating mental health information and its use as a source of social support for such issues, less research has investigated what this content actually looks like or its unintended effects. Mainstream news and health practitioners have been concerned with the rise in mental health problems in conjunction with online trends perpetuated by social media influencers (Bahorsky, 2022). For example, news headlines have highlighted the prevalence of tic movements among adolescent girls who watch a lot of TikTok, or the pathologization of normal behaviors on TikTok as warning signs of mental health conditions whereby users begin to self-diagnose (Bahorsky, 2022; Rutter et al., 2023). In one exception, doctors Hull and Parnes (2021) describe the phenomenon of teenage girls developing tic-like movements, characteristic of Tourette syndrome, after watching online content from an influencer with the condition. In one other example, researchers document the rise in self-harm behaviors and suicide attempts following a popular online trend known as the Blue Whale Challenge in which viewers were encouraged to partake in self-harm until they ultimately killed themselves (Khasawneh et al., 2020). Exposure to this type of suggestive content is particularly harmful to adolescents as a vulnerable population who are more susceptible to social influence (Fernandes et al., 2020) and are already more prone to mental health concerns due to their developmental stage (Khasawneh et al., 2020; Pitt et al., 2021). Though research has begun to consider the effects of exposure to social media influencers, particularly in the context of advertising and marketing (Dopson, 2022; Howard, 2022), less research has explored developmental differences (i.e., self-regulation and

PMU) that may make some populations more susceptible to being influenced in other contexts, such as in mental health. As such, it is important to understand from whom adolescents are receiving information and what this mental health information online looks like.

With this in consideration, this set of studies sought to examine the relationship between adolescent social media use and mental health through an individual susceptibility perspective, as well as to consider the role that social media influencers (SMIs), as modern-day celebrities (Dopson, 2022), play in these effects. Specifically, in Study 1 we content analyzed YouTube videos produced by SMIs that cover mental health topics as there is a growing trend in the amount of mental health information shared on social media, in particular, YouTube (Fergie et al., 2016). In Study 2 and Study 3, we surveyed adolescents about their self-regulation skills, problematic social media use, facets of social media use, including frequency and consumption of mental health content, and mental health symptoms to investigate how exposure to mental health information may impact vulnerable populations. To tie together the content analysis and the two surveys, in Study 4 we conducted an online survey experiment to evaluate the immediate effects of viewing SMI videos about mental health topics. Through these studies, we addressed the gaps in the research on the effects of SMIs on thoughts and behaviors of at-risk populations (i.e., adolescents with poor self-regulation and/or high problematic media use). We also answered the calls for further research into the effects user-generated mental health content can have on viewers (Choi et al., 2021; Fergie et al., 2016), as well as considering more nuanced measures of social media use and current, rather than retrospective, assessments of mental health (Odgers & Jensen, 2020).

Study 1

Introduction

Social media have become ingrained in daily life, not only for adults, but also for children and adolescents who are increasing social media users. In fact, 96% of adolescents ages 13 to 18 report using social media platforms and are using significantly more platforms (four or more) compared to previous years (Robb, 2020). As adolescents at this age are still developing in many ways, primarily socially, and are at risk for impulsive decisions and poor self-control (De-Sola Gutiérrez et al., 2016; Mahapatra, 2019), understanding their social media use is critical as it becomes entwined with these development processes that have lasting impacts throughout adulthood. Furthermore, adolescents begin to seek out and identify role models as they engage in identity formation processes (Erikson, 1968). Where previous studies have identified parents and local community members as potential role models for adolescents as part of their microenvironments (Strasser-Burke & Symonds, 2020), few studies have considered the potential of social media influencers as role models. Social media influencers (SMIs) have the potential to exert significant influence on adolescents who are spending increased amounts of time online and potentially less time with real-world influences (i.e. parents and other adults; Kraut et al., 1998). In fact, SMIs may be more attractive to adolescents as they exist outside of their microenvironments and allow exposure to more diverse ideas and lifestyles (Strasser-Burke & Symonds, 2020) and may be perceived as more relatable (Rivas-Lara et al., 2022). The strength of this influence may be particularly strong for adolescents who experience poor self-regulation as they struggle to inhibit their impulses, regulate their emotions, and focus on their goals (Diamond, 2013; Steinberg, 2007). Though research demonstrates the role of SMIs as effective advertisers teaching audiences which products to buy (Zeljko et al., 2018), little research has considered the effects of influencers as teachers of attitudes, values, and behaviors, or the effects on particularly vulnerable audiences such as adolescents with poor self-regulation and susceptibility to mental health struggles. With alarming rates of mental health problems among adolescent populations (U.S. Department of Health & Human Services, 2022), it is important to consider who they are looking to and seeking out as role models to provide information about mental health.

Literature review

Social influence

User-generated content (UGC) refers to the creation of content by users of social media sites, such as Instagram or YouTube, who are members of the general public, rather than mental health professionals (Westenberg, 2016). UGC allows for the consumption of details about people's everyday lives and is considered the next iteration of word-of-mouth whereby everyday people share recommendations and experiences (Fergie et al., 2016; Smith, 2009; Westenberg, 2016). Although anyone can create UGC, some creators become known as social media influencers. Social media influencers (SMIs) are individuals who amass an online following on social media platforms, such as YouTube, Instagram, and personal blogs, through practicing microcelebrity, the act of self-presentation and identity curation online through ongoing communication (Chae, 2018; Marwick & Boyd, 2011; Senft, 2008). That is, SMIs strategically select what information to present online that creates the most favorable image of them as a brand and attracts followers (Marwick, 2015). Furthermore, SMIs are known to present information about their personal lives, both textually (e.g., blogs and Twitter) and visually (e.g., YouTube and Instagram; Abidin, 2016; Zeljko et al., 2018) which allows for increased and more detailed exposure. The majority of SMIs are followed on Instagram (Dhanesh & Duthler, 2019);

however, some of the most well-known SMIs who have reached mainstream fame, like PewDiePie, Lilly Singh (or Superwoman), and the Paul brothers, gained their fame from YouTube and then amassed millions of followers across their various platforms including Instagram and Twitter (Reinikainen et al., 2020). In fact, SMIs often cross-promote themselves and redirect their followers from one platform to another (e.g., Snapchat to Instagram, see Gkoni et al., 2017). Therefore, while SMIs may gain the majority of their fame from one platform, they also promote themselves across platforms, prompting followers to use multiple social media sites in order to keep up with them, encouraging fragmented use.

Though SMIs tend to be wealthy and attractive young women, they are more commonly defined by their online behaviors (i.e., engaging in microcelebrity) and large number of followers, rather than who they are (Abidin, 2016; Marwick, 2015; Reagan et al., 2020). As some influencers have grown mass amounts of followers, sometimes exceeding millions, specialists in influencer marketing have begun to categorize SMIs into five groupings based on their follower counts (Dopson, 2022). These include Nano influencers (between 1,000 and 5,000 followers); Micro influencers (between 5,000 and 20,000 followers); Power or mid-tier influencers (between 20,000 and 100,000 followers); Mega influencers (between 100,000 and 1 million followers), and SMI Celebrities (more than 1 million followers). While some SMIs focus on sharing their daily lives, others focus on specific interests or niche categories, such as fashion, beauty, sports, or tourism (Chae, 2018; Magno & Cassia, 2018; Zeljko et al., 2018), that appeal to different audiences. For example, Lokithasan and colleagues (2019) found that females are drawn to SMIs who promote beauty products, whereas males are drawn to SMIs who promote gaming and technology products.

In comparison to traditional celebrities, SMIs intentionally build relationships with their followers in order to garner increased social media engagement metrics (such as likes, comments, and views) and increase financial gain (Reagan et al., 2020). In addition to product advice, SMIs have the potential to influence attitudes and behaviors as viewers both seek to emulate their curated and luxurious lifestyles (Magno & Cassia, 2018) and see them as modern-day opinion and social leaders (Gillin, 2008; Magno & Cassia, 2018). Some researchers argue that SMIs play a key role in social diffusion as their attitudes and values reach a wide audience and can lead to attitude and behavior change (Reagan et al., 2020; Uzunoğlu & Kip, 2014). Therefore, SMIs have significant influential power over their audiences as their job is to market themselves as a brand and sell their image, including their beliefs, attitudes, and behaviors, to their audiences so that they can earn a living (Marwick, 2015).

SMIs are perceived as more authentic, relatable, and reachable in comparison to traditional celebrities (Chae, 2018; Djafarova & Rushworth, 2017; Klassen et al., 2018) and as such, their advice is more readily accepted by their audiences as they are seen as credible sources of information. In fact, 55.1% of teenagers ages 13 to 18 report that social media, compared to other types of media, has the most authentic content (Rivas-Lara et al., 2022) and SMIs are their preferred and most used news source (Robb, 2020). As such, it is important to evaluate what information is being shared and how that information impacts viewer's behaviors and thoughts. For example, the luxurious lifestyles of high-end fashion and frequent travel to exotic locations promoted by SMIs have been linked to increased consumerism (Heinonen, 2020), materialism (Zawadska et al., 2019), and narcissism (Khamis et al., 2017) amongst adolescent and adult audiences as viewers believe they need to live like SMIs to be happy.

This advice can be particularly problematic when SMIs are successful in niche categories as they are looked to as experts by viewers and disseminate information when in fact they are often not qualified to do so (Reagan et al., 2020). The information they share is trusted but may in fact be unreliable and even harmful (Chan et al., 2018; Reagan et al., 2020). For example, a study by Byrne and colleagues (2017) found that SMIs often promote specialized diets, such as vegan or paleo, that can cause nutritional deficiencies if not recommended by a registered physician. Additionally, a content analysis of over 285,000 Instagram posts from health influencers revealed that the information in the posts was primarily related to “cosmetics and appearance, self-promotion, fitness, and general wellness”, as opposed to genuine health information, and in some cases even promoted unhealthy attitudes and ideals, such as the thin ideal (Bak & Priniski, 2020, p. 2). Promotion of thin/slender beauty ideals is common amongst most SMIs, not just in the context of health and fitness, particularly on Instagram (Hendrickse et al., 2017; Manas-Viniegra et al., 2020). Idealised body type, for example hypermuscular, is also prevalent in fitness content geared towards men (Carrotte et al., 2019). This can easily lead viewers to feel dissatisfied with their bodies when they do not look like the filtered images that they see from SMIs and trust are realistic. Furthermore, studies have found that fitness content is focused around exercising for the sake of appearance, rather than for health reasons, restrictive eating, and the idea that an idealized body is the only way to be happy (Boepple et al., 2016; Carrotte et al., 2019; Pilgrim & Bohnet-Joschko, 2019; Tiggemann & Zaccardo, 2018). Coupled with the prevalence of content promoting the thin ideal, this can have serious implications for the eating behaviors of viewers, particularly adolescent girls who are susceptible to disordered eating (Boepple et al., 2016; Syed-Abdul et al., 2013).

Furthermore, mental health becomes more widely spoken about and disclosed by SMIs on social media (Howard, 2022). For example, the majority of YouTube videos on mental health are uploaded by individuals (i.e., SMIs) in comparison to health organizations or professional media sources (Choi et al., 2021). Only 9% of videos on mental health studied by Devendorf and colleagues (2020) were uploaded by health professionals, such as professional organizations and licensed psychiatrists. As noted by Godwin and colleagues (2017), entering "depression" into the search bar on YouTube leads to thousands of results of people sharing their personal experiences, and the same is true for many other mental health conditions. So, there is the potential for vast exposure to non-professional content on mental health. As adolescents seek to copy the lives of SMIs and trust the information that is being shared, mental health content produced by SMIs can have serious implications for adolescent mental health in the real world.

Mental health information online

The creation of mental health content on social media has become increasingly common, with researchers suggesting that users are relying on their social networks and embedded functions on social media sites rather than search engines to seek mental health-related information (Fergie et al., 2016). In fact, online sources are the primary form of health information-seeking for younger populations (Odgers & Jensen, 2020), who are particularly reluctant to seek help when experiencing symptoms (O'Reilly et al., 2019). According to a national survey in 2018, 87% of adolescents surveyed reported going online for mental health information, with anxiety and depression being the most common searches (Odgers & Jensen, 2020; Rideout & Fox, 2018). These rates appear to be increasing rapidly as in a study conducted by Wartella and colleagues in 2016, only 22% of adolescent girls and 10% of adolescent boys reported searching for information about depression online. Further, a large amount of mental health information and content is created by adolescents and young adults (Yonker et al., 2015) who likely have limited professional knowledge. Therefore, it is crucial to understand what this content looks like as it has the potential to shape attitudes, beliefs, and knowledge of mental health at a widespread level, and individually how people choose to manage their conditions (Devendorf et al., 2020; Kang et al., 2017).

While researchers have increasingly been studying UGC as a source of mental health information (Choi et al., 2021), they have also begun to be concerned about the veracity and reliability of this information (Gaus et al., 2021; O'Reilly et al., 2019). First, the defining characteristic of UGC is that it is created by users of the platform. That is, anyone, anywhere in the world can upload content online to be consumed by viewers, largely without a review process. In fact, studies show that around one-third of all videos on YouTube on mental health issues were created by users with lived experiences as opposed to professionals (Baquero, 2018; Devendorf et al., 2020; Oliphant, 2013). Many individuals self-disclose to find support and build community with others (Mickles & Weare, 2020) or to provide treatment advice (Naslund et al., 2014). While these videos may attempt to reduce stigma and encourage viewers to seek treatment, it is equally likely that they may discourage viewers from seeking help if they share negative experiences (Gaus et al., 2021). For example, a study conducted by Gaus and colleagues (2021) found that very few YouTube videos on depression advocated for clinical treatment. Therefore, these videos can have unintended negative consequences on viewers. Second, when this content is posted by SMIs, it may be more easily trusted and less scrutinized. A focus group study conducted by O'Reilly and colleagues (2019) with 54 adolescents found that adolescents value trustworthiness in the mental health information that they consume, but due to ease of access and time constraints, they do not generally check the credibility of the information.

Discerning credibility may be even more difficult for adolescent audiences, especially when content comes from SMIs who they perceive as authentic and trustworthy (Chae, 2018). Research among young adults (ages 18 to 30) found that users may seek UGC about mental health as a source of opinion, rather than fact, which again may be further impactful for adolescents who identify with and trust SMIs and use information from SMIs to form their own understanding of mental health (Gaus et al., 2021).

While mental health information can be uploaded to any platform, content on YouTube is particularly important to consider as it has been one of the most used social media sites by adolescents for nearly ten years (Rideout, 2015; Rideout et al., 2022) and therefore can be highly influential (Khasawneh et al., 2020). YouTube is the second most popular website in the world (Devendorf et al., 2020), with over two billion users globally and a new video uploaded every minute (Choi et al., 2021), meaning that there is constantly new content, including mental health content, that viewers can consume. Some research suggests that YouTube may be used as a source of mental health information more commonly than traditional healthcare websites (e.g., National Alliance on Mental Illness; American Psychiatric Association; Devendorf et al., 2020). In fact, YouTube is the most commonly used social media site among adolescents with existing mental health conditions (Gaus et al., 2021; Naslund et al., 2019) and approximately 20% of adolescents searching for health information online watched YouTube videos (Wartella et al., 2016). Therefore, to address some of the gaps in the literature and expand on the prior work in this area that has examined depression (Gaus et al., 2021), ADHD (Kang et al., 2017), and schizophrenia (Godwin et al., 2017) on YouTube, the goal of the current study is to content analyze user-generated videos that cover the top mental health concerns among adolescents:

depression, anxiety, ADHD, and eating disorders (Center for Disease Control; CDC; Choi et al., 2021). We ask the following research questions:

RQ1: Who is making mental health content on YouTube?

RQ2: How are mental health conditions being discussed on YouTube by content creators?

RQ3: How often is information discussed with credible sources provided?

RQ4: Do videos about mental health receive more engagement than videos that don't mention those topics?

Methods

Sample and procedure

A sample of 144 YouTube videos were used for analysis in this study. Videos were included in the sampling frame using the following selection criteria. First, a list of mental health conditions was sourced from the website for the National Alliance on Mental Illness (National Alliance on Mental Illness, n.d.). Of these conditions, four were selected for inclusion in the content analysis: depression, anxiety, Attention Deficit Hyperactivity Disorder (ADHD), and eating disorders. These were selected as they are the most common mental health conditions among adolescents (Centers for Disease Control and Prevention, 2023). Following this, each of the mental health conditions was entered into the YouTube search bar in quotation marks along with the word "vlog" (e.g., "depression" "vlog"). The word vlog was used as it is one of the most common video types produced by SMIs (Ferchaud et al., 2018) and a common format for mental health content on YouTube (Devendorf et al., 2020; Gaus et al., 2021). Additionally, adolescents are more likely to consume this type of content compared to professionally-produced, informative videos on mental health (Gaus et al., 2021). From these search results, videos that met the criteria of being produced by an SMI, rather than an organization or professional, were entered into the sampling frame. Next, the top two most recent videos over two minutes in length from each of the identified SMI channels were entered into the sampling frame to allow for a comparison of their general channel content. This process was repeated for each of the four mental health conditions, with the first 12 SMIs for each condition being selected. As mental health conditions are often comorbid (Al-Asadi et al., 2015), we made sure to exclude any duplicates in SMIs if they appeared in search results for more than one condition, resulting in a final sample of 144 videos.

Coding scheme

Each video was coded as a whole for the presence or absence of a set of 20 mental health codes. If the behavior was displayed, the coders were instructed to code “yes” which was entered into the coding sheet as “1”, and if the behavior was absent, the coders were instructed to code “no” which was entered into the coding sheet as “0”. A full description and coding instructions for each variable is presented in Appendix IA.

Video metrics.

Before coding for mental health content, a few objective measures of the videos were recorded. First, the number of views and likes at the time of the analysis in early 2023 were recorded to assess the overall popularity of the video. We also coded for whether comments were turned off (0) or were viewable (1), as previous YouTube content analyses have found that videos about mental health tend to receive high numbers of comments (Choi et al., 2021) and act as a space for peer-to-peer support (Gaus et al., 2021), as well as the number of comments. We also entered the run time of the videos in seconds, and how many months for which the video had been posted.

SMI characteristics.

To address RQ1 about who is creating mental health content on YouTube, we also coded a series of demographic characteristics of the SMIs. First, the number of subscribers at the time of the analysis in early 2023 was recorded to assess the overall popularity of the SMI, in line with the categorization reported by Dopson (2022). We also coded both gender and race of the SMI.

Mental health codes.

The codebook used for this study was created through an iterative process. We primarily relied on a combination of the codebooks used by Kang and colleagues (2017), that focused on ADHD representation on YouTube, and by Green and colleagues (2015), that examined conversations on YouTube among the LGBTQ community. These codes cover general experience with mental health conditions, including self-disclosure, comorbidity, and experience with bullying, as well as condition and treatment information, including information credibility and medication disclosure. We also added variables during the reliability coding process as we noticed recurring elements in videos that were not in the original codebook (i.e., suicidal ideation and valence of presented opinions). A full list of mental health codes and definitions is provided in Appendix IA.

Coding process and reliability

A team of three coders, including the first author, was assembled to conduct the content analysis. 48 videos (approximately 33% of the final sample) were coded by all three members of the team to establish reliability following training on the codebook. For each of the variables, we calculated intercoder reliability using Gwet’s AC2 statistic as the absence of the behavior was more prevalent than the presence across most variables, resulting in skewed distributions, and there was a high level of agreement among coders. The results indicated good reliability, with Gwet's AC2 ranging from 0.76 to 1.00 (see Table 1A with coefficients between 0.8 and 1.0 considered "very good" (Aubrey et al., 2020; Gwet, 2002). Only three codes, self-opinion valence, information on treatment, and information sources had reliability coefficients lower than 0.8 (0.78, 0.76, and 0.77 respectively). Following this, the remainder of the sample of 96 videos was randomly distributed across coders to code independently over the course of four weeks. Coders entered their codes electronically into one master Google Sheets file with separate pages and video lists for each coder.

Results

Preliminary analyses.

Before conducting our main analyses, we examined correlations among all study variables to identify any patterns in appearance of certain variables. These results are presented in Table 2A in the Appendix.

First, we looked at relationships between video metrics and SMI characteristics and the presence of mental health codes. Videos that were longer (r = -.18, p = .03) and received more views (r = -.20, p = .02), likes (r = -.21, p = .01), and comments (r = -.22, p = .01) were negatively associated with providing credible information sources. We also observed significant positive correlations between the number of comments and discussion of self-opinion (r = .20, p = .02), others' opinion (r = .20, p = .02), and the valence of others' opinions (r = .20, p = .02). Though we did not observe any significant correlations between the number of followers and any of our mental health codes, there were significant negative correlations between SMI type and mental health related content (r = -.25, p = .002), discussions of one's own experience (r = -.25, p = .01), and medication disclosures (r = -.26, p = .002), suggesting that lower-tier SMIs (i.e., Nano or Micro influencers) are more likely to consistently talk about mental health and their experiences on their channels. We did not observe any significant correlations between gender or race with any mental health codes. However, gender was significantly negatively related to subscriber count (r = -.80, p = .000), views (r = -.34, p = .000), likes (r = -.40, p = .000), and comments (r = -.50, p = .000), suggesting that male SMIs receive higher levels of engagement.

Next, we examined correlations between key mental health codes. Disclosure of bullying was significantly correlated with providing self-opinion (r = .17, p = .04), expressing empathy (r = .17, p = .04), comorbidity of conditions (r = .22, p = .01), providing factual information (r = .21, p = .01), and disclosing medication (r = .24, p = .004). Experience of comorbidity was significantly correlated with self-opinion (r = .31, p = .000), others' opinion (r = .18, p = .03), empathy (r = .21, p = .01), factual information (r = .32, p = .000), information on treatment (r = .23, p = .01), and medication disclosure (r = .37, p = .000). Interestingly, comorbidity of conditions was negatively associated with providing a credible information source (r = -.17, p = .04). As a last key variable, suicidal ideation was significantly correlated with self-opinion (r = .30, p = .000), others' opinion (r = .21, p = .01), empathy (r = .40, p = .000), exhort (r = .33, p = .000), factual information (r = .23, p = .000), information on treatment (r = .37, p = .000), and medication disclosure (r = .18, p = .03). Again, suicide was also negatively correlated with providing credible information sources (r = -.20, p = .02). These associations suggest that SMIs who disclose more severe mental health experiences may be more likely to provide more mental health opinions and information.

Main analyses.

The majority of our analyses required to answer our four research questions are descriptive. Means for main study variables across video type (mental health-related and non-mental health-related) are listed below in Table 1. Table 3A in Appendix IC lists the overall mean, range, and frequency for each variable.

Table 1
Descriptive Statistics for Video metrics and SMIs

Variable	*Total Sample (N = 144)*	*Mental Health Videos (n = 88)*	*Non-Mental Health Videos (n = 56)*
Video metrics			
Video views	421,545.59	574,344.15	181,433.57
Video likes	23,581.34	31,055.03	11,836.96
Video length (in seconds)	985.00	1,016.40	935.64
Months posted	11.72	15.97	5.05
Comments	1,328.72	1,869.27	479.27
SMI characteristics			
Channel subscribers	1,408,116.00	1,253,181.52	1,651,584.46
SMI type	3.27	2.97	3.75
Gender	1.97	1.97	1.98
Race	2.25	2.35	2.09

In response to RQ1 regarding who is making mental health content on YouTube, the results of our analyses revealed that creators are overwhelmingly female (97.9%, n = 47). However, it is interesting to note that gender was significantly negatively correlated with subscriber count despite the small number of males in our sample (n = 3), suggesting male SMIs may have more subscribers in general than female SMIs. Mental health content creators are also limited in racial diversity with the majority 60.4% of SMIs (*n* = 29) being white; 14.6% (*n* = 7) were Asian, 8.3% (*n* = 4) African American, 6.3% (*n* = 3) Hispanic, and the remaining 10.4% (*n* = 5) mixed, other, or unspecified. Interestingly, SMIs who create mental health content fall on two sides of a vast spectrum in influencer categorization. Over half (58.3%, *n* = 28) of the SMIs are considered 'mega' or 'celebrity' influencers, whereas 20.8% (*n* = 10) are considered 'nano' or below that threshold, with very little variation in between.

Further, 58.33% (*n* = 56) of the most recent videos produced by SMIs did not discuss or reference mental health in any way. In fact, of those SMIs who appeared in the search results for mental health vlogs, 47.9% (*n* = 18) did not mention mental health in their two most recent videos, 14.6% (*n* = 7) did mention mental health in one of the two, and 37.5% (*n* = 23) did in both of their videos. This suggests that mental health content may be the focus for some channels, but is infrequently mentioned by the majority.

Research Question 2 sought to understand how mental health conditions are being discussed online. To answer this, we narrowed our descriptive analysis to just the videos in the sample that discussed or referenced mental health in any way (61%, *n* = 88). Frequencies for each mental health code are presented below in Table 2. The majority of videos on mental health focused on the SMI (97.7%; *n* =86) rather than others or general experience (11.4%, *n* = 10). For an example of others' experience, one SMI made a video with her sister in which they both discussed their daily routines and experience with ADHD. In half of the videos, the SMI presented their opinion on mental health and living with a mental health condition, and those opinions were predominantly negative (77.3%, *n* = 34). Further, while only 14.8% (*n* = 13) of videos discussed others' opinions, those that did were all negative opinions. Suicidal ideation was discussed in 13 (14.8%) of the videos, and experience being bullied in 2.3% (*n* = 2). Approximately one-third (35.2%, *n* =31) of videos included a discussion of comorbidities, ranging from experiences of both anxiety and depression, or depression and bipolar disorder, to anxiety, post-traumatic stress disorder, depression, and obsessive compulsive disorder, and 31.8% (*n* = 28) included a disclosure of being medicated for condition(s). Over half of the videos (52.3%, *n* = 46) encouraged viewers to do something (i.e. to seek help or to look after their friends), while just under half (45.5%, *n* = 40) expressed empathy towards their viewers. Further, 5.7% (*n* = 5) asked for information or suggestions from their viewers, and 4.6% (*n* = 4) advertised a product or service related to mental health.

Table 2
Frequencies for Mental Health Codes

Variable	*Mental Health Videos*
Own general experience	86 (97.7%)
Others' general experience	10 (11.4%)
Experience of being bullied	2 (2.3%)
Others' experience of being bullied	0 (0%)
Self-opinion	44 (50.0%)
Self-opinion valence	44 (50.0%)
Negative	34 (77.3%)
Positive	10 (11.4%)
Others' opinion	13 (14.8%)

Others’ opinion valence	13 (14.8%)
Negative	13 (14.8%)
Positive	0 (0%)
Empathy	40 (45.5%)
Exhort	46 (52.3%)
Demographics on self	86 (97.7%)
Comorbidity	31 (35.2%)
Suicidal ideation	13 (14.8%)
Demographics on others	6 (6.8%)
Factual information for others	35 (39.8%)
Information on treatment	49 (55.7%)
Information sources	88 (100%)
No source	53 (60.2%)
Credible source	11 (12.5%)
Not applicable	24 (27.3%)
Disclosure of medication	28 (31.8%)
Solicit information	5 (5.7%)
Advertise	4 (4.6%)

Furthermore, in response to RQ3, of the videos that discussed mental health, 39.8% (*n* = 35) provided factual information for others (i.e., discussion of symptoms or study findings) and 55.7% (*n* = 49) provided information about treatment options. However, credible sources were only given in 17.2% (*n* = 11) of these videos, where 60.2% (*n* = 53) presented no source.

Finally, to answer RQ4 about engagement on mental health-related videos, we looked at the number of views, likes, and comments videos about mental health received compared to those without such reference. Overall, videos had an average of 421,546 views (ranging from 101 to 9,572,953). an average of 23, 581 likes (ranging from 4 to 484,000), and an average of 1,329 comments (ranging 0 to 31,000). Videos focused on mental health appear to have greater engagement on all metrics (574,344 views, 31,055 likes, and 1,869 comments) compared to videos that do not discuss mental health (181, 434 views, 11,837 likes, and 479 comments). We followed up by conducting a series of independent samples t-tests. We found that these differences are significant for views $t(104.65) = -1.96$, $p = .05$, with a mean difference of 392,910.58 (95% CI, -791,395.27 to 5,574.11) and number of comments $t(112.60) = - 2.16$, $p = .03$, with a mean difference of 1390.01 (95% CI, -2662.57, -117.44), but not for likes.

Discussion

From the results of this content analysis, we were able to answer the calls for further investigation into user-generated content on mental health topics (Gaus et al., 2021; Kang et al., 2017) and extend previous work to consider a wider range of mental health conditions. We found that the SMIs that appeared in the algorithm when searching for mental health content were predominantly female (97%) and white (60.4%). We also found that the majority of SMIs were at two sides of a spectrum; over half (58.3%, *n* = 28) are considered ‘mega’ or ‘celebrity’ influencers, and 20.8% (*n* = 10) are considered ‘nano’ or below that threshold. In an influencer marketing report, Dopson (2022) states that mega and celebrity influencers are rare and only account for 0.5% of all SMIs. In fact, the most common type of SMI overall are micro influencers who have between 5,000 and 20,000 followers. The fact that over half of the SMIs included in our sample are the most rare when considering all online content suggests that mental health content can help garner an increased subscriber base. In line with previous research (Choi et al., 2021; Gaus et al., 2021), we found that mental health content on YouTube received significantly higher engagement, specifically on metrics of views and comments. The fact that we did not observe a significant difference for likes may be that likes have a positive valence and are seen as a form of endorsement (Burrow & Rainone, 2017), and for serious and potentially triggering content viewers may not find it appropriate. Indeed, YouTube removed the dislike option from videos to try to foster a more positive environment on the site (Southern, 2022).

Our analysis also found evidence of the concerns over credibility in UGC on mental health content (Gaus et al., 2021; Naslund et al., 2014) as only 11 (17.2%) videos contained a credible source either in the video or its description box. Though sharing personal stories and experiences seem to be a preferred source for mental health information (Choi et al., 2021), and viewers are looking for opinions (Fergie et al., 2016), it is concerning that viewers are receiving such little professional information as opinions can inform beliefs, perceptions, and behaviors in harmful ways (Devendorf et al., 2020). Of the opinions expressed in videos, 82.5% were classified as negative and/or self-stigmatizing. For example, in one video by Johanis Sani, she states (about her mental illness) that “it’s my own fault”, and Samantha Randahl states “I’m a piece of s***, I’m lazy, I’m f***ing useless.” In contrast, in a video by Madison Van Dine on her channel madi’s nursing journey, she states that “it will get better.” While these are the SMIs opinions, they can negatively impact viewers and discourage them from seeking help, as well as further contribute to and perpetuate stigma surrounding mental health (Fergie et al., 2016). On the other hand, positive opinions and stories of recovery can help viewers feel uplifted and empowered to be able to get better themselves.

We also observed significant correlations between presenting opinions (both self and others') and disclosures of bullying, comorbidity, and suicidal ideation. This suggests that SMIs who self-disclose more detail and more severe experiences with mental health struggles are also providing more valenced content to their viewers that can have unintended consequences. Though only 13 videos (14.8%) contained suicidal ideation, there was a significant negative correlation between discussion of suicide and providing credible information sources ($r = -.20$, $p = .02$). A content analysis of self-harm content on YouTube (Khasawneh et al., 2020) also found a lack of resources and professional recommendations in videos mentioning suicide. As there is growing concern of suicide risk and suicide contagion in adolescents (Khasawneh et al., 2020), it is worth further exploration into how this content, particularly when it is discussed without professional support, impacts viewers, particularly as this content violates YouTube guidelines yet remains on the platform and can be watched by young impressionable audiences. Further, though only 4 (4.6%) videos contained an advertisement directly related to mental health, 3 of those 4 were a sponsorship from BetterHelp, a mobile application that is designed to match users with therapists. This application has received significant criticism and been in controversy for selling users sensitive information (Rizzi, 2023). This is concerning as vulnerable viewers may take the recommendation from the SMI and not receive the quality of support they need or deserve.

Limitations and future directions.

One limitation of our study was the sample size. Though we included 144 videos in our sampling frame, only 88 were related to mental health and may not have been a wide enough representation of the mental health content on YouTube. Indeed, the content analysis conducted by Devendorf and colleagues (2020) had a sample more than double the size (N = 327 videos). However, they also note that the typical sample size in other studies on YouTube is 120 videos, so our sample size is above the average. Further, we found similar findings to other studies with regard to engagement (Choi et al., 2021), the prevalence of sharing personal experience stories (Naslund et al., 2014), and the discussion of treatment options (Devendorf et al., 2020).

In the following studies, we answer the call for further research on the potential effects of mental health UGC as it becomes increasingly common and adolescents use social media more frequently as a source of information, yet we have limited knowledge on how this content actually impacts viewers (Choi et al. 2021; Fergie et al., 2016; Kang et al., 2017). We focus on how exposure to mental health content influences viewer's affective state after consuming such content, as well as presentation of anxiety and depression symptoms and perception of having mental health conditions.

Study 2

Introduction

Previous research and the results of the content analysis described in Study 1 show that there is an overwhelming amount of mental health information available through user-generated content on social media. Now that we have investigated what that content looks like, in the following studies we sought to understand the potential effects of this content on adolescent mental health symptoms and beliefs. Some researchers have posited that social media may be a more effective way to reach adolescents and help them with their mental health struggles compared to more traditional methods (O’Reilly et al., 2019; Odgers & Jensen, 2020). However, though adolescents turn to social media to share their experiences (self-disclose), seek social support, and seek mental health information (Naslund et al., 2020), they also admit that they do not often check the credibility of the information they receive (O’Reilly et al., 2019). In fact, though many studies in this area have focused on the benefits of mental health information on social media, they have also noted a concern over the veracity of information posted and called for further research (Fergie et al., 2016; Gaus et al., 2021), as misinformation is a challenge in social media in general and can be particularly harmful in this context (Choi et al., 2021). This potential for misinformation is concerning as viewers may engage in harmful behaviors they are told may help them (Khasawneh et al., 2020). For example, Ahern and colleagues (2015) described the trend in videos featuring self-harm behaviors, including cutting and setting oneself on fire to cope with feelings of depression and suicidal ideation. Further, in consideration of the rise in self-diagnoses and symptom-mimicking behaviors (Rutter et al., 2023), it may also be that these videos unintentionally make viewers think that they have a mental health condition and they may copy damaging behaviors they see online.

Though these risks of mental health information provided via UGC are concerning for all users, adolescents may be a particularly vulnerable population due to their ability, or lack thereof, to self-regulate. Self-regulation is still developing during adolescence and is not stable until mid-twenties, particularly for facets of social and emotional development (Steinberg, 2014; Steinberg et al., 2018). Though the majority of social media platforms have a minimum age requirement of 13 years old for users to make an account without parental consent, many children younger than 13 circumvent this requirement (George et al., 2020). A study conducted in 2017 found that nearly half (49%) of children aged 11 had a social media account (George et al., 2020) and as a result, adolescents are exposed to age inappropriate content for many years and are trying to manage social media and its integration into their lives at a crucial developmental period of increased change and risk for mental health struggles (Odgers & Jensen, 2020; Pitt et al., 2021). Further, social influence, like that from SMIs, is salient for adolescents at this age as they engage in social developmental processes of identity formation, gain independence from parents, and seek out role models (Erikson, 1968; Meeus et al., 2019; Siebers et al., 2021). For adolescents with poor self-regulation skills, this is particularly powerful as they experience difficulties resisting social influence (Burkley et al., 2011; Welsh et al., 2014). In fact, poor self-regulation has been linked to increased persuasion, advertising susceptibility, and acceptance of peer norms - all key effects of SMI exposure for children and adolescents (Burkley, 2008; Lapierre & Rozendaal, 2019; Robinson et al., 2016). Finally, adolescence is characterized as a period of high impulsivity and decreased self-control (De-Sola Gutiérrez et al., 2016; Mahapatra, 2019), in which adolescents are susceptible to engaging in risky and unhealthy behaviors (Steinberg, 2007) which are associated with poor self-regulation (King et al., 2018). For adolescents with poor self-regulation and difficulties resisting social influence, exposure to SMIs promoting risky behaviors (e.g., self-harming behaviors) and misinformation can be particularly harmful as they are more likely to accept the information and mimic behaviors. This potential risk is further exacerbated in the context of mental health information as adolescents with poor self-regulation are susceptible to mental health problems (Atherton et al., 2020). Indeed, harmful challenges that go viral on social media like the Blue Whale challenge, Tide Pod challenge, and the most recent Benadryl challenge, tend to be most prevalent and influential among adolescent users (Khasawneh et al., 2021). Therefore, if adolescents with poor self-regulation view harmful information about mental health online from their favorite SMIs, they may be more likely to accept the information as truth and develop damaging beliefs and behaviors as this information is not necessarily credible or in line with professional recommendations.

In addition, how adolescents consume content can impact mental health outcomes. Researchers investigating media use and mental health are concerned with the rise in problematic social media use in adolescent populations (PSMU: Arness & Ollis, 2022; Bailey & Young, 2015). Recent research estimates that between 7 and 11% of all adolescents engage in PSMU (van den Eijnden et al., 2016; van den Eijnden et al., 2018). PSMU refers to an addictive-like use of social media characterized by uncontrolled usage (Arness & Ollis, 2022) and has been linked to poor self-regulation skills, as both are characterized by a lack of self-control (Burnell et al., 2022). This is exacerbated for adolescents in a developmental period in which self-regulation is in flux (LaRose et al., 2003; Mahapatra, 2019; Meeus et al., 2019) and they experiment with increased autonomy from their parents (Pitt et al., 2021; Zimmer-Gembeck & Collins, 2008). As such, both self-regulation and PSMU influence how adolescents consume social media and what subsequent effects they experience.

Therefore, the goal of this study is to examine the relationships between adolescent mental health risk factors (i.e, self-regulation and PSMU), social media use, and mental health outcomes. Using data from an online nationally representative survey of 1,194 U.S. adolescents, we provide evidence that adolescents with poor self-regulation skills and those who engage in PSMU spend more time on social media, consume more mental health information, and also experience more negative mental health outcomes.

Literature review

Social media as a source of mental health information

Social media is increasingly being used as a source for mental health information (Fergie et al., 2016). For example, research shows that individuals with serious mental health conditions, including bipolar disorder and schizophrenia, post content to disclose their experiences, seek advice, and also form online support communities (Naslund et al., 2016). This prevalence of mental health content on social media can be beneficial in symptom management, receiving support, and also providing an opportunity for early intervention by health professionals (Fergie et al., 2016; Naslund et al., 2020). Individuals may turn to social media to share their experiences and seek support due to difficulties and distrust disclosing to doctors (Gaus et al., 2021; Gulliver et al., 2010), low mental health literacy (Coles et al., 2016), or the general stigma that still exists around mental illness (Choi et al., 2021; Mickles & Wearer, 2020; Rutter et al., 2023). A meta-analysis by Gulliver and colleagues (2010) found that stigma was the largest and most frequent barrier to seeking help. Adolescents in particular benefit from this use of social media to find mental health information as the use of the internet has become normative for them as they use it for social interaction, information-seeking, and schoolwork (Burnell & Odgers, 2023; Khasawneh et al., 2020). Additionally, adolescents demonstrate a preference for self-reliance as they begin to practice newfound autonomy from their parents and do not want to rely on professional help (Gulliver et al., 2010). Therefore, they are more used to receiving and searching for information in this way (Odgers & Jensen, 2020). As around 80% of adolescents with a mental health condition do not receive treatment and struggle to recognize mental health conditions (Coles et al., 2016), UGC about mental health can be a valuable tool in helping improve adolescent mental health literacy as they are exposed to experiential understanding of conditions and may be likely to also seek help if they see others doing so (Devendorf et al., 2020). As research shows that a large proportion of mental health content is created by adolescents and young adults (Fergie et al., 2016), they may already be starting to perceive lower stigma and see the benefits of self-disclosure.

However, this content warrants further investigation as there are also many potential risks of unregulated information from non-professional sources online (Naslund et al., 2014). Not only is there a risk of misinformation and unsourced material (Choi et al., 2021), opinions that are presented can also have detrimental impact on behavior and perpetuating stigma (Devendorf et al., 2020; Gaus et al., 2021). For example, if a user posts about negative experiences with a specific treatment, it may discourage viewers from trying that treatment or seeking help at all (Gaus et al., 2021). In fact, in their content analysis of YouTube videos about depression, Gaus and colleagues (2021) found a low rate of creators advocating for clinical treatments. Stories of personal experience may also contradict professional recommendations or structured treatment programs (Naslund et al., 2014), or may discourage viewers from thinking there is a way to manage symptoms and feel better. Further, the framing of discussions on mental health can influence viewer opinion and possibly contribute to further stigmatization of those with mental health conditions; for example, discussing depression as an outcome of biological factors versus environmental ones (Devendorf et al., 2020) or embarrassment of needing help from others (Gulliver et al., 2010). Exposure to personal experience stories also creates a risk of comparison whereby viewers may become anxious and confused about their symptoms or feel negatively if they perceive someone doing better than they are (Naslund et al., 2014).

A majority of mental health content is posted to YouTube and TikTok - which are also the two most popular sites among adolescents and are largely unregulated (Bahorsky, 2022;

Naslund et al., 2014). While studies note YouTube has the highest volume of mental health content (Godwin et al., 2017) and may be more used than traditional healthcare websites for finding information (Devendorf et al., 2020), TikTok has surged in popularity over the last three years and become known as a tool for self-diagnosis of mental health conditions (Bahorsky, 2022). While individuals may self-diagnose in order to feel a sense of validation in their feelings or connect with others to find support (Bahorsky, 2022), self-diagnosing can be problematic as it confuses discourse around mental health conditions.The medicalization of normal emotions (i.e., guilt, sadness, nervousness) and replacement with clinical words like depression and anxiety can minimize the impact when people actually are experiencing mental health struggles. It can also lead to increased stress through overestimating the severity of a problem and reduces the ability to recognize normal challenges that can be worked through and learned from. There is also a high risk of misdiagnosis as diagnosing a mental health condition requires years of schooling to understand that some behaviors are symptomatic of multiple conditions and it is the pattern of behaviors, rather an individual one, that leads to diagnosis (Bahorsky, 2022). Misdiagnosis is dangerous as it can lead to mismanagement of symptoms and lack of getting appropriate help. Further, this rise in self-diagnoses has led to a concerning over-prescription of medications (Bahorsky, 2022). Indeed, nearly one-third of the videos on mental health in our content analysis contained an overt disclosure of taking medication.

Research has also been concerned with the prevalence of self-harming displays on social media, particularly on video-based platforms such as YouTube as video content is more likely to attract attention and evoke an affective response (Devendorf et al., 2020; Rottenberg et al., 2007). The prevalence and accessibility of these videos may lead to self-harm being perceived as normative (Ahern et al., 2015) and to increased self-harm behavior through imitation and modeling (Khasawneh et al., 2020). Social learning theory (Bandura, 1971; 1977) suggests that individuals learn behavior from watching others, either deliberately or inadvertently, through repeated exposure (Strasser-Burke & Symonds, 2020). This is particularly concerning for adolescent populations as suicide is the second leading cause of death (Center for Disease Control, 2020) and this age group are most susceptible to modeling behavior due in part to their still-developing self-regulation (Insel & Gould, 2008; Khasawneh et al., 2020). Online communities, such as those in comment sections of YouTube or TikTok videos or Reddit channels (commonly referred to as subReddits), can also allow people to share methods of self-harm that otherwise may not have been considered (Peterson et al., 2008). In one study of inpatient adolescents, the majority of participants saw depictions of self-harm (in this case referred to as nonsuicidal self-injury or NSSI) on social media before their first self-harm behavior (Khasawneh et al., 2020; Zhu et al., 2016). This suggests that viewers of mental health information on social media can be heavily influenced by the content. In fact, though controversial, Facebook's study on emotional contagion found that users' affective states could be influenced by the content to which they were exposed (Kramer et al., 2014). Specifically, exposure to emotional posts on Facebook led users to experience the same affective state even without direct interaction with the posts. Therefore, it also may be the case that viewers of mental health information online can be influenced in a similar way through repeated exposure, modeling, and emotional contagion to believe they have mental health symptoms or conditions themselves. As such, we expect that:

H1: Adolescents who follow mental health topics on social media will report increased (a) anxiety, (b) depression, and (c) self-reported mental health conditions compared to those who follow less or no mental health topics.

Anxiety and depression were chosen as the mental health outcomes as the two most common disorders among adolescents (Centers for Disease Control and Prevention, 2023). Studies suggest an estimated prevalence of depression in 11% of adolescents (American Psychiatric Association, 2013; Gaus et al., 2021) and anxiety in 31.9% (Kessler et al., 2005).

Self-regulation

Though there are inconsistent definitions and operationalizations across disciplines and studies (Meeus et al., 2019; Rothbart et al., 2004), self-regulation generally refers to a set of top-down cognitive processes whereby individuals modulate their cognitions, behavior, emotions, and attention (Karoly, 1993; Siebers et al., 2021). Individuals tend to self-regulate, actively or passively, in service of their goals (Meeus et al., 2019; Posner & Rothbart, 2000). Self-regulation is linked to long term functioning and outcomes such as academic performance, wealth, longevity, health, and relationship functioning (Atherton et al., 2020). Numerous constructs have been studied and discussed interchangeably as indicators of self-regulation, including self-control, impulsivity, decision making, self-monitoring, and executive functions (EF; King et al., 2013; King et al., 2018; Wisniewski et al., 2017). Executive functioning is a closely-related and overlapping process with self-regulation as EF development is necessary for successful self-regulation (Anderson, 2002; Roebers, 2017). However, they are distinguishable by the different parts of the brain that are involved and by how they have been studied (Lapierre & Rozendaal, 2019). Traditionally, EF researchers have focused on cognition and intentional action, whereas self-regulation researchers have typically focused on the control and functional use of emotions (Blair & Diamond, 2008; Diamond, 2013).

EF generally refers to a set of neurocognitive processes that allow an individual to concentrate and pay attention in order to engage in goal-directed and self-regulatory behavior

(Diamond, 2013; Lillard et al., 2015; Miyake et al., 2000). These processes broadly include inhibitory control, cognitive flexibility, and working memory (Diamond, 2013; Miyake et al., 2000). Inhibitory control refers to the ability to resist temptations, distractions, and habits, and to resist acting impulsively in response to environmental stimuli (Blair & Diamond, 2008; Diamond, 2013). Deficits in EF, particularly in the domain of inhibitory control, lead to deficient self-regulation (Barkley, 2010). In fact, some researchers argue that inhibitory control, along with executive attention (together referred to as effortful control; Rothbart et al., 2000), are precursors to self-regulation ability, especially for emotion regulation (Blair & Diamond, 2008; Diamond, 2013). Emotion regulation in particular has been linked to increased problematic media use (Elhai et al., 2018) and poor mental health (Rasmussen et al., 2020).

Deficient self-regulation, or poor self-regulation, refers to the inability to direct or control behavior (LaRose et al., 2003; Lee et al., 2017). Though self-regulation has a relatively high plasticity and is constantly changing (McClelland et al., 2015), deficient self-regulation generally refers to stable, long-term difficulties in regulatory ability. However, self-regulatory ability can also be depleted temporarily due to the presence of cognitively-demanding tasks or engaging stimuli (Baumeister et al., 2000; Welsh et al., 2014). For example, watching content that is attention-grabbing and highly involving, like online video content, may take up cognitive resources and deplete regulatory resources to turn away from the content or process its messages (Boerman & Van Reijmersdal, 2020; Buijzen et al., 2010). Deficient self-regulation can be a result of biological and neurophysiological factors, such as motivation and attention systems in the brain (Rothbart et al., 2000) and various genotypes (Blair & Diamond, 2008), as well as environmental factors, such as social environments (King et al., 2013; McClelland et al., 2015). Indicators of poor or deficient self-regulation are the inability to inhibit impulses (i.e. poor inhibitory control; Barkley, 2010), difficulty modulating emotions (Lengua, 2002), distractibility (Siebers et al., 2021), externalizing behaviors (Eisenberg et al., 2003; King et al., 2013), and insecure attachment (Blalock et al., 2015). As such, low self-regulation is also associated with poor mental health (Atherton et al., 2020). Therefore, we expect that:

H2: Self-regulation will be negatively related to (a) social media frequency, (b) the number of mental health topics followed, (c) affective response, (d) anxiety, (e) depression, and (f) self-reported mental health conditions.

Problematic social media use

Problematic social media use, also often referred to as social media addiction or digital technology dependence (Burnell & Odgers, 2022), refers to the use of social media in an uncontrolled or excessive way that is characterized by many symptoms of addiction, such as preoccupation with social media use, developing tolerance, and disruption to functioning and wellbeing (Arness & Ollis, 2022; Lopes et al., 2022). While high rates of use may be a symptom of problematic social media use (PSMU), high frequency of social media use itself is not problematic (Burnell & Odgers, 2023). Social media use becomes problematic when it interferes with one's basic functioning (i.e., sleep, eating, and mood) as well as social relationships (i.e., family and friends) and academic performance (Dekkers & van Hoorn, 2022; Lopes et al., 2022).

PSMU is a growing concern for clinicians and researchers, with recent studies estimating a prevalence rate of up to 11% among adolescents across the globe (Fernandes et al., 2020; van den Eijnden et al., 2016; van den Eijnden et al., 2018), with a further 33.5% at risk of developing PSMU, the majority being female (Arness & Ollis, 2022; Paakkari et al., 2021). This is concerning as PSMU has been associated with a host of negative outcomes, including poor mental health (Fernandes et al., 2020; Mamun et al., 2020), poor academic performance (van den

Eijnden et al., 2018), and poor sleep quality (Arness & Ollis, 2022; Paakkari et al., 2021). In fact, some researchers have considered mental health conditions as a comorbidity with addiction, including PSMU (Bailey & Young, 2015; Mamun et al., 2020). For adolescents in particular, PSMU is also linked with a greater likelihood of self-harming (Hynes et al., 2022), so this risk may be further amplified in the context of mental health content and challenges online.

Furthermore, several studies have documented a link between self-regulation difficulties and PSMU, with low self-regulatory ability (Arness & Ollis, 2022), ADHD symptomatology (Dekkers & van Hoorn, 2022), and low effortful control (Atherton et al. 2020) associated with increased risk for and severity of PSMU. Indeed, individuals who experience addiction and are susceptible to engaging in addictive-like behaviors often experience disrupted cognitive development for skills like inhibitory control (Vishwakarma, 2022). Self-regulation difficulties are directly linked to the development and experience of PSMU and how an individual subsequently uses media (Arness & Ollis, 2022; Reinecke et al., 2022). These relationships are only exacerbated for adolescents as they are in a developmental stage where social media use can be particularly rewarding as addiction behaviors are linked to problems with reward centers in the brain (Burnell et al., 2022; Vishwakarma, 2022). Therefore, while many studies consider PSMU an outcome of media use, it can also be considered a developmental susceptibility factor predicting media use as it is primarily defined by *how* an individual uses media which can subsequently relate to media use outcomes. As such, we expect that:

H3: Problematic social media use (PSMU) will be positively related to (a) social media frequency, (b) the number of mental health topics followed, (c) affective response, (d) anxiety, (e) depression, and (f) self-reported mental health conditions.

Differential Susceptibility to Media Effects Model

The Differential Susceptibility to Media Effects Model (DSMM; Valkenburg & Peter, 2013) offers a model to integrate all of these separate bodies of literature. The DSMM framework allows for simultaneous investigation of the relationships between individual-based characteristics (susceptibility factors), media use, response states (i.e., affective response), and media effects. It also encourages the investigation of media use and effects at an individual level, proposing that individual-based characteristics predict media use and moderate the strength of responses to media content and subsequent effects (Nikkelen, 2016; Valkenburg & Peter, 2013). Susceptibility factors include social (social-context factors at micro-, meso-, and macro-levels; Valkenburg & Peter, 2013), dispositional (person-based characteristics including personality, moods, temperament, demographics, values, and beliefs; Piotrowski & Valkenburg, 2015), and developmental (social, emotional, and cognitive development processes; Valkenburg & Peter, 2013) characteristics of an individual. Self-regulation and PSMU act as both a dispositional and a developmental susceptibility factor for adolescents that both predict media use and moderate media effects via response states. More specifically, self-regulation and PSMU predict SM frequency and the number of mental health topics followed, which influence how adolescents affectively respond to SMI content. Responses to SMI content, which are most likely affective for these adolescents (Pham & Avnet, 2004), happen during the exposure, and the influence effects (i.e., anxiety, depression, and self-reported mental health) last beyond the viewing situation (Valkenburg & Peter, 2013). The theoretical model illustrating these relationships is presented in Appendix IIA.

The model further posits that media effects are transactional; that is, media effects outcomes can subsequently affect all other stages of the model (i.e. individual susceptibility characteristics, media use, and response state). In this way, mental health conditions can lead to differences in self-regulation and problematic social media use, how an adolescent consumes media, and how they respond to media. Though this reverse relationship may also indeed be likely, in this set of studies, we are specifically interested in how adolescents may come to self-diagnose mental health conditions and potential discrepancies with reported symptomatology. Therefore, using the DSMM framework, we expect that:

H4: (a) Social media (SM) frequency and (b) the number of mental health topics followed will mediate the relationship between self-regulation and mental health outcomes.

H5: (a) Social media (SM) frequency and (b) the number of mental health topics followed will mediate the relationship between PSMU and mental health outcomes.

H6: Affective response will mediate the relationship between self-regulation and (a) anxiety, (b) depression, and (c) self-reported mental health conditions.

H7: Affective response will mediate the relationship between PSMU and (a) anxiety, (b) depression, and (c) self-reported mental health conditions.

Methods

Sample and procedure

A national sample of U.S. adolescents ages 14 to 16 (N = 1256) were recruited through a Qualtrics panel to take part in an online survey between May, 2021 and June, 2021. A majority of the participants were female (n = 813; 65%) with 28% (n = 349) identifying as male, and 8% (n = 78) identifying as other or not disclosing. The sample was racially diverse; 47.9% (n = 602) of respondents described themselves as White, 42% (n = 530) Hispanic, Latino/a, or Spanish origin, 23.6% (n = 296) Black or African American, 11.4% (n = 143) Asian or Asian American, 4.7% (n = 59) American Indian or Alaskan Native, 12.1% as other (n = 152), and 6.2% self-described (n = 78).

Measures

Self-regulation.

To measure self-regulation, we used the Adolescent Self-Regulatory Inventory (Moilanen, 2007) that is designed to assess self-regulation skills specifically in adolescents. The scale consists of 36-items, from which eight were selected to maintain consistency with other scale lengths in the survey and minimize the risk for participant fatigue. Example items include "If there are other things going on around me, I find it hard to keep my attention focused on whatever I'm doing" and "Little problems distract me from my long-term plans." Each item was responded to on a 3-point scale ranging *Not at all true for me* to *Really true for me* (M = 1.84, SD = 0.36), with higher scores reflecting better self-regulation.

Social media use.

Problematic social media use.

To assess problematic social media use, we used five items from the Problematic Media Use Measure (Domoff et al., 2019). Each item is rated on a five-point scale ranging from *Never* to *Always.* Anchored by the phrase "In the past 30 days, how often did each of these happen?", sample items include "Using social media made me feel better about myself" and "Social media interfered with my school work." Items were coded such that higher scores reflected more problematic social media use (M = 2.42, SD = 0.91).

Social media (SM) frequency.

To assess social media frequency, participants were shown a list of 11 screen media activities and asked "On an average school day, how much time do you spend...?" for each of the options with eight response options ranging from *None* to *More than 8 hours*. The responses for social media (e.g., Instagram, Snapchat, Twitter, Marco Polo) were used as an overall metric of social media frequency (M = 4.11, SD = 1.67).

Mental health

Anxiety.

We used the Anxiety PROMIS Short Form (PROMIS-SF; APA, 2013) to measure participant's anxiety symptoms. This measure consists of eight items, each answered on a five-point scale ranging from *Never* to *Always* (M = 3.02, SD = 1.00), with higher scores representing greater anxiety symptoms. Anchored by the phrase "Think back over the last 7 days, please indicate how often you have been bothered by the following problems:", sample items include "I felt uneasy" and "I had sudden feelings of panic."

Depression.

We used the Patient Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001) to measure depression symptoms. The measure consists of nine items with each question answered on a four-point scale ranging from *Not at all* to *Nearly every day*, but the final item regarding suicidal ideation was dropped from the survey in consideration of participant safety. Therefore, our final measure consisted of eight items (M = 2.41, SD = 0.81), with higher scores representing greater depression. Anchored by the phrase "Over the last 2 weeks, how often have you been bothered by any of the following problems?", sample items include "Little interest or pleasure in doing things" and "Feeling tired or having little energy".

Self-reported mental health conditions.

Finally, participants were asked to indicate whether or not they experienced any health or mental health problems over the last 30 days, to which they selected all that applied from a list of seven conditions (for a full list, please see Appendix IIB). These were then binary coded for whether they were selected (1) or not selected (0). Finally, a total sum of health conditions was calculated by summing the responses to each of the seven conditions and/or symptoms (*M* = 2.26, *SD* = 1.88).

Influence

Topics followed.

As a metric of following SMIs, participants were asked “Do you follow or connect to others on social media around any of the following health topics?” to which they were shown a list of ten conditions (see Appendix IIB). Five of these were selected as relating to mental health conditions or symptoms as stated by the National Alliance on Mental Illness (NAMI, n.d.). These were then binary coded for whether they were selected (1) or not selected (0) and summed to reflect a total of mental health topics followed (M = 1.35, SD = 1.32).

Affective response.

To assess participants’ affective response to social media content, they were asked: “When I’m feeling depressed, stressed, or anxious, using social media usually…” with response options *makes me feel worse, makes me feel about the same*, and *makes me feel better*. Higher scores reflected participants feeling better after using social media (*M* = 2.40, *SD* = 2.95).

Results

Preliminary analyses.

Before testing our hypotheses, we first cleaned the data as it was part of a larger data collection effort. As such, participants who did not respond to the questions relating to the key variables in this study were excluded (*n* = 62), resulting in a final analytical sample of 1,194 participants. We also recoded gender and race for a more even split in the categories. As such, gender was coded into three categories: male (*n* = 321, 26.8%), female (*n* = 785, 65.7%), and non-binary or other (*n* = 88, 7.4%). Race was binary coded into white (*n* = 571, 47.7%) and non-white/racial or ethnic minority (*n* = 623, 52.3%).

We next examined correlations between key variables in the study. As expected, self-regulation was negatively correlated with all of the mediating (SM frequency, topics followed, and affective response) and dependent variables (anxiety, depression, and mental health self-report). PSMU was positively correlated with each mediating and dependent variable. Further, participant gender was negatively correlated with self-regulation, and positively correlated with all other variables of interest. Participant race was negatively correlated with self-regulation and SM frequency, and positively related to mental health topics followed, anxiety, and mental health self-report. As such, we controlled for both gender and race in the subsequent analyses. See Table 4A in Appendix IIC for bivariate correlations and descriptive statistics.

Main analyses.

To test our hypotheses, we used Hayes PROCESS model 80 (Hayes, 2017), which allows for one independent variable, two dual process mediators (SM frequency and topics followed), a third mediator (affective response) and one dependent outcome variable. We ran one model for each of our two independent variables (self-regulation and problematic social media use) for each of our three dependent variables (anxiety, depression, and self-reported mental health), resulting in six models. For each model, we controlled for participant gender and race, as both have been demonstrated to impact social media use (Tolbert & Drogos, 2019) and were correlated with our independent variables.

Self-regulation as a predictor.

First, we tested each dependent variable with self-regulation as the independent variable. For each of the three models, self-regulation was significantly negatively related to SM frequency (β = -.11, p = .0002) and topics followed (β = -.16, p = .0000), supporting H1a and H1b. This means that participants with poorer self-regulation were more likely to spend increased amounts of time on social media and to follow social media accounts about mental health topics. There was no significant relationship between self-regulation and affective response, so H1c was not supported; however, there was a significant positive relationship between the number of topics followed and affective response (β = .90, p = .0000) in each of the models, suggesting that the more mental health topics followed on social media, the more likely participants are to report feeling better after using social media.

Anxiety.

Our first model predicting anxiety symptoms was significant (R = .56, R^2 = .32, F(6, 1187) = 91.58, p = .0000). Results indicated a significant direct negative relationship between self-regulation and anxiety (β = -.33, p = .0000) such that participants with poorer self-regulation reported higher levels of anxiety, supporting H1d. There was a significant mediating effect of the number of topics followed (β = .29, p = .0000) between self-regulation and anxiety, meaning that participants with poorer self-regulation were more likely to report following accounts surrounding mental health topics and this higher rate of following led to greater anxiety symptoms, supporting H3b. However, there was no significant mediating effect of frequency (β = .02, p = .32). There was also no support for the dual mediation process proposed in H7a as there was no significant relationship between self-regulation and affective response or between affective response and anxiety symptoms.

Depression.

The model predicting depression symptoms as the dependent variable was significant (R = .56, R^2 = .31, F(6, 1185) = 88.10, p = .0000). Results indicated a significant direct negative effect of self-regulation on depression symptoms (β = -.35, p = .0000), meaning participants with poorer self-regulation reported greater depression, supporting H1d. There was also a significant mediating effect of both SM frequency (β = .07, p = .004) and topics followed (β = .30, p = .0000) on depression symptoms, such that the more participants followed mental health topics, the more depression they reported, supporting H3a and H3b. There was no support for H7a as there was no significant relationship between self-regulation and affective response or between affective response and depression symptoms.

Self-reported mental health.

The overall model predicting participant's self-reported mental health conditions was significant (R = .55, R^2 = .30, F(6, 1188) = 84.58, p = .0000). This model also revealed a significant negative direct effect of self-regulation (β = -.24, p = .0000), meaning that participants with poorer self-regulation skills reported a greater number of mental health conditions and/or symptoms, supporting H1d. There was also a significant mediating effect of both SM frequency (β = .09, p = .001) and topics followed (β = .18, p = .001) on self-reported mental health, such that participants with poorer self-regulation were more likely to spend more time on social media and to follow more accounts about mental health, and subsequently report a greater number of mental health conditions. So H3a and H3b were supported.

Interestingly, there was also a significant positive effect of affective response on self-reported mental health conditions (β = .13, p = .02), such that participants who reported feeling better after using social media self-reported a greater number of mental health conditions and/or symptoms. This means that H7a was supported between self-regulation and mental health was supported for the topics followed and affective response pathway. Specifically, participants with poor self-regulation skills were more likely to follow more mental health topics, to report feeling better, and to self-report more mental health conditions.

Control variables.

We did observe some significant relationships between our controls and mediating and dependent variables. For gender, there were significant effects on anxiety ($\beta = .18$, $p = .0000$), depression ($\beta = .16$, $p = .0000$), and self-reported mental health ($\beta = .16$, $p = .0000$) such that participants who identified as other than male reported worse mental health outcomes. Additionally, gender was significantly related to both SM frequency ($\beta = .08$, $p = .005$) and topics followed ($\beta = .23$, $p = .0000$), suggesting participants identifying as other than male spend more time on social media and follow more mental health topics on SM.

For race, there was a significant effect on self-reported mental health ($\beta = .10$, $p = .001$) meaning that participants who identified as white reported a greater number of mental health conditions and/or symptoms. Race was also significantly related to both SM frequency ($\beta = -.09$, $p = .001$) and topics followed ($\beta = .06$, $p = .05$). This means that participants identifying as a minority spend more time online, but white participants followed more mental health topics on SM. Results also revealed a significant effect of race on SIEC ($\beta = .06$, $p = .02$) and ISR ($\beta = .06$, $p = .05$), meaning that white participants reported higher levels of social media integration.

Problematic social media use as a predictor.

Next, we tested each of our dependent variables with PSMU as the independent variable. For each of the models, PSMU was significantly positively related to SM frequency ($\beta = .28$, $p = .0000$) and topics followed ($\beta = .24$, $p = .0000$), supporting H2a and H2b. This means that participants who reported more PSMU were more likely to spend greater amounts of time on social media and to follow more mental health topics. There was no significant relationship between self-regulation and affective response, so H2c was not supported; however, there was also a significant positive relationship between the number of topics followed and affective response ($\beta = .90$, $p = .0000$) in each of the models, suggesting that the more mental health topics followed on social media, the more likely they are to report feeling better after using social media.

Anxiety.

The model predicting anxiety symptoms as the dependent variable was significant ($R = .52$, $R^2 = .27$, $F(6, 1187) = 71.88$, $p = .0000$). Results indicated a significant direct positive effect of PSMU on anxiety symptoms ($\beta = .26$, $p = .0000$), supporting H2c. There was also a significant mediating effect of the number of topics followed on anxiety ($\beta = .27$, $p = .0000$), supporting H4b; however, there were no other significant mediating effects and H4a and H8a were rejected. This means that participants who use social media in more problematic ways are more likely to follow accounts about mental health, and subsequently report greater levels of anxiety.

Depression.

The model predicting depression symptoms as the dependent variable was also significant ($R = .50$, $R^2 = .25$, $F(6, 1185) = 64.52$, $p = .0000$). Results indicated a significant direct positive effect of PSMU on depression symptoms ($\beta = .23$, $p = .0000$), supporting H2c. There was a significant mediating effect of number of topics followed on depression ($\beta = .29$, $p = .0000$), supporting H4b. This means that participants who use social media in more problematic ways are more likely to follow accounts about mental health, and subsequently report greater levels of depression. However, there was no significant effect of frequency (H4a) nor was there support for a dual mediation hypothesis (H8a) as there was no significant relationship between PSMU and affective response or between affective response and depression.

Self-reported mental health.

The overall model predicting participant's self-reported mental health conditions was significant (R = .51, R^2 = .26, F(6, 1188) = 70.32, p = .0000). This model also revealed a significant direct positive effect of PSMU on self-reported mental health (β = .12, p = .0000), supporting H2c, meaning that participants who used social media in more problematic ways reported a greater number of mental health conditions and/or symptoms. There was also a significant mediating effect of both SM frequency (β = .08, p = .003) and topics followed (β = .19, p = .001) on self-reported mental health, such that participants with higher PSMU were more likely to spend more time on social media and to follow more accounts about mental health, and subsequently report a greater number of mental health conditions. H4a and H4b were supported.

There was also a significant positive effect of affective response on self-reported mental health conditions (β = .13, p = .02), such that participants who reported feeling better after using social media self-reported a greater number of mental health conditions and/or symptoms. This means our dual-mediation hypothesis (H8a) between PSMU and self-reported mental health was supported for the topics followed and affective response pathway.

Control variables.

Similarly to the models with self-regulation as the predictor, we did observe some significant relationships between our controls and mediating and dependent variables. For gender, there were significant effects on anxiety (β = .21, p = .0000), depression (β = .19, p = .0000), and self-reported mental health (β = .21, p = .0000) such that participants who identified as other than male reported worse mental health outcomes. Additionally, gender was significantly related to both SM frequency (β = .06, p = .03) and topics followed (β = .22, p = .0000), suggesting participants identifying as other than male spend more time on social media and follow more mental health topics on SM.

Interestingly, we observed that race has a significant effect on depression symptoms (β = .05, p = .05), and self-reported mental (β = .12, p = .0000), meaning that participants who identified as white reported a greater number of mental health conditions and/or symptoms, but not on anxiety symptoms. Race was also significantly related to both SM frequency (β = -.08, p = .003) and topics followed (β = .07, p = .02) for both adolescents with poor self-regulation and those who use social media more problematically. This means that participants identifying as a minority spend more time online, but white participants followed more mental health topics on SM.

Discussion

Overall, the results of our analyses suggest that self-regulation and PSMU have a significant relationship with adolescent social media use and mental health outcomes. Adolescents with poor self-regulation skills and those who use social media more problematically are at risk for spending more time on social media, for following more mental health topics online, and for poorer mental health. That is, spending increased time on social media and following more mental health content explains some portion of why those with poor self-regulation and those with high rates of PSMU experience more mental health problems, in line with the expectations of Odgers and Jensen (2020) that adolescents with existing mental health vulnerabilities, such as self-regulation difficulties and high PSMU, are more susceptible to experiencing negative outcomes of social media use. These findings also support prior research that self-regulation is an important boundary condition in the relationship between social media use and mental health (Valkenburg et al., 2022). Specifically, for adolescents with poor self-regulation, spending increased time on social media was associated with higher self-report of mental health conditions and depression symptomatology, but not anxiety. In the case of PSMU, adolescents who used social media in more problematic ways and who spent more time online consuming mental health content were more likely to report having mental health conditions, where no relationship was observed for actual measurement of symptoms. This finding suggests that adolescents who engage in PSMU may be particularly vulnerable to the information that they consume online from a social learning perspective, as they believe they have conditions of which they do not actually display symptoms.

Further, this provides support for the research call to examine the content that is consumed online, and not just blanket measures of frequency (Burnell & Odgers, 2022; Odgers & Jensen, 2020), as we observed differential mediating relationships for SM frequency and topics followed. The number of mental health topics followed consistently mediated the relationship between our individual susceptibility variables (i.e., self-regulation and PSMU) and mental health outcomes, whereas we observed less consistent relationships for frequency. Interestingly, frequency was more consistently related to self-reported mental health conditions, compared to measurements of actual symptomatology. This suggests that frequency is important to consider in the relationship between social media use and mental health as it may be influencing perceptions of having a mental health condition where no clinical diagnosis may be made. Therefore, the amount of time online in conjunction with the type of content followed can have an impact on adolescent mental health in that more frequent, repeated exposure to mental health content can make adolescents believe they have a mental health condition they may actually not.

Furthermore, adolescents who experience positive affect when using social media self-reported more mental health problems, where no such effects were observed for clinical measurements of symptoms. This further suggests that SMIs and social media have a powerful impact on what adolescents believe; adolescents seem to self-diagnose more mental health conditions than they actually experience when they follow more mental health topics online and feel positively when using social media. This is in contrast to the findings by Rutter and colleagues (2023) who found no difference in symptoms between participants who were clinically diagnosed with a mental health condition and those who thought they should be diagnosed. However, that study did not assess social media use directly and did not consider adolescent populations, where these effects are likely different. As SMIs intentionally try to induce relationships and liking with their audiences, it is likely adolescents think they feel more positively when viewing them, and as they want to be like them, they may self-diagnose to be similar to their favorite SMIs. In fact, adolescents are inclined to self-diagnose as a way to connect to others and feel recognized and validated (Bahorsky, 2022). This also provides explanation as to why increased amounts of time online was associated with self-report of conditions and not symptomatology as consistently.

We also observed some interesting differences with our control variables of gender and race. Participants who identified other than male were both more likely to follow mental health content online, to exhibit increased anxiety and depression symptoms, and to self-report more mental health conditions. Additionally, white participants were more likely to follow mental health content online and to self-report more mental health conditions. However, for adolescents with poor self-regulation, those who identified as a minority presented more depression symptoms. Therefore, in the context of adolescents who struggle with self-regulation, white adolescents may be more likely to report having a mental health condition, though no relationship is observed with actual symptomatology and it is minority participants who show a greater level of depression, yet they do not engage with mental health content or report having any conditions. Indeed, our content analysis shows that the majority of mental health content uploaded to YouTube and TikTok is created by white females (56.3% of our content analysis sample), and the majority of SMIs tend to be of the same demographic (Bishop, 2019; Thorpe, 2023) and as a result, that demographic may be the more likely viewers. This further exacerbates the concern over self-diagnoses among this particular group, as female adolescents are more at risk to the negative effects of social media use on mental health (Odgers & Jensen, 2020; Twenge et al., 2018).

Limitations and future directions

This study launched in Spring, 2021 while there were lockdown restrictions as a result of the COVID-19 pandemic which may have biased our findings for several reasons. First, despite differing school contexts, adolescents had been spending more time at home than ever before and relied on social media and other forms of media to not only keep them entertained, but to maintain social connections that are vital for healthy adolescent development and wellbeing. Therefore, the social media rates and use patterns we observed may have occurred due to the context of when data was collected. Second, mental health was a widely-discussed concern during the lockdowns as adolescents were largely isolated and had copious amounts of unstructured free time (Pitt et al., 2021). Indeed, at the onset of lockdown restrictions, researchers reported an increase in anxiety, obsessive-compulsive, thought, and post-traumatic stress problems among children and adolescents aged 1.5- to 18-years-old (Limone & Toto, 2021). As a result, the high rates of anxiety and depression symptoms we observed may also have been contextual and due to increased salience. Third, our findings on the high use of social media for following mental health topics and subsequent observed relationships may also have been a result of the context, as Fergie and colleagues (2016) note that health information-seeking is time-sensitive to help with immediate needs.

However, despite the inflated rates we may have observed, the relationships were robust and are likely the same outside of that specific context as rates of PSMU (Schivinski et al., 2020), frequency of social media use (Rideout et al., 2022), and the use of social media for mental health information (Fergie et al., 2016) have been of concern prior to the COVID-19 pandemic as they have increased exponentially over the recent years (Odgers & Jensen, 2020). Though, to properly investigate any potential limitations, we planned a second data collection for when lockdown restrictions were uniformly lifted in Spring, 2022.

Study 3

Introduction

Given that Study 2 data collection occurred during national lockdowns as a result of the COVID-19 pandemic, we were interested in replicating the study once restrictions were lifted to see if the results would be consistent. Research into adolescent media use during the COVID-19 pandemic found that, unsurprisingly, media use increased across the board (Nilsson et al., 2022), including video games (Burke et al., 2021), use of streaming services (Fernandes et al., 2020), and social media use (Marciano et al., 2022). In fact, research estimates that media use increased approximately 15 percent from pre-pandemic rates, which were already high (Odgers & Jensen, 2020; Rideout et al., 2022), and that smartphone use accounted for nearly two-thirds of this use (Limone & Toto, 2021). Along with this increased frequency, rates of problematic use and addiction also increased (Fernandes et al., 2020; Marengo et al., 2022). As adolescents missed the social connection opportunities afforded by in-person schooling, they relied on online methods, including social media, to maintain contact with friends (Marciano et al., 2022) and manage feelings of loneliness and anxiety (Cauberghe et al., 2021). This increased use of and reliance on social media as a way to regulate emotions are symptoms of PSMU and are concerning as PSMU has been shown to relate to negative effects on overall wellbeing and mental health (Marengo et al., 2022; Nilsson et al., 2022) even outside of the context of the disruptive lockdowns.

Further, numerous studies have begun to be published examining the relationship between increased social media use during the lockdown restrictions and subsequent mental health outcomes. This research has primarily focused on adolescents as they were the group most impacted by restrictions (Bahorsky, 2022; Pitt et al., 2021). Though there is large consensus that increased social media use as a result of the amount of unstructured and independent time during lockdowns led to increased mental health symptoms at the wider level (Limone & Toto, 2021; Pitt et al., 2021), more nuanced studies find that the motivations for social media use played a significant role in the effects that adolescents experienced. For example, Stockdale and Coyne (2020) found that social media use for information-seeking is not associated with negative effects on mental health; however, we found that following mental health topics on social media *was* linked to increased anxiety and depression symptoms, as well as self-report of mental health conditions. Therefore, specific types of information-seeking, such as mental health, may lead to differential outcomes, particularly in this context as health information-seeking is time-sensitive compared to general information-seeking (Fergie et al., 2016).

Research also suggests that the relationship between social media use and mental health is moderated through the use of social media for social connection (Burke et al., 2021). For example, the use of social media to maintain social connections was not associated with poor mental health outcomes, but the use to find new connections has been linked to higher levels of depression and anxiety (Arness & Ollis, 2022; Rae & Lonborg, 2015). Echoing the work of Rae & Longborg conducted outside of the context of COVID-19, Burke and colleagues (2021) found that using social media to maintain social connection led to improved wellbeing. In fact, some researchers argue that the use of technology can be a protective factor against disrupted mental health when used in meaningful ways, like for social connection or to pursue interests, that result in satisfaction (Pitt et al,, 2021). Cauberghe and colleagues (2021) also found that participants with pre-existing anxiety used social media to manage their symptoms during lockdowns. However, though the use of social media for social connection may have moderated direct effects on mental health in the short-term, adolescents who reported using social media in this way also reported higher levels of PSMU (Cingel et al., 2022) which can cause negative effects on mental health in the long-term (Arness & Ollis, 2022). Indeed, adolescents believed that even though the time spent online with their friends was meaningful, it could not replace actual face-to-face interactions (Pitt et al., 2021).

In consideration of the heightened emotional context in which Study 1 data was collected, the mixed findings around COVID-19 social media use and mental health (Burke et al., 2021), as well as the mixed effects in the social media literature overall (Valkenburg et al., 2022), this study sought to replicate Study 2 and examine whether or not these same patterns held after lockdown restrictions were uniformly lifted. To achieve this, we used a second Qualtrics national sample of 1,151 adolescents and found that there were a similar pattern of relationships to those documented in Study 2, suggesting that these relationships are stable across contexts.

Methods

Sample and procedure

As with Study 2, we again recruited a national sample of U.S. adolescents ages 14 to 16 using a Qualtrics panel (N = 1255). These adolescents completed an online survey that replicated the first survey between the dates of April and May 2022. A majority of the participants were female (n = 819; 65.3%) with 29.2% (n = 366) identifying as male, and 5.5% (n = 69) identifying as other or not disclosing. The sample was racially diverse; 47.5% (n = 596) of respondents described themselves as White, 44.5% (n = 558) Hispanic, Latino/a, or Spanish origin, 25.1% (n = 315) Black or African American, 11.7% (n = 147) Asian or Asian American, 6.5% (n = 82) American Indian or Alaskan Native, 12.4% as other (n = 155), and 3.2% self-described (n = 40). This demographic breakdown is almost identical to that of Study 2, allowing us to make more robust comparisons between the two studies.

Measures

The measures used for Study 3 were the same as those for Study 2 (Appendix IIB contains a full list of measures and questions asked). We conducted a series of independent samples t-tests to evaluate any differences in the two survey samples. The means and standard deviations for measures for both Study 2 and Study 3, along with results of the t-tests, are presented below in Table 3. We observed significant improvements in self-regulation and mental health symptoms in our Study 3 sample collected after lockdown restrictions lifted. However, frequency of social media use and the use of social media for mental health information, as well as positive affect in response to mental health content, were significantly higher than the means observed in Study 2 when adolescents were in lockdowns. The only variable that was not significantly different between samples was PSMU (*p* = .29), suggesting the stability of this disorder regardless of social context.

Table 3
Results of Independent Samples T-tests for Study 2 and Study 3 Variables

	Study 2 *N* = 1191		Study 3 *N* = 1151					
	M	*SD*	*M*	*SD*	*t*	*df*	*p*	*Mean difference*
Self-regulation	1.84	0.36	1.94	0.39	-6.75	2399	.000	-.10
Problematic social media use	2.42	0.91	2.47	1.04	-1.06	2399	.29	-.04
Anxiety	3.02	1.00	2.92	1.11	2.43	2398	.02	.11
Depression	2.41	0.81	2.31	0.86	2.80	2398	.01	.10
Mental health conditions	2.26	1.88	2.08	1.83	2.35	2399	.02	.18

Social media frequency	2.43	0.50	4.15	1.69	2.35	2395	.02	.13
Topics followed	1.35	1.32	1.49	1.34	-2.46	2373	.01	-.13
Affective response	2.40	2.95	2.63	3.01	-1.99	2372	.05	-.24

Results

Preliminary analyses.

Before testing our hypotheses, we first cleaned the data. As the data used in this study was part of a larger data collection, participants who did not respond to the questions relating to the key variables in this study were excluded (*n* = 104), resulting in a final analytical sample of 1,151 participants.

We next examined correlations between key variables in the study and observed similar patterns to those found in Study 2 (See Table 5A in Appendix IIC for bivariate correlations and descriptive statistics). Self-regulation was negatively correlated with all of the mediating (SM frequency, topics followed, and affective response) and dependent variables (anxiety, depression, and mental health self-report). PSMU was positively correlated with each mediating and dependent variable. Further, participant gender was negatively correlated with self-regulation, and positively correlated with all other variables of interest aside from SM frequency. In this sample, participant race was positively correlated with self-regulation and SM frequency, and negatively related to depression. As such, we controlled for both gender and race in the subsequent analyses.

Main analyses.

For consistency between studies, we again used Hayes PROCESS model 80 (Hayes, 2017) to test our hypotheses. We ran one model for each of our two independent variables (self-regulation and problematic social media use) and each of our three dependent variables (three mental health outcomes), resulting in six models, in each of which we controlled for participant gender and race.

Self-regulation as a predictor

First, we tested each dependent variable with self-regulation as the independent variable. For each of the five models, self-regulation was significantly negatively related to SM frequency (β = -.06, p = .04) and topics followed (β = -.56, p = .0000). This means that participants with poorer self-regulation were more likely to spend increased amounts of time on social media and to follow social media accounts about mental health topics.

Anxiety.

Our first model predicting anxiety symptoms was significant (R = .63, R^2 = .40, F(6, 1226) = 134.9, p = .0000). Results indicated a significant direct negative relationship between self-regulation and anxiety (β = -.40, p = .0000) such that participants with poorer self-regulation reported higher levels of anxiety. There was a significant mediating effect of both SM frequency (β = .10, p = .0000) and number of topics followed (β = .25, p = .0000) between self-regulation and anxiety, meaning that participants with poorer self-regulation were more likely to spend more time on social media and to follow more accounts relating to mental health topics, resulting in greater anxiety symptoms reported. There was also a significant relationship between gender and anxiety symptoms (β = .17, p = .0000), suggesting that participants identifying other than male are more likely to experience anxiety.

Though there was a significant direct relationship between both SM frequency (β = .03, p = .02) and number of topics followed (β = .88, p = .0000) on affective response, there was no significant relationship linking affective response to self-regulation or to anxiety, so there was no support for a dual mediation process.

Depression.

The model predicting depression was also significant (R = .60, R^2 = .36, F(6, 1226) = 112.28, p = .0000). Results indicated a significant direct negative relationship between self-regulation and depression (β = -.35, p = .0000) such that participants with poorer self-regulation reported higher levels of depression. There was a significant mediating effect of both SM frequency (β = .12, p = .0000) and number of topics followed (β = .26, p = .0000) between self-regulation and depression, suggesting that participants who reported higher SM frequency and followed more mental health topics were more likely to report higher levels of depression when they reported poor self-regulation. There was also a significant relationship between gender and depression symptoms (β = .14, p = .0000), suggesting that participants identifying other than male are more likely to experience depression.

Though there was a significant direct relationship between both SM frequency (β = .03, p = .02) and number of topics followed (β = .88, p = .0000) on affective response, there was no significant relationship linking affective response to self-regulation or to depression, so there was no support for a dual mediation process. Interestingly, there was also a significant effect of race on affective response (β = .03, p = .04), suggesting that participants who identified as white were more likely to report a positive affective response after using social media.

Self-reported mental health.

Similarly, the model predicting the number of self-reported mental health conditions was also significant (R = .52, R^2 = .27, F(6, 1227) = 76.31, p = .0000). Results indicated a significant direct negative relationship between self-regulation and self-reported mental health (β = -.29, p = .0000) such that participants with poorer self-regulation reported experiencing more mental health conditions in the past 30 days. While there was a significant mediating effect of number of topics followed (β = .17, p = .001) between self-regulation and self-reported mental health, there was no significant mediating effect of SM frequency (β = .03, p = .20). This suggests that individuals with poor self-regulation are more likely to follow more mental health topics, and the number of topics followed, rather than how much time is spent on social media, relates to the number of mental health conditions participants self-report. There was also a significant relationship between gender and self-reported mental health conditions (β = .23, p = .0000), suggesting that participants identifying as other than male self-report more mental health conditions. As with the other models, there was a significant direct relationship between both SM frequency (β = .03, p = .02) and number of topics followed (β = .88, p = .0000) on affective response, but there was no significant relationship linking affective response to self-regulation or to self-reported mental health.

Control variables

We did observe some significant effects in our control variables. For gender, there were significant effects on anxiety (β = .18, p = .0000), depression (β = .15, p = .0000), and self-reported mental health conditions (β = .23, p = .0000) such that participants who identified as other than male reported worse mental health outcomes. Additionally, gender was significantly related to topics followed (β = .22, p = .0000), suggesting participants identifying as other than male follow more mental health topics on SM. Interestingly, we did not observe a significant effect of gender on SM frequency as we did in Study 2.

We observed no significant effects of race on any of our mental health outcomes or social media use variables. However, we did observe a significant effect on affective response ($\beta = .03$, $p = .02$), suggesting that participants who identified as white reported feeling more positively when viewing mental health content.

Problematic social media use (PSMU) as a predictor.

Next, we tested each dependent variable with PSMU as the independent variable. For each of the five models, PSMU was significantly related to SM frequency ($\beta = .34$, $p = .0000$) and topics followed ($\beta = .36$, $p = .0000$). This means that participants who use social media in more problematic ways were more likely to spend increased amounts of time on social media and to follow social media accounts about mental health topics.

Though there was a significant direct relationship between both SM frequency ($\beta = .03$, $p = .02$) and number of topics followed ($\beta = .88$, $p = .0000$) on affective response, there was no significant relationship linking affective response to PSMU or to any of our dependent variables, so there was no support for a dual mediation process. However, there was also a significant effect of race on affective response ($\beta = .03$, $p = .02$), suggesting that white participants were more likely to report feeling positively after using social media.

Anxiety.

The model predicting anxiety symptoms was significant ($R = .57$, $R^2 = .33$, $F(6, 1160) = 92.90$, $p = .0000$). Results indicated a significant direct relationship between PSMU and anxiety ($\beta = .27$ $p = .0000$) such that participants with higher PSMU reported higher levels of anxiety. While there was a significant mediating effect of number of topics followed ($\beta = .22$, $p = .0000$)

between PSMU and anxiety, there was no significant mediating effect of SM frequency ($\beta = .04$, $p = .09$). This means that participants who use social media more problematically are more likely to follow more mental health topics and to experience more anxiety.

Depression.

The model predicting depression was also significant ($R = .56$, $R^2 = .32$, $F(6, 1160) = 89.20$, $p = .0000$). Results indicated a significant direct relationship between PSMU and depression ($\beta = .30$, $p = .0000$) such that participants with higher PSMU reported higher levels of depression. There was a significant mediating effect of both SM frequency ($\beta = .06$, $p = .03$) and number of topics followed ($\beta = .21$, $p = .0001$) between PSMU and depression, meaning that participants who use social media more problematically were more likely to experience depression, particularly when they spend more time on social media and follow more mental health topics.

Self-reported mental health.

Similarly, the model predicting self-reported mental health conditions was also significant ($R = .46$, $R^2 = .21$, $F(6, 1161) = 50.81$, $p = .0000$). Results indicated a significant direct relationship between PSMU and self-reported mental health ($\beta = .12$, $p = .0000$) such that participants who used social media in more problematic ways reported experiencing more mental health conditions and symptoms. While there was a significant mediating effect of the number of topics followed ($\beta = .18$, $p = .002$) between PSMU and self-reported mental health, there was no significant mediating effect of SM frequency. This means that for participants who used social media more problematically, the more mental health topics they followed, the greater number of mental health conditions and symptoms they reported. For this model, there was no significant effect of race, but gender was significant (β = .28, p = .0000), meaning that participants who identified other than male self-reported more mental health conditions.

Control variables.

As with the models predicting self-regulation, we did observe some significant effects of gender and race for PSMU and our outcome variables. Gender was significantly related to all mental health outcomes: anxiety (β = .25, p = .0000), depression (β = .21, p = .0000), and self-reported mental health conditions (β = .28, p = .0000), suggesting that non-male participants who reported high PSMU had greater mental health symptoms and self-reported more conditions.

In these models, we observed significant effects of race on social media use and mental health outcomes. Specifically, race was negatively related to anxiety (β = -.06, p = .01) and depression (β = -.08, p = .002), suggesting that minority participants experienced worse mental health outcomes compared to white participants when they use social media more problematically. We also found a negative effect on SM frequency (β = -.05, p = .05), suggesting minority participants use social media more often. Finally, we again observed a positive relationship between race and affective response (β = .03, p = .02), such that white participants experience more positive affect in response to social media content on mental health topics.

Discussion

Overall, the results of Study 3 mostly replicated those of Study 2 with a few exceptions. There were interesting differences between Study 2 and 3 concerning the relationship between SM frequency and mental health self-report. Specifically, for adolescents who reported high levels of PSMU, after restrictions were lifted, frequency of social media use was significantly related to higher anxiety and depression symptoms, and lost significance for predicting the number of self-reported mental health conditions. This means that adolescents who used social media problematically experienced worse mental health symptoms after the full return to in-person schooling, but did not self-report as having those conditions. This is in contrast to adolescents in Study 2 who reported high PSMU and also a greater number of mental health conditions, where there were no significant relationships for clinical measures of anxiety and depression symptoms. So, adolescents who reported high levels of PSMU experienced poor mental health outcomes as a result of increased time online and following mental health content. Additionally, in Study 3 we did not observe a significant effect of affective response on self-reported mental health as we did in Study 2. Considering this, and the significant differences in means between the two studies, it may be the case that adolescents were hyper aware of their social media use during the lockdowns, as was also noted in the work of Pitt and colleagues (2021), as well as the warnings about protecting one's mental health. Indeed, adolescents surveyed in previous research expressed guilt over spending increased amounts of time online and for spending longer with technology than anticipated (Pitt et al., 2021).

It is also important to note the additional SM frequency measure between Study 2 and 3 in conjunction with these differences in findings. For Study 2, we only included social media use in the metric for SM frequency, but in Study 3, we used a composite measure of social media sites and online video sites (e.g., YouTube and TikTok). TikTok grew 180% among adolescents during the lockdowns, and as it has become known as a tool for self-diagnoses, that may have contributed to increased self-report in Study 2 (Bahorsky, 2022). Adolescents also may have self-diagnosed more frequently during lockdowns so as to provide a sense of meaning to and a way of speaking about the confusing emotions they experienced and to feel connected to a larger community at a time of heightened isolation (Bahorsky, 2022). As technology use and mental health were more salient topics, this may have resulted in higher self-report of mental health conditions and less experienced negative effects of social media use as adolescents were more conscious of their media use; once restrictions lifted and adolescents returned to a more “normal” life, they likely began using social media more passively again, resulting in increases in clinical anxiety and depression symptoms and lower self-reported conditions. From these findings, it seems that online video sites in particular may be damaging to adolescent mental health and can be influencing them inadvertently. Indeed, prior research notes that video-based content is more likely to induce affective responses and attract attention (Devendorf et al., 2020).

Additionally, the differences in findings between the two surveys regarding race reinforce the fact that minorities were disproportionately affected by the COVID-19 lockdown restrictions. Specifically, during the restrictions when Study 2 was conducted, white participants were more likely than minorities to follow mental health topics on social media, as well as to self-report more mental health conditions. Once lockdown restrictions were lifted in Study 3 data collection, there was no effect observed of race on the number of topics followed or the number of self-reported mental health conditions. However, white participants were more likely to report positive affect in response to mental health information in Study 3, a relationship that was not observed during the restrictions. This suggests that mental health information online may be more beneficial and accessible in times of need for white individuals. Indeed, in our content analysis of mental health content on YouTube, approximately 60% of the videos were created by white individuals. This finding aligns with previous research that suggests we tend to watch UGC by those we can identify with (Tolbert & Drogos, 2019). If the majority of mental health content is created by white individuals, then it is not surprising that white participants were more likely than minorities to follow that content during lockdowns as mental health became a timely issue (Gaus et al., 2021). Further, with increased identification, participants may have self-reported more conditions as they wish to be the same as and increase the sense of identification with SMIs (Tolbert & Drogos, 2019). When the restrictions were lifted, white participants may not have been drawn to mental health content in the same way as it lost salience, and thus, the loss of significance for the number of topics followed and self-report. However, when white individuals were exposed to mental health content in Study 3, they felt better after viewing it. Perhaps their perceived need was not so salient as it was at the time of data collection in Study 2 and the lockdowns, or perhaps the high levels of empathy and exhort in YouTube content in particular (see Study 1 findings), helped them feel more positively.

We also found significant effects of race on anxiety and depression symptoms in Study 3 that were not observed in Study 2. That is, adolescents of racial minority backgrounds and who used social media in problematic ways demonstrated greater anxiety and depression symptoms post-restrictions, yet there was no relationship with self-diagnosing conditions. In contrast, in Study 2 we observed that white adolescents were more likely to self-report, and that, for those who used social media problematically, they reported greater depression symptoms. This is concerning as minority individuals are already less likely than white individuals to receive treatment for mental health conditions when they have been diagnosed (National Alliance on Mental Illness, 2022I) and experience greater stigma in relation to disclosing (Choi et al., 2021). In this case, minority adolescents who engage in high PSMU experience higher rates of symptoms, but may not be aware they need help. Therefore, minorities may need more mental health content available to them as they are already less likely to seek and receive help compared to white individuals (CDC, 2022, July 12; NeMoyer et al., 2019), yet there is a lack of diversity in creators to encourage them to do so, further exacerbating treatment gaps. Supporting the call from Choi and colleagues (2021), these findings emphasize that researchers and professionals need to encourage SMIs from minority backgrounds to create more accessible and culturally-sensitive content about their experiences with mental health as it can help encourage adolescent viewers from similar backgrounds to seek help.

Considering these differences in conjunction with the lack of change in findings between the two surveys in relation to PSMU rates and relationships with mental health outcomes, we show the powerful impact of problematic use among adolescents. Though there is debate surrounding the term "addiction" in relation to PSMU (Arness & Ollis, 2022; Burnell & Odgers, 2022), it is concerning that regardless of social context, problematic use of social media has significant detriment to adolescent mental health, just as any other addiction may (Samaha & Hawi, 2016). In the long term, this can have a severe impact on optimal functioning including decreased academic and job performance (Samaha & Hawi, 2016), increased risk of severe health conditions such as cardiovascular disease (National Alliance on Mental Illness, 2022), and decreased financial stability (National Alliance on Mental Illness, 2022). As adolescents became reliant on social media during the pandemic lockdowns and demonstrated increased PSMU (Fernandes et al., 2020), it seems those behaviors maintained post-restrictions. Therefore, there is a large group of adolescents at critical risk for mental health struggles and subsequent effects.

Limitations and Future Directions

Overall, the results of these two surveys (Study 2 and Study 3) provide evidence that exposure to mental health content online can in some cases lead to increased self-diagnoses among at-risk populations (i.e., adolescents with poor self-regulation, those with high PSMU, and females). Further, there is a discrepancy between actual symptomatology of conditions (as assessed through clinical measures of anxiety and depression) and the self-report of having a condition for certain groups (i.e., white adolescents and those who spend more time on social media sites). Therefore, vulnerable adolescents may not be getting the help or attention they need with the gaps between displays of symptoms and self-report. It is important to note the limitation in our coding of race as a binary code (white vs. not white), as research shows that there are different levels of mental health diagnoses and treatment-seeking behaviors across minority groups as a function of differential SES and cultural norms. However, this type of binary coding is normative in research and we did not have enough power in each sample to be able to look at each racial minority group individually in the analyses. Future research should consider not only diverse samples, but equally-distributed racial groups to be able to further investigate the relationships between social media use and mental health outcomes for varying backgrounds. We also show that SMIs can have significant power of suggestion and influence on adolescent populations who report having mental health conditions after seeing mental health content online. As these two surveys were cross-sectional and are limited in the ability to make causal claims, we planned a final study to experimentally test the impact of immediate exposure to SMI content on adolescent mental health symptoms and self-report.

Study 4

Introduction

Following from the conclusions drawn from the two cross-sectional surveys, we sought to experimentally test the observed relationships to provide more empirical support for the directionality of our hypotheses as research notes the difficulties in separating cause from effect in this area of research (Odgers et al., 2020). We also sought to build on the findings from the content analysis conducted in Study 1 to see how self-disclosure from a specific influencer, rather than more general exposure as was asked in the surveys, relates to adolescents' experience of anxiety and depression. Research demonstrates that increased liking and trust of SMIs results from parasocial relationships (PSRs) and that the stronger the PSR, the more likely the viewer is to enact on advice or accept information from the SMI (Ferchaud et al., 2018; Sokolova & Perez, 2020). As adolescents are more susceptible than other populations to form strong parasocial bonds with their favorite celebrities and influencers and to learn from them (Bond, 2016; Theran et al., 2010), they are more at risk for accepting information that these SMIs disseminate. Thus, when it comes to SMIs discussing mental health content that is primarily experiential and not based on research or professional recommendations (Naslund et al., 2014), adolescents who are already vulnerable to mental health struggles (i.e. poor self-regulation and high rates of PSMU) may be further at risk for accepting information and behaving in harmful ways. Using data from a sample of 100 high school students at a private school in Central California, we provide further empirical support for the theoretical model discussed in Study 2 and 3 and show that adolescents with poor self-regulation and high levels of PSMU are critically at-risk populations for experiencing negative effects of social media use on mental health. We also show that even a single exposure to mental health videos can induce an effect on viewers' anxiety symptoms, particularly when they experience a strong sense of PSR.

Literature review

Parasocial relationships

Building relationships with audiences is a necessary skill for SMIs to be successful (Berryman & Kavka, 2017). In order to build these relationships with their viewers, SMIs intentionally manipulate parasocial interaction with viewers (Ferchaud et al., 2018; Kurtin et al., 2018). Though social media affords the opportunity for interaction between SMIs and their viewers, the majority of communication is still directed from the SMIs to their audiences and mirrors a one-way format that can be considered parasocial (Colliander and Dahlén, 2011; Labrecque, 2014). Parasocial interaction (PSI) was first introduced to explain the process by which television viewers engaged in one-sided interactions or emotional responses with radio and television personalities (Horton & Wohl, 1956). These interactions are one-sided as they are controlled by the media personality and are not reciprocal, yet viewers experience the interaction as though it is directed at them (Rubin et al., 1985). PSI are bounded by the duration of the media exposure and the presence of the media personality, but can generate strong emotional responses and a sense of reciprocity in the moment (Hartmann, 2016). As these feelings of intimacy and pseudo-reciprocity begin to last longer than the duration of the media interaction and PSI becomes more frequent, it is deemed a parasocial relationship (PSR) whereby the viewer feels a deeper sense of intimacy with the media personality and thinks about them outside of the media experience (Dibble et al., 2016; Rubin et al., 1985). These relationships develop like real-world relationships and are influenced by duration of exposure and knowledge of the media personality (Hartmann, 2016; Rubin & McHugh, 1987).

Social media influencers rely on this perceived intimacy on the part of the viewers to be able to successfully advertise, persuade, and ultimately, increase their profits, so they do all that they can to foster PSI (Dopson, 2022). Because SMIs are perceived as more authentic, relatable, and reachable in comparison to traditional celebrities (Chae, 2018; Djafarova & Rushworth, 2017; Klassen et al., 2018), it is easier for them to foster PSI and strong PSRs with their audiences (Marwick, 2015; Yuan & Lou, 2020). They are also seen as more admirable than traditional celebrities (Westenberg, 2016), meaning their advice may be more readily-accepted. Additionally, research suggests that social media is the "perfect place" for users to develop PSI and PSR as there is greater opportunity to interact with media personae (i.e., SMIs) through features such as likes and comments, and users can continually and repeatedly expose themselves to content, both new and existing content, from SMIs, allowing for increased exposure (Boerman & Van Reijmersdal, 2020, p. 5; Marwick, 2015). Further, features such as livestreams allow SMIs to directly interact with viewers through comments and chats that are synchronous, increasing the sense of reciprocity on the part of the viewer (Mickles & Weare, 2020). This also helps the SMI as increased engagement rate (i.e., likes, comments, and shares) is directly linked to having greater influence on what viewers think (Dopson, 2022). As SMIs produce constant updates and reveal personal details about their lives, including mental health, it not only increases exposure, but also the detailed knowledge that audiences have of them. Together, this creates an increased sense of intimacy and fosters the development of strong and intense PSR (Mickles & Weare, 2020; Zeljko et al., 2018).

Though research has examined the development of PSI and PSR with SMIs across various social media platforms (see Boerman & Van Reijmersdal, 2020; Kurtin et al., 2018), recent research has focused on the context of YouTube as it's video-focus allows for manipulation of videography features in ways similar to traditional television that reproduces a sense of face-to-face communication (Burgess & Green, 2009; Kurtin et al., 2018; Labrecque, 2014). Some of these features include direct address of the audience and manipulation of camera angles to be front-facing, close-up, and allow for eye contact (Burgess & Green, 2009; Ferchaud et al., 2018). Additionally, SMIs use self-disclosure, revealing personal information about oneself, such as mental health diagnoses, and sharing everyday moments, to increase intimacy with their audience (Berryman & Kavka, 2016). Though these techniques have been examined in the context of YouTube, the majority of social media platforms now include some sort of video-sharing or live streaming feature that allows SMIs to successfully use these video-based techniques across platforms (e.g., Instagram reels and TikTok videos).

It is also important for SMIs to not only create PSRs with their audience, but to maintain them. In fact, it is suggested that the sense of presence and connection offered by SMIs is more important than the actual content they produce (Gkoni et al., 2017; Licoppe & Smoreda, 2005). Research suggests that increased strength of PSR moderates the effectiveness of SMIs, as stronger PSR felt by viewers relates to increased liking of the SMI, decreased criticism of the SMI and their content, greater intent to watch and time spent watching, increased sense of loyalty, and intent to follow displayed behaviors (Boerman & Van Reijmersdal, 2020***;*** Ferchaud et al., 2018; Ko & Wu, 2017; Sakib et al., 2020). Strength of PSR with SMIs also increases their success in advertising products and purchase intentions of viewers (Lee & Watkins, 2016) as the perceived credibility and authenticity of SMIs leads users to view them as a trusted source for information. In fact, PSRs are one of the strongest antecedents of users following the advice from and being influenced by SMIs (Sokolova & Perez, 2020). Indeed, 61% of consumers trust information and recommendations from SMIs, compared to only 38% who trust branded content online (Dopson, 2022), further illustrating the influential power SMIs have. In the context of mental health information, trust and liking of the SMI and heightened PSR can lead viewers to be influenced by the opinions presented. With concerns over the medicalization of normal behaviors (Bahorsky, 2022), adolescents may see normative behaviors online that are discussed as symptoms of mental health and believe that they have a mental health condition.

Social learning and social norms

As introduced above, the influential power of SMIs can be understood through social learning theory (Bandura, 1971; 1977). The likelihood of learning from social models (i.e., an SMI) has been shown to increase with liking of the model (Coates et al., 2019). Therefore, adolescents may learn behavior from SMIs and are particularly likely to copy SMIs when they have a strong parasocial relationship as PSR strength is associated with increased liking of an SMI (Coates et al., 2019).

Further, in accordance with Social Norms Theory (Perkins and Berkowitz, 1986), individuals learn what is normal and acceptable behavior through descriptive social norms, what they perceive is common, and injunctive norms, what they perceive is approved (Cialdini and Trost, 1999; Hendriks et al., 2020). Descriptive norms act as a form of informational influence where individuals believe that what they see others do is what they should do (Robinson et al., 2016). This type of influence is particularly strong amongst peers or those who are seen as similar (Cialdini et al., 1990; Robinson et al., 2016). Injunctive norms often influence behavior when there is concern for social acceptance, as they affect what individuals believe they should be doing and what is approved by others (Eyink et al., 2020; Robinson et al., 2016). In the context of SMIs who have a large following, viewers may perceive the behaviors of SMIs as acceptable due to the social status they have and something that should be mimicked (Hendriks et al., 2020). As SMIs are perceived as peers and often similar to viewers (Chae, 2018; Qutteina et al., 2019), the behavior of SMIs is likely viewed as both normative and acceptable by viewers and subsequently copied. Therefore, if an SMI engages in self-harming behaviors or maladaptive coping strategies for mental health, viewers may see it as normative and mimic the behavior. With increased disclosures of mental health online and opinionated discussions, viewers also may be influenced on their perceptions of what is normative experience (e.g., how symptoms should present) and treatment options. As mental health conditions are often comorbid (Al-Asadi et al., 2015; Kessler et al., 2005), with high rates of co-occurrence between anxiety and depression and as they were the most commonly discussed comorbidities in our content analysis sample, we expect that:

H1: Participants who watch a video about mental health will report higher (a) anxiety symptoms, (b) depression symptoms, and (c) self-reported conditions compared to participants who watch a video that does not reference mental health.

H2: Strength of PSR with the SMI reported by participants will be positively correlated with the strength of PSR they report for the SMI in their video condition.

H3: Strength of PSR with the SMI in the anxiety condition will positively predict (a) anxiety symptoms, (b) depression symptoms, and (c) self-reported conditions.

H4: Strength of PSR with the SMI in the depression condition will positively predict (a) anxiety symptoms, (b) depression symptoms, and (c) self-reported conditions.

Furthermore, as SMIs encourage viewers to follow them across various social media platforms (Reinikainen et al., 2020), adolescents may be more likely to fragment their use across multiple platforms. In fact, over 56% of adolescents report using four or more social media platforms (Robb, 2020). Low self-regulatory ability has been linked to excessive time online and addictive smartphone use for this age group (LaRose et al., 2003; Mahapatra, 2019; Meeus et al., 2019), and may influence the likelihood for adolescents to create multiple accounts and fragment their use across platforms to keep up with SMIs (Gkoni et al., 2017). Therefore, adolescents with poor self-regulation and proclivity to addictive (problematic) social media use likely spend increased time online and increase their exposure to SMIs, particularly with stronger PSRs, and may be more likely to be influenced. As such, we also re-tested the theoretical model from Study 2 and 3 in an experimental context to include more specific SMI measures and PSR. As PSRs involve a sense of liking and emotion towards an SMI, we are interested here in PSR as an indicator of affective response. Therefore, we expect that:

H5: Adolescents with poor self-regulation will report higher (a) SM frequency, (b) SMI exposure, (c) strength of PSR, and greater (d) anxiety, (e) depression, and (f) number of mental health conditions.

H6: Adolescents with higher levels of PSMU will report higher (a) SM frequency, (b) SMI exposure, (c) strength of PSR, and greater (d) anxiety, (e) depression, and (f) number of mental health conditions.

Methods

Sample and procedure

Participants were recruited from a small private high school in the California Central Valley. Students from all of the English classes across four teachers were asked to take part in the study. First, they were given consent forms in class to take home to their parents. After one week, the students who received parental consent were sent a link (by their teachers) via email to an online survey hosted on Qualtrics. Participants completed the online survey during their English class period on April 3rd, 2023 (N = 100). Each student who returned a consent form, regardless of consent or refusal, were entered into a drawing for one of ten $50 Amazon gift cards. A slight majority of the participants were male (*n* = 55; 55%) with 45% (*n* = 45) identifying as female. No participants identified as other or did not disclose gender. The sample was racially diverse; 54.5% (*n* = 55) of respondents described themselves as White, 33.7% (*n* = 34) Hispanic, Latino/a, or Spanish origin, 14.9% (*n* = 15) Asian or Asian American, 5.9% (*n* = 6) Black or African American, 5.9% (*n* = 6) Native Hawaiian or Other Pacific Islander, 5.9% (*n* = 6) chose to self-describe, and 5% selected Other race, ethnicity, or origin (*n* = 5). Participants came from all grade levels with the majority being in 10th grade (57.4%, *n* = 58), followed by 9th grade, 21.8% (*n* = 22), and 11th grade, 20.8% (*n* = 21). None of the participants were seniors as the majority of seniors at the school were 18 and outside of the age range of interest.

Measures

Self-regulation.

To measure self-regulation, we used the Adolescent Self-Regulatory Inventory (Moilanen, 2007), as we did in the two previous surveys, and used the same eight items. Each item was responded to on a 3-point scale ranging *Not at all true for me* to *Really true for me* (*M* = 1.96, *SD* = 0.39), with higher scores reflecting better self-regulation.

Social media use.

Problematic social media use.

To assess problematic social media use, we used the same nine items used in the two surveys from the Problematic Media Use Measure (Domoff et al., 2019). Each item is rated on a five-point scale ranging from *Never* to *Always.* Items were coded such that higher scores reflected more problematic social media use (*M* = 2.42, *SD* = 0.8).

Social media (SM) frequency.

To assess social media frequency, participants were shown a list of 7 social media sites, along with the option of "other (please specify) and asked to select which they used (*M* =3.96, *SD* = 1.07). Following this, for each that they selected, they were asked "How much time do you spend on the platform in an average day?" with eight response options ranging from *None* to *More than 8 hours*. A social media frequency score was created by summing these responses and dividing by the number of platforms they indicated using (*M* =2.36, *SD* = 0.70).

SMIs

To assess familiarity with and general proclivity to SMIs, participants were asked a series of questions. First, they were asked to enter the name of their favorite influencer on social media. Next, they were asked to indicate how often they check the posts of that influencer on each of the platforms they indicated using in the previous question. We created an overall SMI exposure frequency score by summing these responses and dividing by the number of platforms used (*M* = 2.46, *SD* = 1.27).

Parasocial relationship (PSR)

We used the Experience of Parasocial Interaction Scale (EPSI-Scale; Dibble et al., 2016) scale to assess PSR strength with the SMI identified in the previous question. The scale consists of 13 items, each answered on a five-point scale ranging from *Strongly disagree* to *Strongly agree* (*M* = 3.43, *SD* = 0.89), with higher scores representing a stronger parasocial relationship. Sample items include "I miss seeing my favorite SMI when they do not post on time" and "My favorite SMI makes me feel comfortable, as if I am with a friend."

After exposure to the video condition, participants were asked to assess the strength of their parasocial relationship with the SMI in the video. For this, we used six items from the original 13-item EPSI-Scale (Dibble et al., 2016), as some of the items did not seem to apply to a single exposure. The six items selected are in Appendix IIIA, along with all other survey questions, and include “I see (SMI) as a natural, down-to-earth person” and “I look forward to seeing (SMI)’s next post.” Items were summed such that higher scores represent stronger PSR with the influencer in the video ($M_{anx.}$ = 1.15, $SD_{anx.}$= 1.64; $M_{dep.}$ = 1.04, $SD_{dep.}$= 1.54; $M_{con.}$ = 0.57, $M_{con.}$= 0.95).

Mental health

Anxiety.

To maintain consistency, we used the PROMIS Short Form (PROMIS-SF; APA, 2013) to measure participant’s anxiety symptoms. This measure consists of eight items, each answered on a five-point scale ranging from *Never* to *Always*, with higher scores representing greater anxiety symptoms (*M* = 2.80, *SD* = 0.96).

Depression.

We used the Patient Health Questionnaire-9 (Kroenke et al., 2001) to measure depression symptoms. The measure consists of nine items with each question answered on a four-point scale ranging from *Not at all* to *Nearly every day*, but the final item regarding suicidal ideation was again dropped from the survey in consideration of participant safety. Therefore, our final measure consisted of eight items (*M* = 1.91, *SD* = 0.72), with higher scores representing greater depression (*M* = 1.91, *SD* = 0.72).

Self-reported mental health.

Finally, participants were asked to indicate whether or not they experienced any health or mental health problems over the last 30 days, to which they selected all that applied from a list of six conditions (for a full list, please see Appendix IIIA). These were then binary coded for whether they were selected (1) or not selected (0). Finally, a total sum of health conditions was calculated by summing the responses to each of the seven conditions and/or symptoms (M = 1.18, SD = 1.24).

Stimuli selection

YouTube videos were selected as the visual stimuli for the experiment for several reasons. Not only is YouTube the most-used platform among this age group (Bahorsky, 2022), in line with Study 1 and previous research, mental health information is the most prevalent on YouTube (Godwin et al., 2017; Kang et al., 2017). Further, from the results in our two survey studies, online video content may be more influential on adolescent mental health as when online video content was included in the measure of frequency, SM frequency predicted symptoms, rather than self-report. The videos used for the experimental conditions were identified using a series of selection criteria. First, videos had to feature an SMI who at the time of filming was a similar age to study participants. Second, the videos could not mention any potential age-inappropriate topics (i.e., sex, cursing, mentions of suicide). Third, in an attempt to control for any potential gender effects, we selected one video, the anxiety condition, with a female SMI and one video, the depression condition, with a male SMI. Then, the video for the control condition was selected to feature both one female and one male SMI. Finally, to maximize participant attention, videos over ten minutes were not considered for selection. The final videos that were used for the experimental conditions are listed in Appendix IIIB.

Results

Preliminary analyses.

Before testing our hypotheses, we first cleaned the data. There were a total of 107 responses, but seven were removed for missing and/or incomplete data if they did not answer any questions relating to the video condition, resulting in a final sample of $N = 100$. We also examined correlations between key variables in the study. Self-regulation was negatively correlated with PSMU and the three mental health outcomes (anxiety, depression, and mental health self-report). PSMU was positively correlated with SM frequency and depression symptoms, and negatively correlated with PSR strength for the depression video condition.

Age was positively correlated with PSR strength, supporting prior research (Bond, 2016). Additionally, gender was negatively correlated with PSR strength, and positively correlated with the three mental health outcomes. As a result, we controlled for age and gender in the main analyses. Descriptive statistics and correlations between variables are presented in Table 6A in Appendix IIIC.

There was no correlation between the strength of PSR with the SMIs reported by participants and the strength of PSR with the SMI in the video condition, so H2 was rejected.

Main Analyses.

Video condition and mental health outcomes.

To test our first hypothesis, we ran a one-way analysis of variance (ANOVA) which allows for the comparison of three or more group means, in this case, each of our three video conditions (anxiety, depression, and control). Table 4 below lists the descriptive statistics for each condition. We ran one test for each of our three dependent variables [anxiety (H1a); depression (H1b); and mental health conditions self-reported (H1c)]. In each test, we controlled for participant gender as it was the only demographic characteristic correlated with mental health outcomes. All ANOVA model results are reported in Table 7A in the Appendix.

Anxiety.

Though we approached significance, results of an ANOVA found no significant main effect of experimental condition on anxiety symptoms $F(2, 96) = 2.75$, $p = .07$. However, we did find a significant difference between the anxiety video condition and the control video condition in the follow-up simple contrast tests ($p = .04$, 95% CI: [-.91, -.03]). This means that participants in the control video condition reported significantly ($M = 2.70$, $SD = 1.04$) lower anxiety symptoms than those in the anxiety video condition ($M = 3.06$, $SD = 0.84$), partially-supporting H1a. We also observed a significant effect of gender $F(1, 99) = 4.89$, $p = .03$, suggesting that females reported significantly higher anxiety symptoms compared to males.

Depression.

We observed no significant effect of experimental condition on depression symptoms $F(2, 95) = .013$, $p = .99$. Indeed, it seems that depression symptoms reported were almost identical across conditions, so H1b was rejected. We again observed a significant effect of gender F(1, 99) = 4.09, p = .05, suggesting that females reported significantly higher anxiety symptoms compared to males.

Self-reported mental health.

We also observed no significant effect of experimental condition on self-reported mental health conditions $F(2, 96) = .78$, $p = .46$, so H1c was also rejected. There were also no significant differences in the number of conditions reported across experimental groups. Again, we did observe a significant effect of gender, $F(1, 99) = 13.76$, $p = .000$, such that females reported significantly more mental health conditions compared to males.

Table 4
Descriptive Statistics by Condition

	Condition 1 Anxiety N = 36		*Condition 2 Depression N = 34*		*Condition 3 Control N = 30*		*Total N = 100*	
	M	*SD*	*M*	*SD*	*M*	*SD*	*M*	*SD*
Self-regulation	1.99	0.39	1.95	0.39	1.94	0.40	1.96	0.39
PSMU	2.48	0.81	2.21	0.73	2.59	0.83	2.42	0.80
SM Frequency	2.43	0.75	2.23	0.71	2.43	0.63	2.36	0.70
SMI Frequency	2.52	1.44	2.61	1.21	2.24	1.14	2.46	1.27
Parasocial relationship (with SMI)	3.31	1.04	3.41	0.73	3.58	0.89	3.43	0.89
Parasocial relationship (by video condition)	3.22	0.93	3.10	0.78	1.85	0.73	NA	NA
Anxiety	3.06	0.84	2.61	0.94	2.70	1.04	2.80	0.95
Depression	1.88	0.70	1.88	0.62	1.97	0.85	1.91	0.72
Mental health conditions	1.22	1.07	1.24	1.28	1.07	1.39	1.18	1.24

Strength of parasocial relationship.

For our second hypothesis concerning the effect of parasocial relationship strength, we ran a series of linear regression models, one for each of our three mental health outcomes. In each model, we entered demographic control variables (i.e., age and gender) in the first block, and PSR strength variables (i.e., PSR proclivity and PSR by video condition).

Anxiety.

First, we tested a regression model for the effects of PSR strength on anxiety symptoms. The regression results indicated that the demographic characteristics explained only 7% of the variance in the outcome variable, $F(2, 97) = 3.74$, $p = .03$, $R^2 = .07$. While we did not observe a significant effect of age, gender was significantly positively related to anxiety symptoms (β = .23, $p = .02$) such that females reported higher symptoms. Next, we added in the four dimensions of PSR strength $F(6, 93) = 5.15$, $p = .000$, $R^2 = .25$. Interestingly, we observed no significant effect of PSR strength with the participant-identified SMI, but we did find significant effects for the strength of PSR with the SMIs in the video conditions and reported anxiety symptoms (anxiety, β = .77, $p = .000$; depression, β = .56, $p = .001$; control, β = .53, $p = .002$), supporting H3a and H4a. Once these PSR variables were entered, gender lost significance in the model. This means that, regardless of gender, participants who felt a sense of PSR with the SMIs in the video conditions reported higher anxiety symptoms.

Depression.

Next, we ran a model to predict depression symptoms. The first block of demographic variables did not significantly explain any variance in depression symptoms $F(2, 96) = 2.29$, $p = .11$, $R^2 = .05$. However, there was a significant effect of gender (β = .21, $p = .04$). The second block of PSR strength variables was also not significant $F(6, 92) = 1.96$, $p = .08$, $R^2 = .11$, meaning that PSR strength does not significantly predict variation in depression symptoms, so H3b and H4b were rejected. However, we again found a significant effect of PSR strength for each condition (anxiety, β = .44, $p = .02$; depression, β = .40, $p = .03$; control, β = .44, $p = .01$).

Self-reported mental health.

Lastly, we tested a regression model for the effects of PSR strength on self-reported mental health conditions. The regression results indicated that the demographic characteristics were significant and explained 12% of the variance in the outcome variable, $F(2, 97) = 6.72$, $p = .002$, $R^2 = .12$. While we did not observe a significant effect of age, gender was significantly positively related to anxiety symptoms (β = .35, $p = .000$) such that females were more likely to self-report mental health conditions. Next, we added in the four dimensions of PSR strength $F(6, 93) = 2.63$, $p = .02$, $R^2 = .15$, which significantly reduced the predictive value of the model as there were no significant effects of any metric of PSR strength, so H3c and H4c were rejected.

Overall model.

Next, to test hypotheses 3 and 4, as we did for Study 2 and 3, we ran a series of PROCESS Model 80 tests. We ran one model for each of our two independent variables and three dependent variables, resulting in six models. For each model, we included participant age and gender as covariates, as they were significantly correlated to some of the variables of interest and race was not correlated as it was in Study 2 and 3.

Self-regulation as a predictor.

First, we tested self-regulation as a predictor of each of our dependent variables. In each of the models, self-regulation was not significantly related to any of our three mediating variables (SM frequency, SMI exposure frequency, and PSR strength). Thus, H5a, H5b, and H5c were not supported. However, both age (β = .19, $p = .05$) and gender (β = -.21, $p = .03$) were significantly related to PSR strength, suggesting that older male participants with poor self-regulation reported stronger PSR.

Anxiety.

Our overall model predicting anxiety symptoms was significant (R = .38, R^2 = .14, F(6, 92) = 2.53, p = .03). Results indicated a significant direct negative relationship between self-regulation and anxiety (β = -.22, p = .03) such that participants with poorer self-regulation reported higher levels of anxiety, supporting H5d. There were no significant relationships between any of the mediating variables and anxiety; however, there was a significant effect of gender (β = .21, p = .04), such that females were more likely to report higher anxiety symptoms.

Depression.

Next, we tested the model with depression symptoms as the outcome variable. The overall model was significant (R = .47, R^2 = .22, F(6, 92) = 4.31, p = .001). Results indicated a significant direct negative relationship between self-regulation and depression (β = -.34, p = .001) such that participants with poorer self-regulation reported higher levels of depression, supporting H5e. There was also a significant relationship between SM frequency and depression (β = .21, p = .03) such that those who used social media more frequently reported more depression symptoms. No other significant relationships were observed.

Self-reported mental health.

Finally, we tested self-reported mental health conditions as the dependent variable. The overall model was significant (R = .49, R^2 = .24, F(6, 92) = 4.96, p = .001). Results indicated a significant direct negative relationship between self-regulation and self-reported mental health conditions (β = -.33, p = .001) such that participants with poorer self-regulation reported a greater number of mental health conditions, supporting H5f. There were no significant relationships between any of the mediating variables and mental health; however, there was a significant effect of gender (β = .39, p = .0001), such that females self-reported more mental health conditions.

Problematic social media use as a predictor.

Next, we tested PSMU as a predictor of each of our dependent variables. In each of the models, PSMU was significantly related to SM frequency (β = .46, p = .0000), supporting H6a, but not to either of the other mediating variables, so H6b and H6c were rejected. We again included age and gender as covariates in each model and both age (β = .20, p = .05) and gender (β = -.21, p = .03) were significantly related to PSR strength, such that older male participants who engage in PSMU reported stronger PSR

Anxiety.

Our overall model predicting anxiety symptoms was significant (R = .36, R^2 = .13, F(6, 92) = 2.24, p = .05). Results indicated no significant relationship between PSMU and anxiety (β = .20, p = .07) meaning H6d was not supported. There were also no significant relationships with any of the mediating variables; however, gender was significantly positively related (β = .20, p = .05) suggesting females were more likely to report anxiety symptoms.

Depression.

Next, our model predicting depression symptoms was significant (R = .46, R^2 = .21, F(6, 92) = 4.03, p = .001). Results indicated a significant direct negative relationship between PSMU and depression (β = .37, p = .001) such that participants who used social media more problematically reported higher levels of depression, supporting H6e. There were no other significant relationships observed in the model.

Self-reported mental health.

Finally, though the overall model predicting self-reported mental health conditions was significant (R = .38, R^2 = .15, F(6, 92) = 2.63, p = .02), we observed no significant relationships between PSMU or the other mediating variables, so H6f was rejected. There was, however, a significant effect of gender (β = .38, p = .001), suggesting females self-reported more mental health conditions.

Discussion

Though we found limited support for our first two hypotheses addressing the effects of mental health disclosures by an SMI on adolescent mental health and PSR, we did further support the conclusions drawn from the two national surveys conducted in Study 2 and Study 3. In particular, we again provide evidence that adolescent self-regulation skills and PSMU have significant impact on their social media use and mental health outcomes. Though we found limited support for social media mediators in this study, we did still observe a significant mediating effect of SM frequency in the relationship between PSMU and depression, further emphasizing the intensity of effects that PSMU is having on adolescents. Even in a small sample size with low levels of mental health struggles, we still observed a relationship between PSMU and mental health outcomes. Despite the limitations of frequency measures, SM frequency appears to be a significant predictor of mental health outcomes and should be considered alongside more nuanced measures of content and use. For this study, we assessed frequency using a composite score of the use of each social media platform in an average week. This increased specificity may have aided in better recall, a limitation noted by Odgers and Jensen (2020) in response to blanket frequency measures. Therefore, more specific measures of frequency bounded by a time frame and individualized by platform may be a useful way to assess the construct.

Our first hypothesis predicted that video condition would significantly relate to mental health outcomes. Indeed, we found that adolescents who watched a video with an SMI talking about anxiety reported significantly higher anxiety symptoms than the adolescents who watched a control video that did not reference mental health in any way. Though we found no other significant differences between experimental groups and mental health outcomes, this does suggest that even after a single exposure, adolescent mental health can be influenced by the content they watch. In this case, it may be that mentioning a condition can prime adolescents to experience and mimic symptoms subconsciously. This is concerning as we also found that the strength of PSR adolescent viewers feel with an SMI has differential effects. Adolescents who reported stronger PSR with SMIs in the videos exhibited increased anxiety and depression symptoms, but did not report that they have been diagnosed with those conditions. Further, PSR strength reduced the predictive value of our model in the case of self-reported mental health conditions. Therefore, exposure to mental health content may have subconscious effects, particularly in the case of anxiety, and these effects can be heightened through stronger PSRs. In fact, strength of PSR likely has a significantly powerful role in the relationship between media use and mental health outcomes, as the consistent links we observed between gender and mental health symptoms, not only in this study but in the two survey studies as well, were not present once PSR strength was entered into the model. We also found a significant relationship between PSMU and depression that was mediated by SM frequency. Collectively, this provides further explanation for the differential relationships observed in Study 2 and 3 whereby SM frequency had an effect on symptomatology, but not on adolescent self-reports of mental health conditions, suggesting that frequency plus exposure to mental health content is having an effect on adolescent experiences of mental health to which they may not be aware.

Limitations and future directions.

Part of the lack of significance in findings regarding video condition, PSR strength, and mental health outcomes may be due to the single video exposure. Prior research notes that a single exposure to online content is likely not enough to elicit an immediate effect (Aftab & Murphy, 2022). Further, we may not have had enough power in the sample, as only 78 participants provided a valid response to the question asking for their favorite SMI, with 13 names being duplicated. Of the final list of 59 identified persons, 11 are considered traditional celebrities (and Donald Trump) not SMIs. Therefore, this population may have limited exposure to and understanding of SMIs. Indeed, many participants noted that they just watch whatever comes up in their recommended feeds, rather than following specific influencers. TikTok may have changed the way that younger adolescents consume content online. However, we did observe one difference in anxiety symptoms between the anxiety condition and control condition, so even if viewers are not aware of who an SMI is, they can still be impacted by exposure to mental health content. Adolescents that do follow SMIs and develop PSRs may be at an elevated risk for being influenced.

Further, the differences observed for anxiety and depression may have been a function of the video stimuli. The video about depression was significantly shorter than the one on anxiety, and the SMI was a male. As there were consistent effects of gender in both this study, and across the previous two surveys, on mental health outcomes, it may be that the females did not feel a sense of PSR with the male SMI in the depression condition enough to observe an effect. Further, the female SMI in the anxiety condition, Emma Chamberlain, was mentioned twice as the favorite SMI by participants in the study, so she may be more well-known than the male SMI, Jack Harries. Indeed, familiarity is a component of PSR (Grave, 2017), and this may have contributed to the significant effects on anxiety symptoms. However, it is still concerning that participants in the anxiety condition demonstrated higher anxiety symptomatology, yet there was no significant effect for self-reported conditions.

This sample was also limited in diverse representation, particularly in comparison to the diversity in our two survey samples. Student participants attended a private Catholic school in the California Central Valley that costs $14,000 annually. Therefore, participants were likely of a higher socioeconomic status (SES) than is average in that region where average household income is $67,011 and only 19.5% of residents hold a Bachelor's degree or higher (United States Census Bureau, 2022). Research shows that SES is a confounding factor in the relationship between social media use and mental health outcomes as it is related to both increased media use and mental health conditions (Odgers et al., 2020; Reiss, 2013). Indeed, adolescents of lower SES are more likely to have negative experiences with social media and experience increased psychological problems with media use, including anxiety and depression (Gracia et al., 2022; Skogen et al., 2022). Researchers also believe that adolescents in lower SES households are more susceptible to engaging in PSMU (Geurts et al., 2022) as they spend an average of up to three hours more each day on screens compared to those of higher SES (Odgers & Jensen, 2020; Rideout & Robb, 2018). Therefore, the adolescents in this sample may spend less time on social media and be at a lower risk of mental health struggles, which also may have contributed to the lack of significant findings.

Considering these limitations, future research should extend to a larger, more diverse sample of adolescents to consider the effects of SMIs, PSR strength, and mental health. We found some significant relationships between PSR strength and mental health symptoms in this small sample, and these associations are likely exacerbated among vulnerable populations. While adolescents with poor self-regulation and those who have high PSMU are vulnerable groups, there are a plethora of other characteristics to consider that may make adolescents vulnerable to the influence of SMIs. For example, adolescents with existing diagnoses, younger adolescent girls (ages 10 to 14 years), and adolescents with low social support, for example from low SES backgrounds or of marginalized groups (e.g., sexual or racial minorities), are identified as at-risk groups for poor mental health resulting from social media use (Odgers & Jensen, 2020; Pitt et al., 2021) and should be more heavily considered in research moving forward.

Conclusion

Overall, the results of these four studies help us identify at-risk populations who are particularly vulnerable to the negative effects of social media use on mental health outcomes (i.e., adolescents with poor self-regulation, those who engage in high PSMU, and females). While there are plenty of professional resources that exist, adolescents are turning to UGC for mental health information and this experiential knowledge may be having detrimental effects. We also answer the call for a more nuanced approach to understanding media effects and mental health by considering specific populations as well as particular types of content that may exacerbate negative effects. Across our three studies, adolescents with poor self-regulation and those who use social media in problematic ways consistently demonstrated worse mental health outcomes on both clinical measurements of symptoms (i.e., anxiety and depression) as well as self-reported mental health conditions. Therefore, this group of adolescents are particularly susceptible to the negative effects that social media use can have on mental health. As suggested by prior research (e.g., Twenge et al., 2018), adolescent females in particular appear to be a highly at-risk group as we found consistent relationships between gender and mental health outcomes across all studies. Indeed, a study conducted by Campbell and colleagues (2021) found that, across 73 countries, female adolescents experience more mental health problems compared to males.

We also found consistent mediating effects of social media use frequency and content type on mental health, meaning that facets of social media use explain some portion of the relationship between self-regulation skills and PSMU and mental health outcomes. Indeed, in our two survey studies (Study 2 and Study 3) we show that adolescents who consumed mental health content on social media exhibited greater anxiety and depression symptoms through clinical measures, and also self-reported more mental health conditions. In the context of COVID-19 restrictions and lockdowns when Study 2 data was collected, this relationship was observed for content, but not frequency of social media use. During the lockdown restrictions, SM frequency was associated with greater self-report of mental health conditions, but not actual symptom displays. These findings underline the importance of investigating the specific content to which adolescents are exposed, as content (mental health in this case) had more of a consistent relationship with mental health outcomes than did sheer frequency of use. Yet, it is necessary to consider both metrics as frequency was related to adolescent perceptions of their mental health more consistently than actual symptomatology. Through repeated exposure to mental health content, adolescents were more likely to think that they had a mental health condition. Therefore, future research should consider both frequency and content to get a more complete picture of how social media use relates to outcomes. Further, in Study 3 frequency of use was significantly related to both symptomatology and self-report, revealing how non-deliberate social media use can exacerbate negative outcomes. During the lockdown restrictions, adolescents were more thoughtful and conscious of their media use in line with increased free time and warnings about negative effects on mental health, which acted as a buffer against negative effects from a frequency perspective. However, once restrictions uniformly lifted and adolescents went back to “normal” life, they began to experience poorer mental health in relation to their frequency of use as it was less salient. This perhaps supports previous research on the harmful effects of fragmented social media use (Siebers et al., 2022). That is, during the restrictions, adolescents were mindful and reported guilt at spending longer than intended on social media (Pitt et al., 2021). Once they were back to school and other activities that structure their time, they likely engaged in more fragmented social media use (e.g., in-between classes, breaks, car journeys home and to other events), as there was very little change in mean time spent on social media between the two studies, yet frequency negatively related to mental health symptoms in Study 3. Therefore, as suggested by (Siebers et al., 2022), quick bursts of social media use in short time frames may actually be more harmful to mental health than spending a few hours at a time online.

The lack of significant findings in our Study 4 experiment in regards to video condition and mental health symptoms may be in part explained by the single exposure. Indeed, both frequency of exposure and the amount of mental health content consumed on social media were predictive of mental health outcomes in our two surveys. Therefore, SMIs may have a significant persuasive effect on the mental health conditions that adolescents self-report over time. Parasocial relationships exist beyond the media exposure and form over time (Sokolova & Perez, 2020), and thus, a single video may not have been enough to evoke a strong response. However, though the relationships were not statistically significant, the parasocial relationship strengths reported for the anxiety ($M = 3.2$) and depression ($M = 3.1$) video conditions were far higher than that of the control condition (*M* = 1.8) that did not reference mental health in any way. This suggests that self-disclosure of mental health can influence viewers, and the relationship likely only strengthens through repeated exposure. Though we only explored mental health symptoms and self-report in this study, if disclosing mental health increases the likelihood and strength of viewers forming PSRs with SMIs, this can have serious implications on various facets of behavior. As discussed above, with increased strength of PSR, viewers more readily accept advice from SMIs as they like and trust them more (Sokolova & Perez, 2020). Our content analysis revealed that videos about mental health contained limited amounts of credible, professional support in discussions of symptoms and treatment options. They also contained a high frequency of negative opinions in relation to mental health and recovery. This is concerning as adolescent viewers, particularly when they experience high PSR, may be discouraged from seeking specific types of treatment, asking for support, or feeling like they can get better. Online video platforms, such as YouTube and TikTok, appear to be more harmful to adolescent mental health due to the prevalence of mental health content coupled with the attention-grabbing, emotion-inducing nature of video content (Devendorf et al., 2020).

Limitations and future directions

A limitation of this set of studies is that we only considered mental health as an outcome of social media use. However, as discussed in the DSMM, media effects are transactional. That is, social media use (i.e., frequency and exposure to mental health content) can be contributing to adolescents' poor mental health, and mental health symptoms and perceptions of having a mental health condition can further influence them to repeatedly seek out mental health content, creating a reinforcing downward spiral. Though we initially set out to identify the populations and mechanisms by which social media users self-diagnose as a result of trends in mental health information online, we ultimately provided further evidence of adolescent populations who are vulnerable to the effects of social media and found that the ones who need help the most are those that may not know it.

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Appendix

I. **Study 1**

A. Codebook

Variable	**Example**	**Instructions**
YouTube content characteristics		
Video title	trying ADHD medication for the first time... (methylphenidate)	Indicate the title of the video as it is stated on YouTube.
Video link	https://www.youtube.com/watch?v=AT-Mqj7WWBE	Copy and paste the link to the video.
Video views	3.2 million = 3200000	Indicate video views numerically.
Video likes	22k = 22000	Indicate video likes numerically. ****Some channels/videos do not have this public, so if this is the case enter NA*
Tags on video *In the description box of the video, YouTubers can hashtag their videos to make them easier to find/searchable.*	#GoodNeighborEveryday #ad	If there are tags on the video, enter them in a single cell in the spreadsheet, separated by commas ****If there are no tags, enter NA*
Mental health tagging *Does the tag(s) reference mental health?*	#Depression	0 = No reference 1 = Reference to mental health
Comments *Are the comments turned off for the video?*		0 = off 1 = on
Number of comments	364	Indicate the number of comments on the video.
SMI characteristics		

Profile	SamanathaNicole222	Indicate the name of the profile as it is stated on the platform
Followers/Subscribers	15.4k = 15400	Indicate the number of followers/subscribers as stated when you select the profile/channel. ****Some profiles/channels have this turned off, so write NA if that is the case*
SMI type *Nano influencers (between 1,000 and 5,000 followers); Micro influencers (between 5,000 and 20,000 followers); Power or mid-tier influencers (between 20,000 and 100,000 followers); Mega influencers (between 100,000 and 1 million followers), and SMI Celebrities (more than 1 million followers).*	15400 = 2	0 = Less than 1,000 1 = Nano 2 = Micro 3 = Power 4 = Mega 5 = Celebrity
Gender		1 = Male 2 = Female 9 = Unspecified
Race		1 = White 2 = Black 3 = Asian 4 = Hispanic 5 = American Indian 6 = Two or more races 7 = Other 9 = Unspecified
Mental disorder *Mental disorders refer to both mental illness and neurodevelopmental disorder (NDD) conditions.*		

Mental health related *Does the video discuss or reference mental disorders in any way?*	'Today I wanted to share a day in my life with anxiety and how I make myself feel better.'	0 = no 1 = yes
Experience		
General experience *Comments on own experience*	'Getting diagnosed was not fun.'	0 = Not present 1 = Present 10 = Not applicable
Others' general experience *Comments on the experience of others*	'This is my sister and she also has ADHD.'	0 = Not present 1 = Present 10 = Not applicable ****Only code if a specific other is being discussed*
Experience of being bullied *Comments on own experience of being bullied or cyberbullied*	'I was laughed at, or I was criticized by the way I acted.'	0 = Not present 1 = Present 10 = Not applicable
Others' experience of being bullied *Comments on the bullying or cyberbullying experience of others*	"Two of my friends were made fun of in college for acting differently.'	0 = Not present 1 = Present 10 = Not applicable ****Only code if a specific other is being discussed*
Opinion		
Self-opinion *The contributor asserts a subjective or evaluative position*	'Things will get easier, people's minds will change.' or 'I am helpless.'	0 = Not present 1 = Present 10 = Not applicable
Self-opinion valence	'I am lazy.' versus 'I do the best I can.'	0 = Not present 1 = Negative 2 = Positive
Others' opinion *Comments on the opinions of others*	'People with depression are lazy.'	0 = Not present 1 = Present 10 = Not applicable
Others' opinion valence	'People with depression are different.' versus 'People with depression deserve support.'	0 = Not present 1 = Negative 2 = Positive
Empathy *Recognises the emotions of others;*	'I want anyone out there who feels different and alone to know	0 = Not present 1 = Present

shows compassion	that I know how you feel.’	10 = Not applicable
Exhort *Encouraging others to do something, for example, view a website, subscribe or to think positively*	‘Subscribe, share, pin me to your homepage - do all the good stuff.’	0 = Not present 1 = Present 10 = Not applicable
Information		
Demographics on self *Information disclosing the name, age, location, contact details or mental disorder conditions of the contributor*	‘My name is [first name], and I’m 30 years old, I live here in [name of a US State]’ incl. disclosure of condition	0 = Not present 1 = Present 10 = Not applicable
Comorbidity *Information disclosing multiple mental disorder conditions of the contributor (i.e., ADHD and Anxiety Disorder)*	‘I have anxiety and depression.’	0 = Not present 1 = Present 10 = Not applicable
Conditions mentioned	Bipolar disorder and depression	String
Suicidal ideation	‘I wanted to not be alive anymore.’	0 = Not present 1 = Present 10 = Not applicable
Demographics on others *Information disclosing the name, age, location, contact details or mental disorder conditions of others*	‘I have a brother who is also autistic.’	0 = Not present 1 = Present 10 = Not applicable
Factual information for others *Comments on statistics, study findings or general information including laws/policies* ** backed by facts and stats*	‘More than 5.4 million U.S. adults are diagnosed with Autism Spectrum Disorder.’	0 = Not present 1 = Present 10 = Not applicable
Information about treatment *Comments on information about treatment options, including therapy, self-help, medication, etc.* **more personal*	‘I went to a psychiatrist to get diagnosed and prescribed medication.’	0 = Not present 1 = Present 10 = Not applicable
Information sources *Were there any sources provided for information presented?*	‘According to the CDC, most mental illnesses are present by age 14.’	0 = Not present 1 = Present 10 = Not applicable

Disclosure of medication *Comments on taking medication for condition*	‘Today is my first day on ADHD medication.’	0 = Not present 1 = Present 10 = Not applicable
Solicit information *Requests information from others, for example, asks for advice*	‘Comment down below and tell me what you do to help manage your anxiety.’	0 = Not present 1 = Present 10 = Not applicable
Advertise *Advertises products and/or services*	‘For $20 a month Better Help will provide a safe space to talk about issues.’	0 = Not present 1 = Present 10 = Not applicable *Note. Only products or services related to mental disorders.*

B. Intercoder Reliability

Table 1A

Intercoder Reliability

Variable	*Gwet's AC2*
SMI characteristics	
Gender	1.00
Race	0.91
Mental health	
General experience	0.91
Others' general experience	1.00
Experience of being bullied	0.98
Others' experience of being bullied	1.00
Self-opinion	0.89*
Self-opinion valence	0.78*
Others' opinion	0.92
Others' opinion valence	0.92
Empathy	0.83*
Exhort	0.92*
Demographics on self	0.97*
Comorbidity	0.83*

Suicidal ideation	0.83*
Demographics on others	0.98
Factual information for others	0.84*
Information on treatment	0.76*
Information sources	0.77*
Disclosure of medication	0.95
Solicit information	0.94
Advertise	1.00

Note. Gwet's AC2 values with an asterisk (*) indicate a second round of reliability was conducted.

C. Results

Table 2A

Correlations between Study Variables

	1	2	3	4	5	6	7	8	9
1. Views	1	**.984****	.038	**.525****	**.955****	**.299****	**.274****	**-.344****	.124
2. Likes	**.984****	1	.035	**.496****	**.951****	**.397****	**.289****	**-.402****	.149
3. Video length	.038	.035	1	**.049**	.011	-.073	.025	.081	.075
4. Months posted	**.525****	**.496****	.049	1	**.577****	-.065	-.064	-.120	.011
5. Comments	**.955****	**.951****	.011	**.577****	1	**.384****	**.257****	**-.495****	.083
6. Followers	**.299****	**.397****	-.073	-.065	**.384****	1	**.338****	**-.796****	-.034
7. SMI type	**.274****	**.289****	.025	-.064	**.257****	**.338****	1	**-.164***	.103
8. Gender	**-.344****	**-.402****	.081	-.120	**-.495****	**-.796****	**-.164***	1	.101
9. Race	.124	.149	.075	.011	.083	-.034	.103	.101	1
10. Mental health related	.133	.120	.080	**.377****	.149	-.044	**-.251****	-.048	.061
11. Experience	.127	.103	.138	**.349****	.139	-.125	**-.220****	.044	.031
12. Others' experience	-.075	-.077	.058	.093	-.066	-.067	-.084	.046	.072
13. Bullying	-.028	-.029	-.005	.087	-.022	-.036	-.099	.020	.043
14. Others' bullying	.a	.a	.a	.a	.a	.a	.a	.a	.a
15. Self-opinion	**.185***	**.164***	**.181***	**.412****	**.199***	-.014	-.004	-.065	.075
16. Self-opinion valence	.131	.115	**.233****	**.330****	.137	-.028	-.005	-.035	.057
17. Others' opinion	.162	.148	**.277****	**.173***	**.203***	-.055	-.008	.053	-.038
18. Others' opinion valence	.162	.148	**.277****	**.173***	**.203***	-.055	-.008	.053	-.038
19. Empathy	-.068	-.070	**.174***	.161	-.053	-.141	-.073	.025	.025
20. Exhort	-.100	-.102	.124	.122	-.089	-.140	-.162	.050	.019
21. Self demographics	.031	.048	**.199***	.119	.067	.024	**-.220****	-.046	.007
22. Comorbidity	-.067	-.072	**.180***	.128	-.048	-.085	.004	.090	.096
23. Suicidal ideation	.047	.064	**.330****	.158	.042	-.050	-.120	.058	.090
24. Others' demographics	-.059	-.061	**.024**	-.036	-.048	-.010	-.123	.041	.073
25. Factual information for others	.131	.111	**.252****	**.263****	.108	-.074	-.079	.096	.072
26. Information on treatment	.152	.148	**.288****	**.341****	.133	-.075	.059	.037	.106
27. Information sources	**-.195***	**-.214****	**-.180***	**-.355****	**-.224****	-.095	.086	.154	-.053
28. Medication	-.125	-.132	**.262****	**.173***	-.102	-.099	**-.260****	.083	.008
29. Solicit information	-.054	-.056	-.043	.025	-.054	-.054	-.133	.032	-.114
30. Advertise	-.036	-.041	.014	-.036	-.041	-.025	.136	.029	.000

10	11	12	13	14	15	16	17	18	19	20
.133	.127	-.075	-.028	.a	.185*	.131	.162	.162	-.068	-.100
.120	.103	-.077	-.029	.a	.164*	.115	.148	.148	-.070	-.102
.080	.138	.058	-.005	.a	.181*	.233**	.277**	.277**	.174*	.124
.377**	.349**	.093	.087	.a	.412**	.330**	.173*	.173*	.161	.122
.149	.139	-.066	-.022	.a	.199*	.137	.203*	.203*	-.053	-.089
-.044	-.125	-.067	-.036	.a	-.014	-.028	-.055	-.055	-.141	-.140
-.251**	-.220**	-.084	-.099	.a	-.004	-.005	-.008	-.008	-.073	-.162
-.048	.044	.046	.020	.a	-.065	-.035	.053	.053	.025	.050
.061	.031	.072	.043	.a	.075	.057	-.038	-.038	.025	.019
1	.912**	.218**	.095	.a	.547**	.490**	.251**	.251**	.363**	.325**
.912**	1	.155	.092	.a	.500**	.475**	.244**	.244**	.377**	.334**
.218**	.155	1	-.032	.a	.047	-.034	.105	.105	-.011	.058
.095	.092	-.032	1	.a	.173*	.121	-.037	-.037	.173*	.147
.a	.a	.a	.a	.a	.a	.a	.a	.a	.a	.a
.547**	.500**	.047	.173*	.a	1	.872**	.304**	.304**	.489**	.237**
.490**	.475**	-.034	.121	.a	.872**	1	.243**	.243**	.506**	.247**
.251**	.244**	.105	-.037	.a	.304**	.243**	1	1.000**	.148	.141
.251**	.244**	.105	-.037	.a	.304**	.243**	1.000**	1	.148	.141
.363**	.377**	-.011	.173*	.a	.489**	.506**	.148	.148	1	.450**
.325**	.334**	.058	.147	.a	.237**	.247**	.141	.141	.450**	1
.230**	.296**	-.033	.032	.a	.129	.168*	.086	.086	.129	.109
.392**	.380**	-.015	.222**	.a	.314**	.301**	.181*	.181*	.207*	.148
.179*	.217**	-.004	.154	.a	.303**	.312**	.210*	.210*	.400**	.328**
.069	.063	.292**	-.029	.a	-.101	-.149	.029	.029	-.166*	-.134
.452**	.439**	.100	.209*	.a	.272**	.262**	.273**	.273**	.237**	.237**
.531**	.544**	.083	.160	.a	.489**	.520**	.172*	.172*	.427**	.321**
-.408**	-.379**	-.125	-.108	.a	-.354**	-.322**	-.122	-.122	-.330**	-.225**
.392**	.381**	.280**	.242**	.a	.228**	.158	.213*	.213*	.115	.284**
.151	.147	-.052	-.023	.a	-.130	-.116	-.060	-.060	.114	.234**
.135	.131	-.046	-.020	.a	-.025	.035	-.053	-.053	.247**	.122

21	22	23	24	25	26	27	28	29	30
.031	-.067	.047	-.059	.131	.152	-.195*	-.125	-.054	-.036
.048	-.072	.064	-.061	.111	.148	-.214**	-.132	-.056	-.041
.199*	.180*	.330**	.024	.252**	.288**	-.180*	.262**	-.043	.014
.119	.128	.158	-.036	.263**	.341**	-.355**	.173*	.025	-.036
.067	-.048	.042	-.048	.108	.133	-.224**	-.102	-.054	-.041
.024	-.085	-.050	-.010	-.074	-.075	-.095	-.099	-.054	-.025
-.220**	.004	-.120	-.123	-.079	.059	.086	-.260**	-.133	.136
-.046	.090	.058	.041	.096	.037	.154	.083	.032	.029
.007	.096	.090	.073	.072	.106	-.053	.008	-.114	.000
.230**	.392**	.179*	.069	.452**	.531**	-.408**	.392**	.151	.135
.296**	.380**	.217**	.063	.439**	.544**	-.379**	.381**	.147	.131
-.033	-.015	-.004	.292**	.100	.083	-.125	.280**	-.052	-.046
.032	.222**	.154	-.029	.209*	.160	-.108	.242**	-.023	-.020
.a	.a	.a	.a	.a	.a	.a	.a	.a	.a
.129	.314**	.303**	-.101	.272**	.489**	-.354**	.228**	-.130	-.025
.168*	.301**	.312**	-.149	.262**	.520**	-.322**	.158	-.116	.035
.086	.181*	.210*	.029	.273**	.172*	-.122	.213*	-.060	-.053
.086	.181*	.210*	.029	.273**	.172*	-.122	.213*	-.060	-.053
.129	.207*	.400**	-.166*	.237**	.427**	-.330**	.115	.114	.247**
.109	.148	.328**	-.134	.237**	.321**	-.225**	.284**	.234**	.122
1	.146	.093	.066	.091	.145	-.148	.134	.052	-.120
.146	1	.146	.016	.320**	.233**	-.169*	.370**	.081	.113
.093	.146	1	-.083	.231**	.365**	-.202*	.177*	-.065	.081
.066	.016	-.083	1	.004	-.053	-.090	.187*	-.046	-.041
.091	.320**	.231**	.004	1	.528**	-.483**	.417**	.069	.200*
.145	.233**	.365**	-.053	.528**	1	-.639**	.260**	.097	.228**
-.148	-.169*	-.202*	-.090	-.483**	-.639**	1	-.292**	-.087	-.125
.134	.370**	.177*	.187*	.417**	.260**	-.292**	1	.003	.024
.052	.081	-.065	-.046	.069	.097	-.087	.003	1	.430**
-.120	.113	.081	-.041	.200*	.228**	-.125	.024	.430**	1

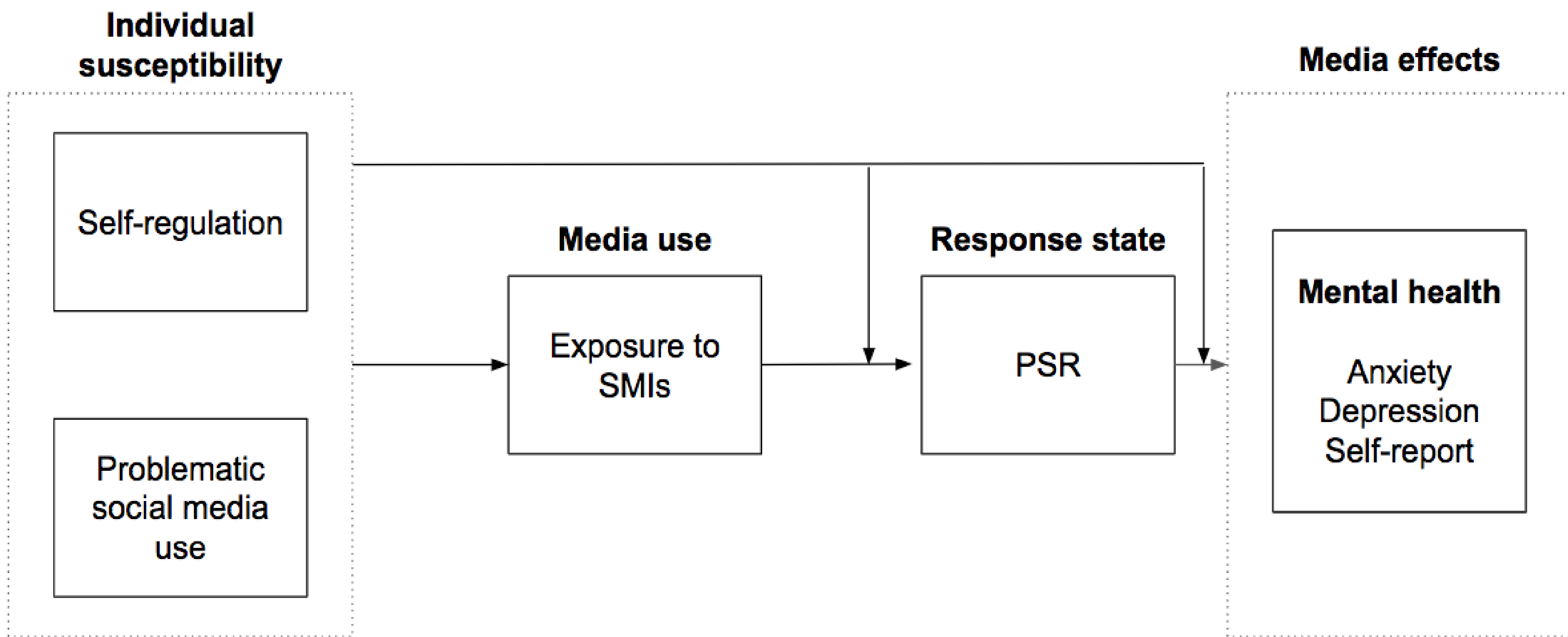
Table 3A
Descriptive Statistics for YouTube Videos

Variable	*Total Sample (N = 144)*		*Mental health-related (n = 88)*		*Not mental health-related (n = 56)*	
	Mean	*Range*	*Mean*	*Range*	*Mean*	*Range*
Video views	421,545.59	101 - 9,572,953	574,344.15	101 - 9,572,953	181,433.57	167 - 2,275,878
Video likes	23,581.34	4 - 484,000	31,055.03	10 - 484,000	11,836.96	4 - 183,000
Video length (in seconds)	985.00	168 - 3,517	1,016.40	168 - 3,517	935.64	270 - 2325
Months posted	11.72	0-87	15.97	1-87	5.05	0-15
Tags on video						
Mental health tags	7.45	0-9	8	0-9	6.59	0-9
Number of comments	1,328.72	0 - 31,000	1,869.27	0 - 31,000	479.27	1 - 12,000
SMI characteristics						
Channel subscribers	1,408,116	374 - 29,300,000	1,253,181.5	374 - 29,300,000	1,651,584.6	1,230 - 29,300,000
SMI type	3.27	0-5	2.97	0-5	3.75	0-5
Less than 1,000	*2*		*2*		*0*	
Nano	*8*		*7*		*1*	
Micro	*4*		*2*		*2*	

Power	*6*		*3*		*3*	
Mega	*17*		*10*		*7*	
Celebrity	*11*		*6*		*5*	
Gender	1.97	1-2	1.97	1-2	1.98	1-2
Male	*3*		*1*		*1*	
Female	*45*		*85*		*56*	
Race	2.25	1-9	2.35	1-9	2.09	1-9
White	*29*		*52*		*35*	
African-American	*4*		*7*		*5*	
Asian	*7*		*13*		*8*	
Hispanic	*3*		*5*		*4*	
Two or more	*1*		*3*		*0*	
Other	*2*		*4*		*2*	
Unspecified	*2*		*4*		*2*	

II. Study 2 and 3

A. Theoretical Model



B. Survey Measures

1. *Self-regulation - Adolescent Self-Regulatory Inventory (Moilanen, 2007)*

How would you respond to the following statements?

1 - Not at all true for me; 2 - Somewhat true for me; 3 - Really true for me

1. When I'm bored, I fidget or can't sit still.
2. I am good at keeping track of lots of things going on around me, even when I'm feeling stressed.
3. I can start a new task even if I'm already tired.
4. Little problems distract me from my long-term plans.
5. I forget about whatever else I need to do when I'm doing something really fun.
6. After I'm interrupted or distracted, I can easily continue working where I left off.
7. If there are other things going on around me, I find it hard to keep my attention focused on whatever I'm doing.
8. I can calm myself down when I'm excited or all wound up.

2. *Problematic social media use (Domoff et al., 2019)*

In the past 30 days, how often did each of these happen?

1 - Never; 2 - Rarely; 3 - Sometimes; 4 - Often; 5 - Always

1. It was hard to stop using social media.
2. I became frustrated when I could not use social media.
3. Social media made it harder to fall/stay asleep.
4. Social media caused problems for me with my family or friends.
5. Social media interfered with my school work.

3. *Social media use frequency*

On an average school day, how much time do you spend doing the following things each day?

1 - None; 2 - Less than 30 minutes; 3 - 31 - 59 minutes; 4 - 1 - 2 hours; 5 - 3 - 4 hours; 6 - 5 - 6 hours; 7 - 7 - 8 hours; 8 - More than 8 hours

a) Social media (e.g., Instagram, Snapchat, Twitter, Marco Polo)
b) Watching YouTube or Tiktok*

4. *Anxiety (PROMIS Short Form; APA, 2013)*

Think back over the last 7 days, please indicate how often you have been bothered by the following problems:

1 - Never; 2 - Rarely; 3 - Sometimes; 4 - Often; 5 - Always

1. I felt uneasy
2. I felt nervous
3. Many situations made me worry
4. My worries overwhelmed me
5. I felt tense

6. I had difficulty calming down
7. I had sudden feelings of panic
8. I felt nervous when my normal routine was disturbed

5. *Depression - Participant Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001)*

Over the last 2 weeks, how often have you been bothered by any of the following problems?

1 - Not at all; 2 - Several days; 3 - More than half the days; 4 - Nearly every day

1. Little interest or pleasure in doing things
2. Feeling down, depressed, or hopeless
3. Trouble falling or staying asleep, or sleeping too much
4. Feeling tired or having little energy
5. Poor appetite or overeating
6. Feeling bad about yourself — or that you are a failure or have let yourself or your family down
7. Trouble concentrating on things, such as reading the newspaper or watching television
8. Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual

6. *General mental health*

In the last 30 days, have you suffered from any health or mental health problems, personally? (check all that apply)

- Frequent headaches or migraines
- Depression
- Anxiety
- Sleep disorders
- Eating disorders
- Frequent stomach aches
- Attention Deficit or Hyperactive Disorder (ADD/ADHD)

7. *Influence*

8. *Topics followed*

Do you follow or connect to others on social media around any of the following health topics? If so how does it make you feel?

1 - I do not do this; 2 - Usually makes me feel worse; 3 - Makes me feel about the same; 4 - Usually makes me feel better

- Anxiety
- Depression
- Stress

9. *Affective response*

Do you follow or connect to others on social media around any of the following health topics? If so how does it make you feel?

1 - I do not do this; 2 - Usually makes me feel worse; 3 - Makes me feel about the same; 4 - Usually makes me feel better

Note. *denotes the item was only included in Study 3.

C. Results

Table 4A
Study 2 Descriptive Statistics and Correlations between Independent and Dependent Variables

	1	2	3	4	5	6	7	8	9	10	11
1. Age	-	-	-	-	-	-	-	-	-	-	-
2. Gender	.01	-	-	-	-	-	-	-	-	-	-
3. Race	.05	.02	-	-	-	-	-	-	-	-	-
4. Self-regulation	-.05	**-.24****	**-.08****	-	-	-	-	-	-	-	-
5. PSMU	.02	**.22****	.01	**-.28****	-	-	-	-	-	-	-
6. SM Frequency	**.11***	**.12****	-.02	**-.13****	**.29****	-	-	-	-	-	-
7. Mental health topics	-.01	**.27****	**.07***	**-.22****	**.29****	**.15****	-	-	-	-	-
8. Affective response	-.00	**.24****	.06	**-.20****	**.25****	**.12****	**.90****	-	-	-	-
9. Anxiety	**.08****	**.34****	**.07***	**-.44****	**.36****	**.13****	**.39****	**.35****	-	-	-
10. Depression	.04	**.32****	-.01	**-.44****	**.36****	**.17****	**.37****	**.32****	**.70****	-	-

11. Mental health self-report	-.01	**.33****	**.13****	**-.36****	**.27****	**.18****	**.42****	**.40****	**.57****	**.63****	-
Mean	15.28	0.8	0.48	1.84	2.42	4.11	1.35	2.4	3.02	2.41	2.26
SD	0.76	0.55	0.50	0.36	0.91	1.67	1.32	2.95	1.00	0.81	1.88

Table 5A

Study 3 Descriptive Statistics and Correlations between Independent and Dependent Variables

	1	2	3	4	5	6	7	8	9	10	11
1. Age	-	-	-	-	-	-	-	-	-	-	-
2. Gender	.04	-	-	-	-	-	-	-	-	-	-
3. Race	-.02	-.04	-	-	-	-	-	-	-	-	-
4. Self-regulation	-.03	-.22**	.10**	-	-	-	-	-	-	-	-
5. PSMU	.06*	.08**	.07*	-.21**	-	-	-	-	-	-	-
6. SM Frequency	.06*	.04	-.03	-.08**	.34**	-	-	-	-	-	-
7. Mental health topics	.10**	.20**	.02	-.19**	.37**	.22**	-	-	-	-	-
8. Affective response	.12**	.19**	.05	-.17**	.33**	.22**	.89**	-	-	-	-
9. Anxiety	.12**	.32**	-.05	-.50**	.40**	.24**	.43**	.40**	-	-	-
10. Depression	.10**	.29**	-.06*	-.45**	.43**	.27**	.42**	.39**	.75**	-	-

11. Mental health self-report	**.11****	**.34****	.01	**-.39****	**.23****	**.14****	**.34****	**.32****	**.61****	**.62****	-
Mean	16.75	0.77	0.48	1.94	2.47	4.15	1.49	2.64	2.92	2.31	2.08
SD	1.18	0.54	0.50	0.39	1.04	1.69	1.34	3.01	1.11	0.86	1.83

III. Study 4

A. Survey instrument

1. Intro/qualification questions
    a) How old are you?
        (1) 13
        (2) 14
        (3) 15
        (4) 16
        (5) 17
        (6) Other (if selected skip to end)
    b) Do you speak English?
        (1) Yes
        (2) No (if selected skip to end
    c) Do you use social media?
        (1) Yes
        (2) No (if selected skip to end)
    d) Do you follow any influencers on social media?
        (1) Yes
        (2) No (if selected skip to end)
2. Demographics
    a) How do you identify?
        (1) American Indian or Alaskan native
        (2) Asian
        (3) Black or African American
        (4) Hispanic, Latino/a/x, or of Spanish origin
        (5) Native Hawaiian or Other Pacific Islander
        (6) White
        (7) Other race, ethnicity, or origin
        (8) Prefer to self-describe (text entry)
        (9) Prefer not to answer
    b) How do you identify?
        (1) Female
        (2) Male
        (3) Transgender
        (4) Non-binary or gender queer
        (5) Prefer to self-describe (text entry)
        (6) Prefer not to answer
    c) What grade are you in?
        (1) 9th
        (2) 10th

        (3) 11th
        (4) 12th
        (5) Other

3. Self-regulation - Adolescent Self-Regulatory Inventory (Moilanen, 2007)
   How would you respond to the following statements?
   1 - Not at all true for me; 2 - Somewhat true for me; 3 - Really true for me
   a) When I'm bored, I fidget or can't sit still.
   b) I am good at keeping track of lots of things going on around me, even when I'm feeling stressed.
   c) I can start a new task even if I'm already tired.
   d) Little problems distract me from my long-term plans.
   e) I forget about whatever else I need to do when I'm doing something really fun.
   f) After I'm interrupted or distracted, I can easily continue working where I left off.
   g) If there are other things going on around me, I find it hard to keep my attention focused on whatever I'm doing.
   h) I can calm myself down when I'm excited or all wound up.
4. Problematic social media use
   In the past 30 days, how often did each of these happen?
   1 - Never; 2 - Rarely; 3 - Sometimes; 4 - Often; 5 - Always
   a) It was hard to stop using social media.
   b) Social media was the only thing that seems to motivate me.
   c) Social media was all I seemed to think about.
   d) Social media caused problems for me with my family or friends.
   e) I became frustrated when I could not use social media.
   f) The amount of time I want to use social media keeps increasing.
   g) Social media made it harder to fall/stay asleep.
   h) Social media interfered with my school work.
   i) When I have a bad day, social media seems to be the only thing that helps me feel better.
5. Social media use
   a) Which of the following social media sites have you used in the last month? (select all that apply)
      (1) YouTube
      (2) Instagram
      (3) TikTok
      (4) SnapChat
      (5) Twitter
      (6) Facebook

(7) Pinterest
(8) Other (please specify)

b) How much time do you spend on (insert logic for responses to Q1)in an average day?

1 - None; 2 - Less than 30 minutes; 3 - 31 - 59 minutes; 4 - 1 - 2 hours; 5 - 3 - 4 hours; 6 - 5 - 6 hours; 7 - 7 - 8 hours; 8 - More than 8 hours

c) Who is your favorite influencer on social media? (text entry)

d) How often do you check the posts of (insert logic for response to Q3) on (insert logic for response to Q1)?

1 – Never; 2 - At least once a month; 3 - Rarely (0 - 1 time per week); 4 - Sometimes (2 - 4 times per week); 5 - Often (5 - 7 times per week); 6 - Very often (at least once a day); 7 = Almost constantly (multiple times each day)

6. Parasocial involvement

1 = Strongly disagree, 2 = Disagree, 3 = Neither disagree nor agree, 4 = Agree, 5 = Strongly agree

a) (insert logic for response to Q3) makes me feel comfortable, as if I am with a friend.
b) I look forward to seeing (insert logic for response to Q3)'s next post.
c) I see (insert logic for response to Q3) as a natural, down-to-earth person.
d) If (insert logic for response to Q3) starts another social media channel, I will also follow.
e) (insert logic for response to Q3) seems to understand the kinds of things I want to know.
f) If I see a story about (insert logic for response to Q3) in other places, I would read it.
g) I miss seeing (insert logic for response to Q3) when they do not post on time.
h) I would like to meet (insert logic for response to Q3) in person.
i) If something happens to (insert logic for response to Q3), I will feel sad.
j) I would invite (insert logic for response to Q3) to my party.
k) (insert logic for response to Q3) is the kind of person I would like to play or hang out with.
l) If (insert logic for response to Q3) lived in my neighborhood we would be friends.
m) (insert logic for response to Q3) would fit in well with my group of friends.

7. Video condition (randomized)
8. Parasocial involvement
   1 = Strongly disagree, 2 = Disagree, 3 = Neither disagree nor agree, 4 = Agree, 5 = Strongly agree
   a) (insert logic for video condition) makes me feel comfortable, as if I am with a friend.
   b) I look forward to seeing (insert logic for video condition)'s next post.
   c) I see (insert logic for video condition) as a natural, down-to-earth person.
   d) If (insert logic for video condition) starts another social media channel, I will also follow.
   e) (insert logic for video condition) seems to understand the kinds of things I want to know.
   f) I would like to meet (insert logic for video condition) in person.
9. Anxiety (PROMIS Short Form)
   Think back over the last 7 days, please indicate how often you have been bothered by the following problems:
   1 - Never; 2 - Rarely; 3 - Sometimes; 4 - Often; 5 - Always
   a) I felt uneasy
   b) I felt nervous
   c) Many situations made me worry
   d) My worries overwhelmed me
   e) I felt tense
   f) I had difficulty calming down
   g) I had sudden feelings of panic
   h) I felt nervous when my normal routine was disturbed
10. Depression - Participant Health Questionnaire-9 (PHQ-9; Kroenke et al., 2001)
    Over the last 2 weeks, how often have you been bothered by any of the following problems?
    1 - Not at all; 2 - Several days; 3 - More than half the days; 4 - Nearly every day
    a) Little interest or pleasure in doing things
    b) Feeling down, depressed, or hopeless
    c) Trouble falling or staying asleep, or sleeping too much
    d) Feeling tired or having little energy
    e) Poor appetite or overeating
    f) Feeling bad about yourself — or that you are a failure or have let yourself or your family down

g) Trouble concentrating on things, such as reading the newspaper or watching television
h) Moving or speaking so slowly that other people could have noticed? Or the opposite — being so fidgety or restless that you have been moving around a lot more than usual

11. In the last 30 days, have you suffered from any health or mental health problems, personally? (check all that apply)
    a) Depression
    b) Anxiety
    c) Sleep disorders
    d) Frequent stomach aches
    e) Attention Deficit or Hyperactive Disorder (ADD/ADHD)

B. Video stimuli

1. Video 1: Anxiety https://www.youtube.com/watch?v=5mRdzsn0cnQ
2. Video 2: Depression https://www.youtube.com/watch?v=gkZiBnL0h7Y
3. Video 3: Control (no mental health) https://www.youtube.com/watch?v=e5CRzuRO8kg

C. Results

Table 6A
Study 4 Descriptive Statistics and Correlations between Independent and Dependent Variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Age	-	-	-	-	-	-	-	-	-	-	-	-	-	-
2. Gender	-.02	-	-	-	-	-	-	-	-	-	-	-	-	-
3. Race	-.02	.09	-	-	-	-	-	-	-	-	-	-	-	-
4. Self-regulation	-.05	.01	-.11	-	-	-	-	-	-	-	-	-	-	-
5. PSMU	.03	.09	-.10	**-.44****	-	-	-	-	-	-	-	-	-	-
6. SM Frequency	-.01	.00	.04	-.06	**.36****	-	-	-	-	-	-	-	-	-
7. SMI Frequency	-.04	-.09	-.05	-.02	.01	-.03	-	-	-	-	-	-	-	-
8. PSR with SMI	**.21***	**-.20***	-.16	-.08	.11	-.03	.17	-	-	-	-	-	-	-
9. PSR - Condition 1	.11	.06	.03	.01	.12	.07	.02	-.06	-	-	-	-	-	-
10. PSR - Condition 2	.11	-.09	-.09	-.03	**-.23***	-.18	.09	.04	**-.48****	-	-	-	-	-

11. PSR - Condition 3	**-.28****	.12	.10	-.04	.13	.10	-.13	.06	**-.42****	**-.41****	-	-	-	-
12. Anxiety	.12	**.23***	.04	**-.27****	.28**	.02	.04	-.04	**.28****	-.05	-.04	-	-	-
13. Depression	.04	**.20***	.15	**-.39****	**.44****	.12	.00	-.05	.07	-.02	.09	**.66****	-	-
14. Mental health self-report	.02	**.35****	.10	**-.33****	.11	-.07	.03	-.01	.07	.05	-.06	**.50****	**.61****	-
Mean	15.52	1.45	0.54	1.96	2.42	2.36	2.46	3.43	1.15	1.04	0.57	2.80	1.91	1.18
SD	0.86	.50	0.50	0.39	0.80	0.70	1.27	0.89	1.64	1.54	0.95	0.95	0.72	1.24

Table 7A
ANOVA Summary of Simple Effects of Video Condition and Mental Health Outcomes

		df	*SS*	*F-value*	*p-value*
Anxiety	$R^2 = .10$				
Intercept		1	48.18	60.13	.000
Gender		1	4.11	5.13	.03
Condition		2	4.41	2.75	.07
Error		96	76.92		
Depression	$R^2 = .04$				
Intercept		1	22.28	46.40	.000
Gender		1	1.97	4.09	.05
Condition		2	.01	.01	.99
Error		95	45.62		
Mental health self-report	$R^2 = .14$				
Intercept		1	.23	.17	.68
Gender		1	19.75	14.42	.000
Condition		2	2.14	.78	.46
Error		96	131.55		