The Power of 'Likes': Exploring X/Twitter Reward Sensitivity and its Associations with Attention-Deficit/Hyperactivity Disorder, Depression, and Anxiety

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Abstract [1]

Social media is a progressively unbridled force of social influence. As the usage, variety of platforms, and influence of social media sites rise, the impact of social media on the mental health of its users becomes of growing significance and concern. However, present research has predominantly focused on the influence of social media on mental health without investigating the bidirectional aspect of this relationship: how pre-existing mental health concerns affect social media usage. Research that has begun to investigate this has relied largely on self-reported usage data or focused primarily on language use. Moreover, this research has largely overlooked a crucial element of social media use: the social reward, in the form of likes, comments, and shares. Research suggests that people with mental illness or neurodivergence respond differentially to reward. Here, we aim to analyze and quantify how ADHD symptoms, disentangled from symptoms of depression and anxiety, moderate user activity patterns and sensitivity to reward on social media. Drawing on reinforcement learning theory, sensitivity to reward is conceptualized as the extent to which the receipt of social reward in the form of likes leads to more future posting. Participants were asked to report their diagnoses, symptom severity, and perceived social media engagement, and subsequently to donate their public X/Twitter data. We hypothesized that users with ADHD would post more frequently, exhibit a higher sensitivity to reward, and self-report higher usage, sensitivity, and addiction to social media. Our results showed that posting frequency and reward sensitivity were only marginally associated with ADHD. However, reward sensitivity was positively associated with depression and age, and negatively associated with anxiety. Self-reported measures of social media usage were only marginally associated with ADHD, however, self-reported social media reward sensitivity and addiction were significantly associated with both ADHD and age. These results suggest that individuals with depression, anxiety, and of older age are particularly sensitive to likes on social media. By contrast, individuals with symptoms of ADHD self-report more sensitivity to likes and problematic social media usage despite not being significantly more sensitive behaviorally, whereas older individuals self-perceive less problematic social media usage despite being significantly more sensitive behaviorally. These findings reveal the additional risk that social media may pose for people with pre-existing mental health concerns and of older age, as well as the importance of the inclusion of behavioral data in analyses of social media.

[1] This section contains text that is based closely on, or identical to, text found in my junior paper.

Table of Contents

Introduction [2]

1.1 Social Media Usage and Mental Health

Social media is increasingly ubiquitous, and its social influence increasingly pervasive. As of January 2024, more than 60% of the global population uses social media, and the percentage continues to rise (DataReportal). With this increase in social media use, the body of research addressing the influence of social media on mental health has also increased, along with corresponding concern. Mounting evidence suggests that, while social media offers much benefit, social media usage poses high risk and potential harm to mental health (Pantic, 2014). In February 2023, the White House released a "Report on Mental Health Research Priorities" highlighting social media and mental health research as a critical national priority (Prabhakar & Rice, 2023); several months later, the U.S. Surgeon General published an "Advisory on Social Media and Youth Mental Health" stating that social media is not conclusively safe for children and adolescents and urging action to mitigate the risk of harm (U.S. Department of Health and Human Services, 2023). In March 2023, Utah became the first state to enact laws limiting how children can use social media, enacting a usage curfew and requiring parental consent for children under 18 to create social media accounts (The Associated Press, 2023). While research efforts are therefore increasingly directed towards the investigation of the influence of social media on mental health, less is yet known about the reverse: the influence of mental health and neurodivergence on the way in which people engage with social media.

1.2 Social Media and ADHD

Attention-Deficit/Hyperactivity Disorder (ADHD) is one of the most common neurodevelopmental conditions of childhood. It is characterized by hyperactivity, impulsivity, and inattention, which extend into disordered learning and conduct in addition to impaired social relationships (American Psychiatric Association, 2022). This has further implications in adulthood, such as the well-established link between ADHD and substance abuse and addiction (Lambert & Hartsough, 1998).

Recent research has begun to explore how individuals diagnosed with ADHD may differentially engage with social media as a result of these characteristics (Gul et al., 2018; Boer et al.,

[2] This section contains text that is based closely on, or identical to, text found in my junior paper.

2019; Dawson et al., 2019). One such study recruited teenagers with ADHD diagnoses and collected self-reports of their Facebook usage patterns and ADHD symptomatology. The authors reported that teens with ADHD, on average, had more fake accounts, had their accounts for longer periods of time, used Facebook for a wider variety of reasons, and overused Facebook more frequently. Higher attentional impulsivity, conduct problem scores, and ADHD symptom severity were specifically correlated with problematic (i.e., addictive) social media usage (Gul et al., 2018). A subsequent study investigated the causal link between social media usage intensity, social media addiction, and ADHD symptom severity to establish directionality. Participants self-reported their general social networking site usage over three years and ranked their ADHD symptom severity. The results suggested that social media addiction increased ADHD symptom severity, but that ADHD symptomatology did not influence social media usage intensity or addiction (Boer et al., 2019). Another study analyzed social media usage through logged Facebook data as opposed to self-reported data (Dawson et al., 2019). Teenagers diagnosed with ADHD, as well as their parents and teachers, reported ADHD symptoms and severity through rating scales and interviews. The authors collected data from the participants' Facebook accounts and found that users with ADHD had a larger number of friends, used Facebook mainly to browse content rather than to post content, and, when posting, mainly shared external content (i.e., memes or web links). These users also commented on their friends' posts more frequently, and these comments constituted a larger percentage of their overall Facebook activity.

While each of these studies found significant correlations between ADHD symptomatology and social media usage, self-reported measures of social media use are of questionable reliability. Research suggests that self-reported media use correlates only moderately with actual (logged) media use, an association that is even weaker in cases of problematic social media use (Parry et al., 2021). Furthermore, the cited studies have all relied on a single social media platform: Facebook. Social media platforms are distinct in the types of content they host, their features, and their reward structures, among other elements; therefore, it is important to explore whether this correlation generalizes across platforms. For these reasons, there is need for further research using logged social media data on distinct social media platforms.

X, formerly known as Twitter, is a comparable social media platform that has been heavily referenced across neuroscience and psychology literature and is popular across age groups. One study analyzed language usage patterns amongst users with ADHD on X/Twitter (Guntuku et al., 2017). Using tweets in which people claim to have a diagnosis of ADHD to collect data from users with ADHD, and comparing them to data from random users, the authors analyzed 1.3 million tweets to examine the language patterns of users with ADHD. In addition to finding increased use of particular words and reference to certain topics, they found that users with ADHD post more frequently, have more followers, and post a higher proportion of tweets during the night; these findings form the basis of some hypotheses in the current study. However, this study was inherently limited in its reliance on users who publicly disclose a diagnosis of ADHD, as people who choose to self-disclose a medical diagnosis on a social media platform may not adequately represent all those with the same diagnosis condition, in particular with regard to posting and other social media behavior. Additionally, this study and the corresponding literature fall short in that they neglect to address an elemental component of the social media experience: the prominent presence of social rewards.

1.3 Social Media, Reward Sensitivity, and ADHD

Social rewards—likes, comments, shares—are central to the social media experience. On X/Twitter, a user can like ("favorite") another user's tweet to publicly mark it as a favorite tweet; the original tweeter is notified of the like, and anyone can see the list of users who have liked a given tweet as well as a list of all tweets liked by any given user. Users can also publicly "reply" to another user's tweet, or share a tweet by "retweeting" it; both actions notify the original tweeter, are posted on the commenter/retweeter's page, and are visible to anyone viewing the original tweet. Retweets typically imply endorsement, whereas replies host original content. Reinforcement learning theory predicts that receipt of these social rewards will act as reinforcers—brain imaging studies have demonstrated that likes, among other social rewards, are processed by neural mechanisms that overlap with those that process non-social rewards (Sherman et al., 2016, 2018). These reinforcers will thus shape various aspects of the user's posting behavior; one such aspect is the length of time between posts. Specifically, reinforcement learning theory predicts that higher rewards should lead users to wait less time before posting again. A recent study tested reinforcement learning models on social media data, evaluating posts across three distinct social media platforms (not including X/Twitter), and found that increased receipt of reward caused the hypothesized decrease in time between posts (Lindström et al., 2021).

A large body of computational psychiatry research links ADHD, among other mental health concerns, to atypical reinforcement learning (Luman et al., 2010, Maia & Frank, 2011, Nigg, 2013, Ziegler et al., 2016). Nonetheless, research to date has not addressed the way in which users with

ADHD might differentially respond to social rewards on social media. Given the prominence of reward in the social media experience, in addition to findings from computational psychiatry, the study of reinforcement learning on social media platforms might be critical to understanding the bidirectional relationship between social media and mental health. Therefore, the present study aims to analyze and quantify how ADHD symptoms influence user activity patterns and response to reward on social media.

It is noteworthy that ADHD, depression, and anxiety are highly comorbid conditions—adults with ADHD have high rates of depression and anxiety, and adults with depression and anxiety have high rates of ADHD. Beyond mere concurrence, however, the symptoms of these conditions are highly interconnected in that they overlap across conditions and reinforce each other (Feifel, 2007). This is particularly relevant in this context because of the established positive relationship between symptoms of depression and anxiety and problematic social media use (Huang, 2022). This study aims to distinguish the specific correlation between sensitivity to social media and ADHD from the relationship with depression or anxiety. Therefore, all our analyses will control for anxiety and depression in addition to age and gender, common demographic factors also known to influence social media activity use (Su et al., 2020; Politte-Corn, 2023).

1.4 Hypotheses

The aim of this research is to understand how individuals with ADHD, as compared to neurotypical individuals, engage with social media and respond to social reward by employing a computational evaluation of behavioral and self-reported social media usage patterns. The study was driven by three primary hypotheses:

1.4.1 *Users with ADHD and with higher symptom severity will post more frequently, and more frequently at night.*

We predicted a replication of Guntuku et al.'s (2017) findings that users with ADHD and with higher symptom severity would post more frequently overall, and more frequently at night than users without ADHD or with lower symptom severity. Guntuku et al.'s (2017) findings were limited in that their dataset only included users who had publicly disclosed their ADHD diagnoses and had done so through Twitter posts, and they had no knowledge of whether, or how many of the users in their control group had ADHD diagnoses. Furthermore, Guntuku et al. (2017) had no measure of symptom severity. Therefore, our findings would not only replicate but also extend these previous findings.

1.4.2 *Users with ADHD and with higher symptom severity will have a higher sensitivity to social media reward.*

We predicted a higher sensitivity to social rewards on X/Twitter (e.g., likes) among users with ADHD and with high symptom severity, such that the same amount of reward would lead to more frequent posting in the immediate future compared with no ADHD/low ADHD symptom levels. Previous research suggested that individuals with ADHD have an abnormal sensitivity to individual instances of reward (Wickens & Tripp, 2005). Therefore, a user with ADHD may be more predisposed to seek continuous reward on the app. Thus, we hypothesized that if a user receives a larger amount of reinforcement—likes, retweets, replies—he will engage with the app for a larger period of time. We predicted that this effect would be found across all users, but would be significantly stronger for users with ADHD.

1.4.3 *Users with ADHD and with higher symptom severity will report higher daily social media usage, higher sensitivity to social media reward, and stronger addiction to social media.*

We predicted that analyses of self-reported data would both replicate past findings and parallel or exaggerate correlations found in behavioral (donated X/Twitter) data. Research suggests that users tend to overreport problematic social media usage compared to logged usage (Parry et al., 2021), and that users with symptoms of ADHD specifically report frequent and problematic social media use (Gul et al., 2018; Boer et al., 2019). Therefore, we predicted that users with ADHD and with high symptom severity would overreport their sensitivity to social media likes, paralleling the correlation between like sensitivity and ADHD found in the behavioral data (which we predicted to be positive, see Section 1.4.1). We further predicted that users with ADHD and with high symptom severity would report high levels of daily social media usage and social media addiction.

Methods [3]

2.1 Participant Recruitment

Participants were recruited for the study through ads on X/Twitter and through the ResearchMatch platform.[4] Ads on X/Twitter were generally advertised to adult users within the U.S. in order to mitigate biases towards people who post most frequently on X/Twitter or who are willing to disclose diagnoses on X/Twitter. The ad contained a graphic inviting interested users to complete a brief, unpaid screener questionnaire assessing fit for our study (Appendix B). Adult ResearchMatch registrants were recruited directly through the ResearchMatch platform, partially through a general query and partially through a query targeted at people diagnosed with ADHD. Following initial contact, participants who indicated interest in the study were invited via email to complete the screener questionnaire.

Participants aged over 18, located in the United States, and who self-reported their X/Twitter posting activity to be above a pre-determined threshold (at least "Once a week") were considered eligible to participate. Additionally, one attention check question was included in the screener questionnaire. Participants who met these criteria and passed the attention check received an immediate, automated email inviting them to participate in the main study and containing a link directing them to the main study questionnaire. Four attention check questions were included in the main study questionnaire. Participants who passed the attention checks were instructed to request their X/Twitter data archive. Twenty-four hours following completion of the questionnaire, participants received an automated email inviting them to upload their social media data. Both questionnaires were hosted on Qualtrics.

In addition to the aforementioned criteria, participants were liable for exclusion at any point throughout the study if they demonstrated a lack of honesty or poor engagement with the study. This was evaluated through discrepancy in answers (e.g., donation of insufficient data, indicating a lack of truthful responding on the screener question regarding frequency of posting on Twitter/X), failure to complete the required study components within a predetermined time frame (7 days), and Qualtrics quality assessment and fraud detection devices (reCAPTCHA, RelevantID), in addition to

[3] This section contains text that is based closely on, or identical to, text found in my junior paper and in my Institutional Review Board (IRB) proposal.

[4] ResearchMatch is an NIH-funded program that connects people interested in research studies with researchers across the U.S.

the aforementioned attention check questions. One participant was included despite having failed one attention check question ("Over the last two weeks, how often have you been bothered by… worrying about how you will never know what an insect feels?") after affirming that their reported answer was intentional. Several participants uploaded empty files, duplicated files, files that had been tampered with, or files that did not constitute sufficient X/Twitter activity to meet the frequency criteria for study inclusion. Therefore, 147 participants were ultimately included in analysis of self-reported data (57 men, 76 women; age, 18-74; mean, 38 years), and 71 in analysis of X/Twitter data (30 men, 31 women; age, 18-72; mean, 37 years). We aimed to recruit 200 full participants (i.e., participants who donated X/Twitter data). Here, we report analysis of initial data while data collection is still ongoing. The complete data collection process is illustrated in Figure 1.

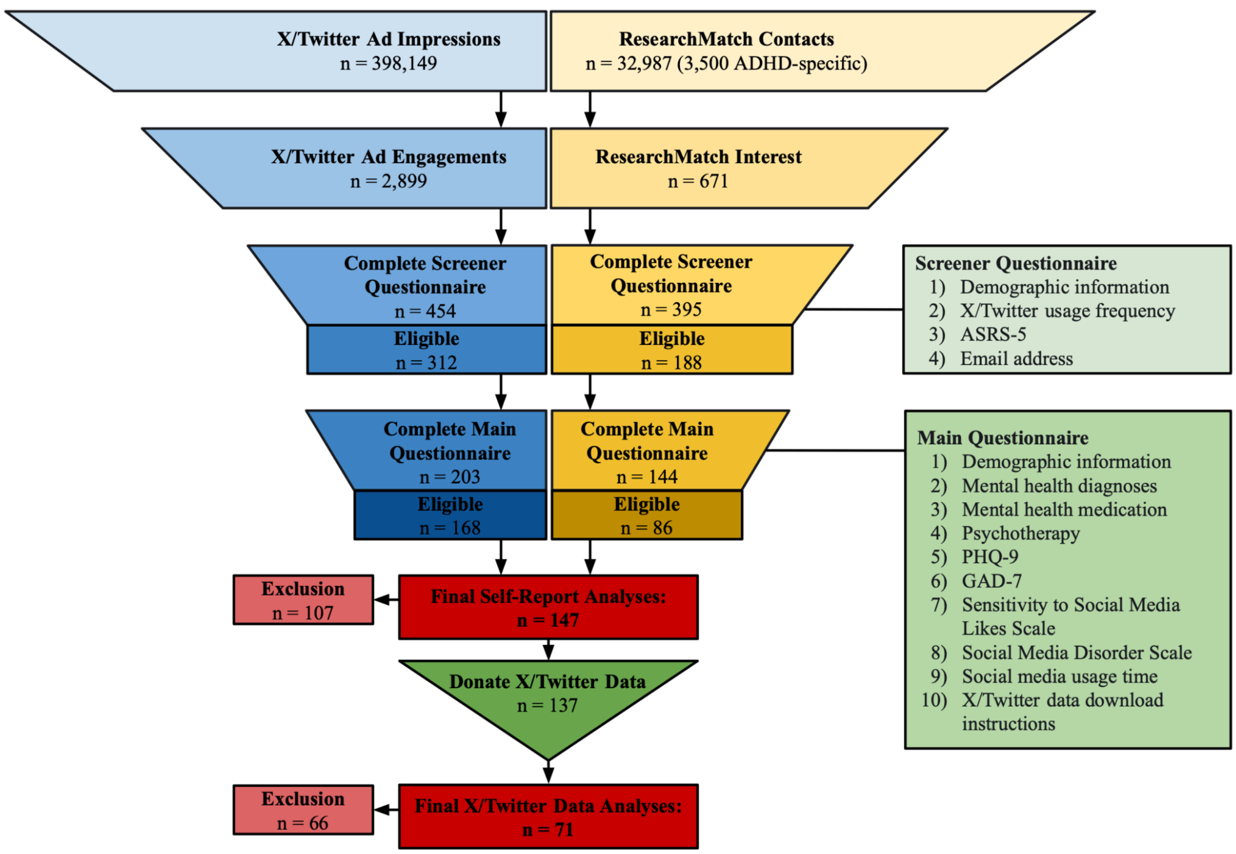

Figure 1. Data Collection Pipeline. Data collection began with initial ad impressions/ResearchMatch contacts, concluded with donation of X/Twitter data, and included ineligibility, inattention, and dishonesty and fraud exclusions.

Participants were compensated for complete participation in the study with a $15 or $20 Amazon gift card.[5] Participants were not compensated for completion of the screener questionnaire

[5] Compensation was initially $15, but was increased to $20 to incentivize participation.

alone, nor for partial completion of the main study questionnaire. Participants who completed the main study questionnaire but did not donate their data, or who were otherwise terminated on grounds of inattention or dishonesty, were compensated with a partial payment of $3.

2.2 Data Collection

Mental Health Measures

The screener questionnaire included questions of location, age, and posting frequency in order to assess inclusion and exclusion criteria. These questions were followed by the Adult ADHD Self-Report Scale for DSM-5 (ASRS-5). The ASRS-5 consists of six questions, developed in line with DSM-5 criteria and established manifestations of ADHD symptoms in adults, that ask participants to rank themselves on a five-point scale ranging from "never" to "very often" (Ustun et al., 2017). The screener questionnaire, including the ASRS-5, is included in Appendix C.

The main study questionnaire included demographic questions (i.e., gender, race, ethnicity), the Patient Health Questionnaire-9 (PHQ-9), the Generalized Anxiety Disorder-7 scale (GAD-7), the Sensitivity to Social Media Likes Scale (adapted from Shabahang et al., 2022), a Social Media Disorder (SMD) Scale (van den Eijnden et al., 2016), a pair of questions on self-perceived daily social media and X/Twitter usage, and a set of questions about mental health diagnoses, medications, and psychotherapy. A breakdown of participant counts for each diagnosis can be seen in Table 1. The PHQ-9, based on the nine diagnostic criteria for major depression outlined in the DSM-IV, asks patients to score the frequency of their experience of each of the nine criteria on a four-point scale ranging from "not at all" to "nearly every day" (Kroenke et al., 2001). The GAD-7, similarly based on the seven diagnostic criteria for generalized anxiety outlined in the DSM-IV, asks patients to score each of the seven criteria on the same scale (Sapra et al., 2020). These scales were included to control for effects of depression and anxiety in analysis..

	Self-Report Analyses (*n* participants)		X/Twitter Data Analyses (*n* participants)	
Diagnosis	**True**	**False**	**True**	**False**
ADHD	42	105	15	56
Depression	46	101	21	50
Anxiety	59	88	28	43

Table 1. Counts of Participants with Self-Reported Diagnoses. Number of participants reporting diagnoses of ADHD, depression, and anxiety, separated into counts included in self-report analyses (Figures 6, 7, and 8) and counts included in X/Twitter data analyses (Figures 2, 3 and 5).

Self-Reported Social Media Measures

The Sensitivity to Social Media Likes Scale was adapted from Shabahang et al., 2022, which developed a ten-question self-report measure of gratification derived from the receipt of "paralinguistic digital affordances," i.e., social media rewards including likes, comments and reposts. We adapted this scale to specifically measure gratification from likes, and termed this the *Sensitivity to Social Media Likes Scale*. On this scale, participants score the degree to which they identify with each of ten statements (e.g., "I feel happy when I receive likes.") on a five-point scale ranging from "strongly disagree" to "strongly agree."

Finally, the SMD Scale (van den Eijnden et al., 2016) is a nine-question self-report measure of addiction to social media based on the nine diagnostic criteria for Internet Gaming Disorder outlined in the DSM-V, adapted to social media use. Participants report whether or not they have experienced each of the nine criteria in the past year (e.g., "During the past year, have you… regularly found that you can't think of anything else but the moment that you will be able to use social media again?"). Each of these scales was included to correlate both with ADHD diagnoses and symptom severity and with behavioral data. The main study questionnaire concluded in a page instructing participants on how to download their X/Twitter data. The full main study questionnaire is included in Appendix D.

Social Media Data

Each participant received their X/Twitter data in the form of a Data Download Package (DDP). DDPs are collections of individual user data "consisting of behavioral (e.g., likes), textual (messages), media (photos, videos), or location data" (Kmetty et al., 2023). On X/Twitter, this takes the form of a collection of folders containing data about posting history, likes, direct messages, media, following history, interests and ad engagement, and more. Using a secure data donation platform created by the Niv Lab,[6] participants were instructed to upload two folders: "like.js" and "tweets.js" (Appendix E). "like.js" included data corresponding to each participant's liking history, i.e. the posts they have liked and the timestamps of these posts; "tweets.js" included data corresponding to each participant's posting history, containing their posts as well as information about these such as timestamps and like and retweet counts.

All methods were approved by the Princeton University Institutional Review Board, protocol number 16266.

2.3 Data Processing [7]

X/Twitter data were processed in Python, including anonymization of posts (removal of names, locations, and handles) and basic calculations of account age and mean posting frequency. Account age was approximated through a calculation of the difference between the date of the oldest post and the date of the most recent post. Mean posting frequency (i.e., the average number of posts per day) was calculated by dividing the total number of posts by the account age, and log-transformed to facilitate linear regression and visualization.

Cross-correlation analysis was performed to analyze data on time of day of posting. The cross-correlation function (CCF) measures the similarity between two time series as a function of their relative delay (Poletto & Miranda, 2022). This function yields a correlation value for a lag/lead of each of a number of hours, i.e., the correlation with a lag of 1 hour, 2 hours, etc. The results of this analysis are described in Section 3.1.

Data on user posting frequency and number of likes received were processed before applying a linear mixed-effects model to address reinforcement-learning-based hypotheses, i.e., the effect of social reward (e.g., likes) on subsequent user engagement (e.g., posts).[8] The processing pipeline calculated the number of posts per hour interval for each user and identified the user's least active period (i.e., the daily period with the fewest posts). This was taken to be the boundary between subsequent days, facilitating the binning of data into equal 24-hour periods. Counts of posts per day—including type of post, i.e., original, reply, retweet, quote retweet—per user across each user's account lifespan, in addition to the reinforcement that each post received—i.e., number of likes and

[6] Created by undergraduate research assistant Stephenie Chen for the purposes of this research.
[7] ChatGPT was consulted throughout data processing to debug code.
[8] The code used for this analysis contained code that was based closely on, or identical to, code written by my graduate student advisor, Dan-Mircea Mirea, for the purposes of his parallel research.

retweets—were stored in a dataframe. These data were merged with the questionnaire data. The results of this analysis are described in Section 3.2.

Linear regression models were employed for all other statistical analyses, which were conducted in R. All analyses controlled for effects of PHQ-9/depression, GAD-7/anxiety, gender, and age.

Results

We first present results on X/Twitter posting frequency, followed by results on behavioral sensitivity to likes on X/Twitter (i.e., social media reward). We conclude with results on self-reported social media usage, sensitivity to likes, and social media addiction.

3.1 Posting Frequency is Marginally Associated with ADHD

We first examined the relationship between mean posting frequency and ADHD. Interestingly, we found only a marginally significant relationship between mean posting frequency and ADHD symptom severity ($\beta = 0.045$, $SE = 0.025$, $p = 0.080$; Figure 2A), and no significant association between mean posting frequency and ADHD diagnosis ($\beta = 0.096$, $SE = 0.229$, $p = 0.318$; Figure 2B). Despite the marginal significance, this result trends in the expected direction, potentially suggesting that individuals with ADHD post more frequently on social media. More statistical power is needed to assess this hypothesis conclusively.

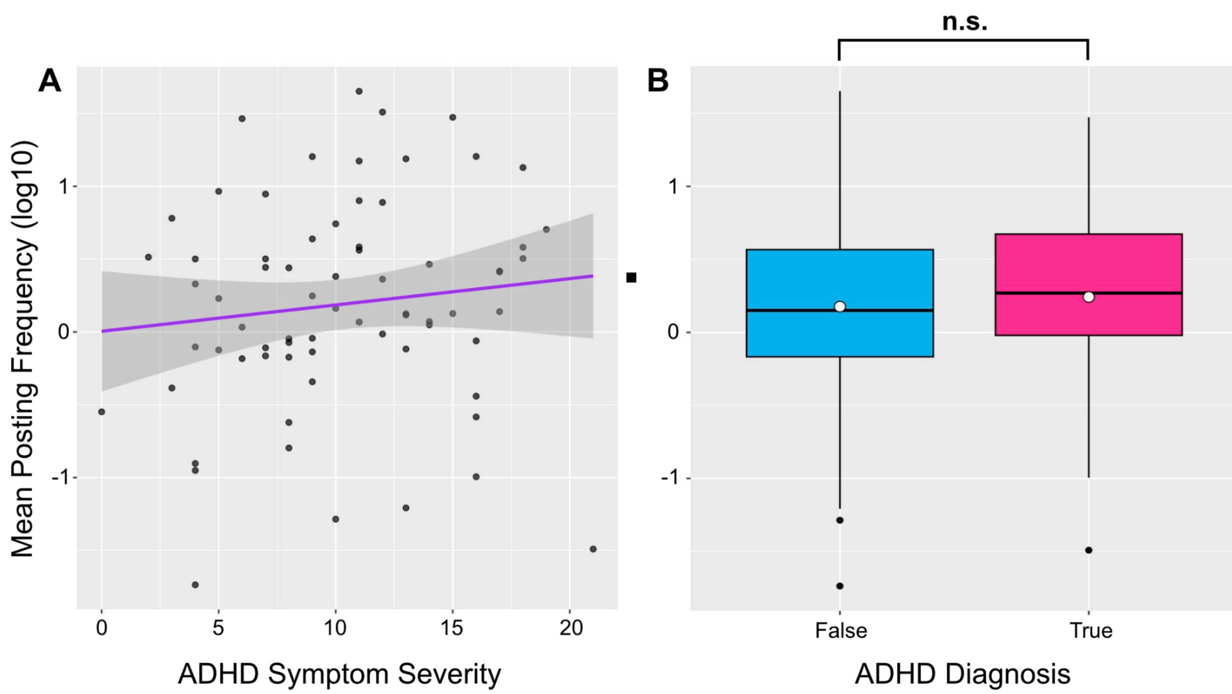

Figure 2. Posting Frequency is Marginally Associated with ADHD Symptom Severity. Relationship between log-transformed mean user posting frequency (log mean number of posts per day) and ADHD symptom severity (A) and self-reported diagnosis (B). In A, the shaded area surrounding the regression line represents the 95% confidence interval. In B, the horizontal line within each box represents the median and the white dot represents the mean. ▪ = $p < 0.1$; n.s. = not significant.

We further examined the relationship between time of day of posting and ADHD diagnosis. Individual hourly post counts were normalized across users by calculating the individual proportion of posts posted in each one-hour interval for each user. The proportion values were averaged across users and plotted by ADHD diagnosis (Figure 3).

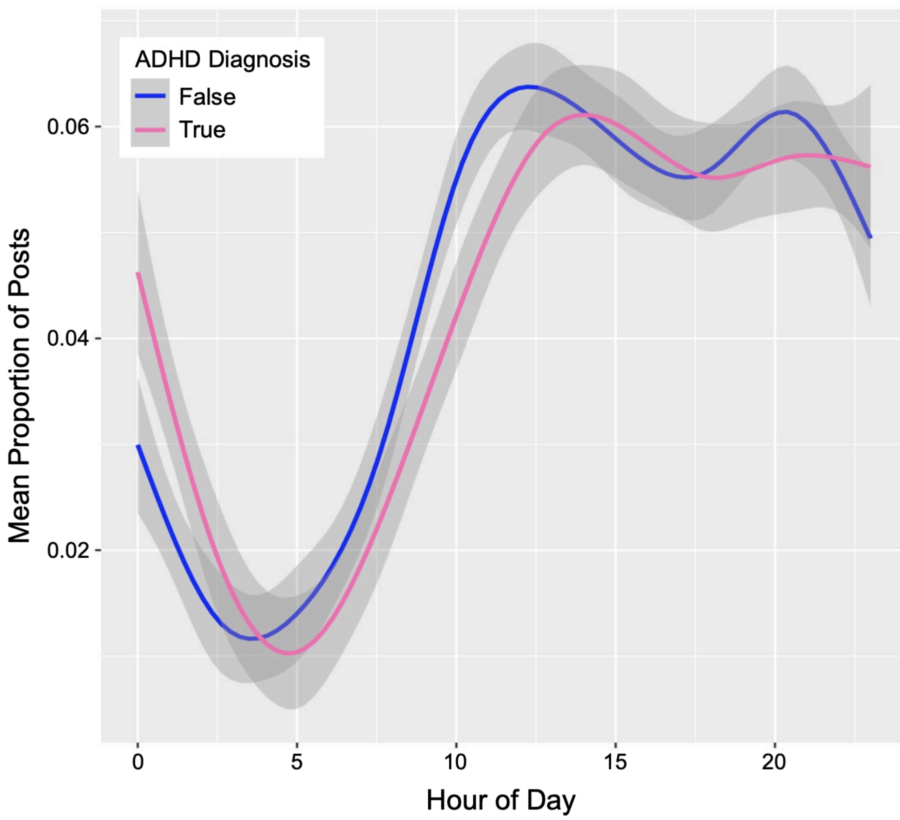

Figure 3. Association between Time of Posting and ADHD Diagnosis. Mean proportion of posts posted across each hour of the day for the ADHD diagnosis group and control group. The curves are fit using a Generalized Additive Model. The shaded area surrounding each curve represents the 95% confidence interval. The means for each bucket of time (0-5, 6-11, 12-17, 18-23) for the ADHD group are: 0.136, 0.177, 0.348, 0.339. The means for the control group are: 0.093, 0.227, 0.355, 0.325.

For linear regression, hours were grouped into four discrete buckets: hours 00:00-05:59, 06:00-11:59, 12:00-17:59, 18:00-23:59. The linear model was fit using this grouping, including an interaction term between ADHD and the hour bucket. We found only a marginal negative interaction between ADHD and posting frequency in bucket 2 (06:00-11:59) (β = -0.087, SE = 0.045, p = 0.054, Figure 3), suggesting that people with ADHD may post less between 6:00-11:59, although a greater sample size is needed to assess this hypothesis conclusively. Further cross-correlation analysis revealed a strong cross-correlation between the ADHD time series and control time series at a lag of 0-2 hours (0.918, 0.978, 0.928), with the strongest correlation at a lag of 1 hour. This suggests that users with ADHD post later in the day and night by approximately 1 hour on average, in line with our hypothesis that people with ADHD post more frequently at night, i.e., at later hours.

3.2 Sensitivity to Likes is Associated with Depression, Anxiety, and Age, and is Marginally Associated with ADHD

We next examined the relationship between sensitivity to likes and ADHD. Sensitivity to likes was modeled as the influence of the receipt of likes on subsequent posting activity. This was calculated by fitting a linear mixed-effects model predicting each user's daily number of posts from the number of likes received on the previous day. The model was fit using random intercepts and fixed rather than random slopes due to the small sample size, and incorporated both ADHD symptom and diagnosis data.

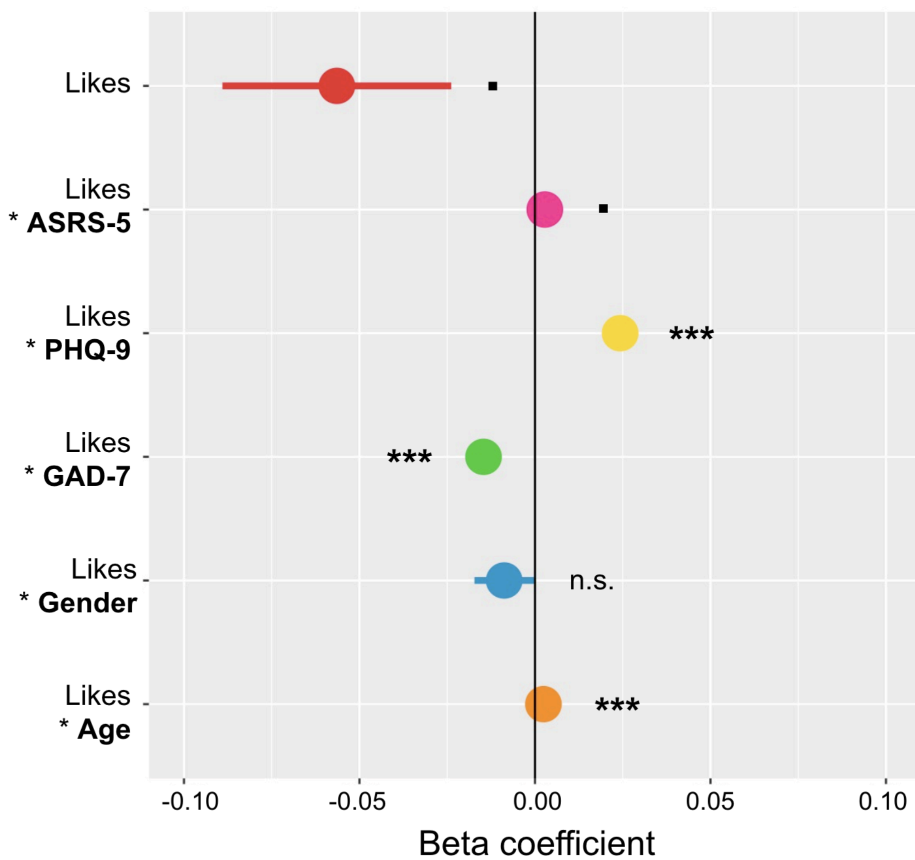

Figure 4. Sensitivity to Likes Positively Correlated with Depression Symptom Severity and Age, Negatively Correlated with Anxiety Symptom Severity. Relationship between sensitivity to likes and each of five variables: ADHD symptom severity (ASRS-5), depression symptom severity (PHQ-9), anxiety symptom severity (GAD-7), gender, and age. The beta coefficients are estimated from a linear mixed-effects model predicting daily number of posts from number of likes received on the previous day, and represent the strength and directionality of the relationship. The whiskers around each point represent the standard error (sometimes too small to be visible). *** = $p < 0.001$; ▪ = $p < 0.1$; n.s. = not significant.

We found only a marginally significant relationship between sensitivity to likes and ADHD (ASRS-5) symptom severity ($\beta = 0.003$, SE = 0.002, $p = 0.067$; Figure 4). By contrast, however, we found a large and significant association between the effect of previous-day likes on current-day posting and depression symptom severity (PHQ-9; β = 0.024, SE = 0.002, p < 0.001, Figure 4). This suggests that individuals with stronger symptoms of depression may be more sensitive to social rewards on X/Twitter, such that they increase their posting more in response to social media likes. Additionally, we found a significant negative interaction between previous-day likes and anxiety symptom severity when predicting current-day posting (GAD-7; β = -0.015, SE = 0.002, p < 0.001, Figure 4), suggesting that anxiety and depression symptoms may have opposing effects on users' sensitivity to social media likes. Finally, we found a significant interaction between the effect of previous-day likes on current-day posts and age (β = 0.002, SE = 0.0004, p < 0.001, Figure 4), suggesting that individuals may become more sensitive to social rewards on X/Twitter with age. We found no significant relationship between sensitivity to likes and gender (β = -0.009, SE = 0.008, p = 0.299, Figure 4). Our data also suggest that volume of previous-day likes is not an independently significant predictor of current-day posting (β = -0.056, SE = 0.033, p = 0.083, Figure 4).

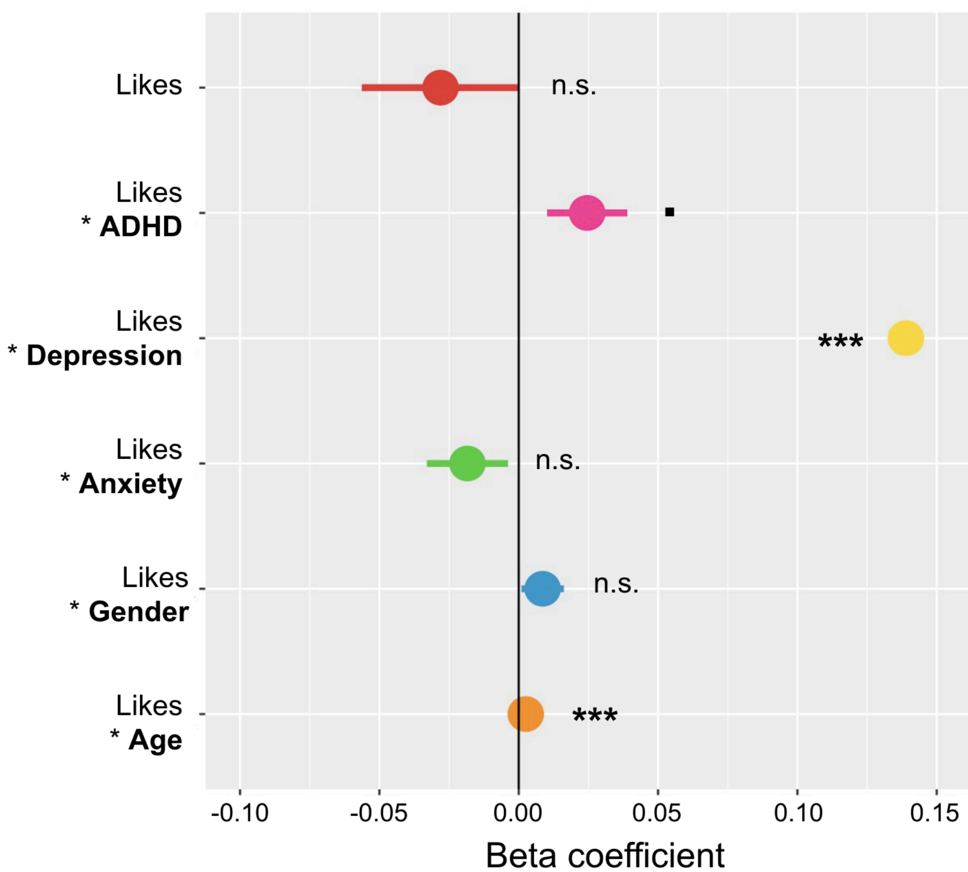

Figure 5. Sensitivity to Likes Positively Correlated with Depression Diagnosis and Age. Relationship between sensitivity to likes and self-reported ADHD, depression, and anxiety diagnoses, gender, and age. The beta coefficients are estimated from a linear mixed-effects model predicting daily number of posts from number of likes received on the previous day, and represent the strength and directionality of the relationship. The whiskers around each point represent the standard error. *** = p < 0.001; ▪ = p < 0.1; n.s. = not significant.

When investigating the effects of diagnoses rather than symptom severity, a similar picture emerged. As with symptom severity (Figure 4), we found only a marginally significant relationship between sensitivity to likes and self-reported ADHD diagnosis ($\beta = 0.025$, SE = 0.014, $p = 0.087$, Figure 5). However, similarly mirroring symptom severity (Figure 4), we found a strong significant association between the effect of previous-day likes on current-day posting and self-reported depression diagnoses ($\beta = 0.139$, SE = 0.002, $p < 0.001$, Figure 5). This further suggests that individuals with depression may be more sensitive to social rewards on X/Twitter, such that they increase their posting more in response to social media likes. Additionally consistent with analyses of symptom severity (Figure 4), we found a significant moderation by age of the effect of previous-day likes on current-day posting ($\beta = 0.003$, SE = 0.0004, $p < 0.001$, Figure 5). This further supports the suggestion that individuals may become more sensitive to social rewards on X/Twitter with age. We found no significant relationship between sensitivity to likes and anxiety diagnosis ($\beta = -0.018$, SE = 0.015, $p = 0.206$, Figure 5) or gender ($\beta = 0.009$, SE = 0.008, $p = 0.260$, Figure 5). Finally, similarly consistent with analyses of symptom severity (Figure 4), our data suggest that the number of likes on the previous day is not an independently significant predictor of current-day posting ($\beta = -0.028$, SE = 0.028, $p = 0.321$, Figure 5).

3.3 Self-Reported Social Media Usage is Associated with Anxiety, and Self-Reported Sensitivity and Addiction are Associated with ADHD and Age

Last, we examined the relationship between self-reported social media usage, sensitivity, and addiction and ADHD symptom severity and diagnosis.

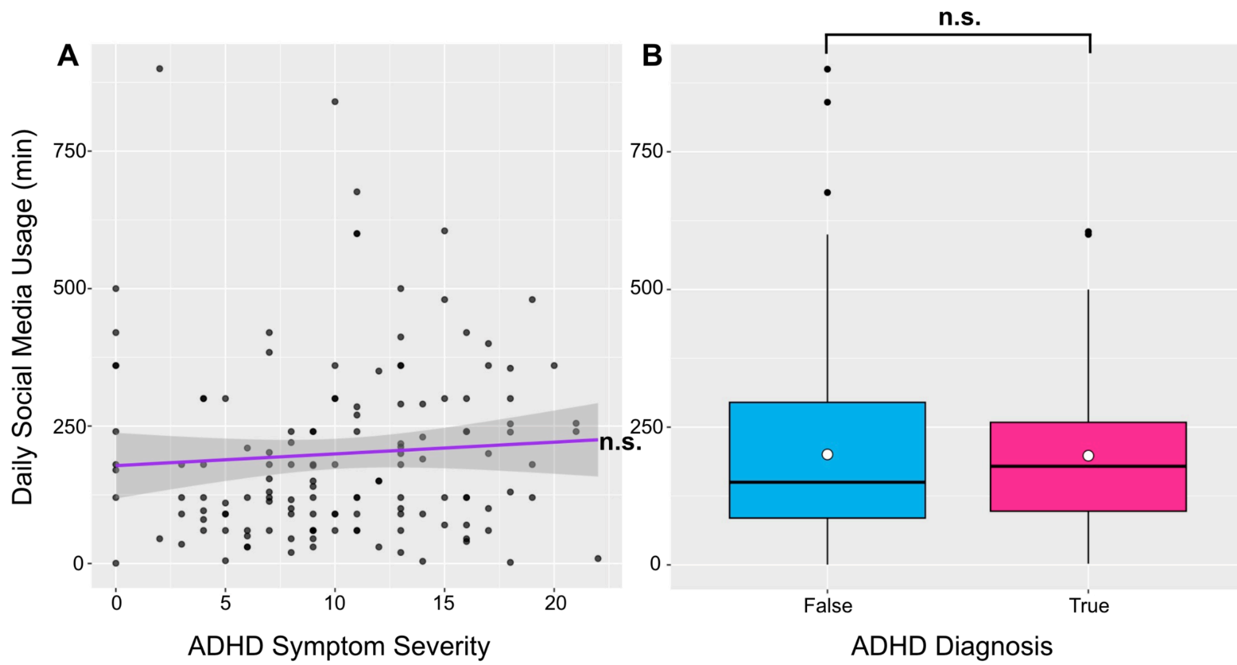

Figure 6. Self-Reported Social Media Usage not Associated with ADHD Symptom Severity or Diagnosis. Relationship between daily self-reported social media usage time and ADHD symptom severity (A) and diagnosis (B). In A, the shaded area surrounding the regression line represents the 95% confidence interval. In B, the horizontal line within each box represents the median and the white dot represents the mean. n.s. = not significant.

We first examined the relationship between self-reported social media usage and ADHD (Figure 6). We found no significant associations between self-reported daily social media usage and ADHD symptom severity ($\beta = 1.929$, SE = 4.698, $p = 0.683$, Figure 6) or diagnosis ($\beta = 19.266$, SE = 20.571, $p = 0.637$, Figure 6). However, we found a significant negative association between self-reported daily social media usage and anxiety diagnosis ($\beta = -105.795$, SE = 41.422, $p = 0.013$), suggesting that users with anxiety perceive spending less time on social media. The same analyses were run on self-reported daily X/Twitter usage and no significant interactions were found.

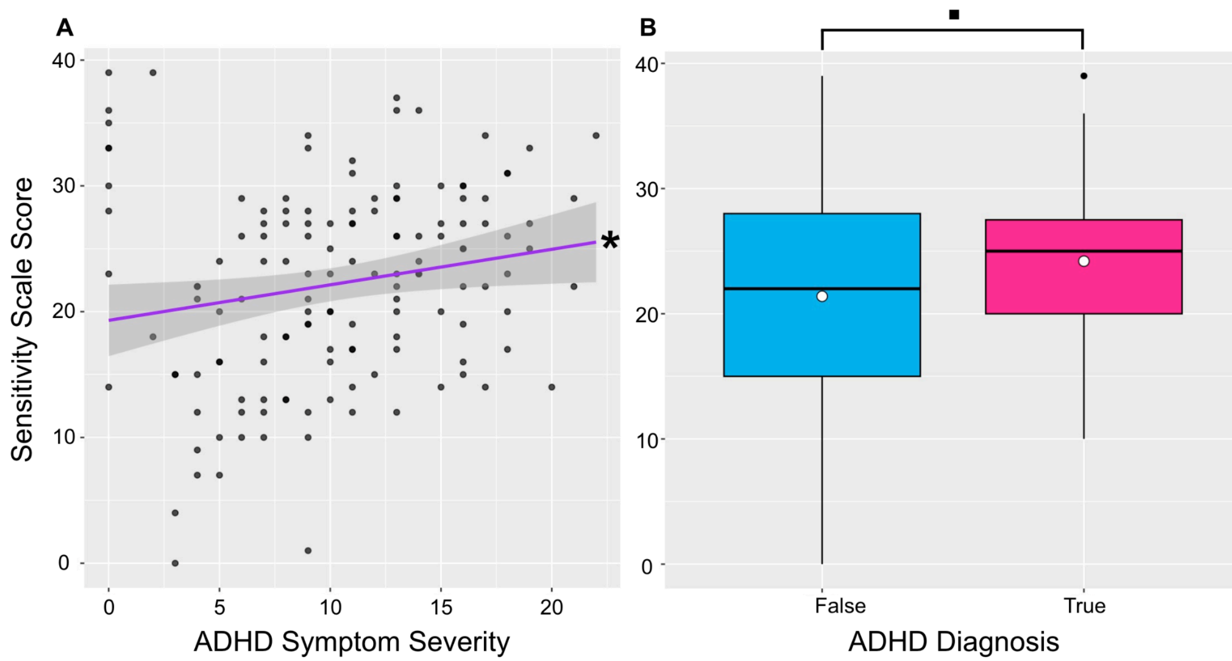

Figure 7**. Positive Correlation Between Self-Reported Social Media Sensitivity and ADHD Symptom Severity.** Relationship between self-reported sensitivity to social media and ADHD symptom severity (A) and self-reported diagnosis (B). In A, the shaded area surrounding the regression line represents the 95% confidence interval. In B, the horizontal line within each box represents the median and the white dot represents the mean. * = $p < 0.05$; ▪ = $p < 0.1$.

We next examined the relationship between self-reported social media sensitivity and ADHD (Figure 7). In contrast to analyses of self-reported usage, we found a significant positive association between self-reported sensitivity to social media likes and ADHD symptom severity (β = 0.540, SE = 0.256, p = 0.039, Figure 7). This suggests that individuals with stronger symptoms of ADHD self-perceive higher sensitivity to social media reward. We additionally found a marginally significant relationship between self-reported sensitivity to social media and ADHD diagnosis (β = 4.540, SE = 2.387, p = 0.062, Figure 7). Although this result trends in the same, expected direction, more statistical power is needed to assess this hypothesis conclusively. Separately, we found a significant negative association between self-reported sensitivity to social media reward and age (β = -0.177, SE = 0.066, p = 0.010), suggesting that individual perception of sensitivity to social media reward *decreases* with age, contrary to what we found in our analyses of the behavioral data.

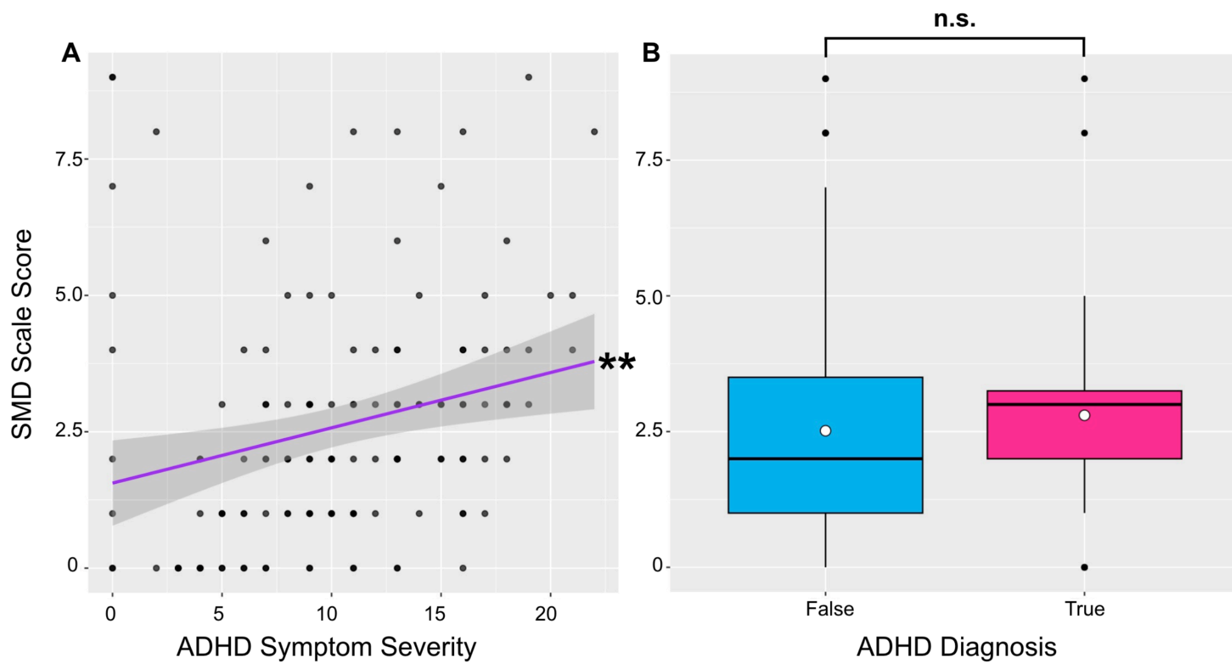

Figure 8. Positive Correlation Between Self-Reported Social Media Addiction and ADHD Symptom Severity. Relationship between self-reported addiction to social media and ADHD symptom severity (A) and diagnosis (B). In A, the shaded area surrounding the regression line represents the 95% confidence interval. In B, the horizontal line within each box represents the median and the white dot represents the mean. ** = $p < 0.01$; n.s. = not significant.

Finally, we examined the relationship between self-reported social media addiction and ADHD (Figure 8). This analysis yielded results parallel to our findings on self-reported sensitivity (Figure 7). We found a significant positive association between self-reported addiction to social media and ADHD symptom severity ($\beta = 0.132$, SE = 0.048, $p = 0.008$, Figure 8), suggesting that people with more severe symptoms of ADHD experience stronger self-perceived addiction to social media. We found no association between self-reported addiction to social media and ADHD diagnosis ($\beta = 0.272$, SE = 0.489, $p = 0.580$, Figure 8). However, we found a significant negative association between self-reported addiction to social media and age ($\beta = -0.043$, SE = 0.014, $p = 0.003$), suggesting that perception of addiction to social media decreases with age.

Discussion

In this study, we explored the relationship between ADHD and user activity patterns and response to reward on social media, aiming specifically to distinguish the effects of ADHD from those of anxiety and depression. We approached this through the analysis of three primary relationships: ADHD and posting frequency, ADHD and behavioral sensitivity to likes, and ADHD and self-reported daily social media usage, sensitivity to social media, and social media addiction.

We first examined the relationship between ADHD and posting frequency. We found only a marginal relationship between ADHD and overall posting frequency (Figure 2). This effect, although marginal, trended in the expected direction. We additionally found that the average time of day of posting of users with ADHD lagged approximately one hour behind controls (Section 3.1), suggesting that users with ADHD post later throughout the day and night, in line with our hypothesis. Modeling the relationship between previous-day likes and current-day posting within the donated behavioral data, we next examined the interaction between sensitivity to social media rewards and ADHD. We found only marginal relationships between sensitivity to likes and ADHD (Figures 4-5). These effects similarly trended in the expected direction. However, we found significant relationships between sensitivity to likes and depression, anxiety, and age. Depression and age were associated with higher sensitivity (Figures 4-5), i.e., posting more in response to more likes, whereas anxiety was associated with lower sensitivity (Figure 4), i.e., posting less in response to more likes. This depression effect was found with both symptom severity and self-reported diagnostic status, whereas the anxiety effect was found only with symptoms.

Of the self-reported social media sensitivity metrics, ADHD symptoms were significantly positively correlated with both sensitivity to likes on social media (Figure 7A) and social media addiction (Figure 8A). We found only a marginal positive relationship between ADHD diagnosis and sensitivity to likes (Figure 7B), and no relationship to addiction (Figure 8B). Additionally, we found a negative association between anxiety diagnosis and social media usage (Figure 6), as well as negative associations between age and both sensitivity (Figure 7) and addiction (Figure 8). Interestingly, we found no significant relationships between depression and any of these self-reported metrics.

Our results do not support the idea that individuals with ADHD symptoms or diagnoses are particularly sensitive to likes on social media. Rather, our findings suggest that individuals with depression symptoms or diagnosed depression, individuals with anxiety symptoms, and older individuals are particularly sensitive to likes on social media. By contrast, however, our results suggest that individuals with ADHD symptoms—and not individuals with depression or anxiety symptoms or diagnoses—perceive more problematic social media usage, including increased sensitivity to likes, despite not showing that effect behaviorally. Our results similarly suggest that older individuals self-perceive less problematic social media usage, including sensitivity to likes, despite being more sensitive behaviorally.

The lack of correlation between ADHD and posting frequency contradicts Guntuku et al.'s (2019) finding that users with ADHD post more frequently. This may be attributed to the fact that Guntuku et al.'s sample was collected exclusively from users who disclosed a diagnosis of ADHD on X/Twitter. This may have generated a biased sample, as the users they collected data from may have been those who post most frequently, and are therefore potentially most likely to disclose such information on the platform. However, it is interesting that our results found no parallels between sensitivity and usage, i.e. that older people or people with depression, who are more sensitive to likes, do not also spend more time on the app, and the inverse for people with anxiety. A potential explanation may be that users who are more sensitive to likes do not necessarily receive more likes than, or even as many likes as, the average user. Consequently, they might not have an increased incentive to post. Future research may consider the mean number of likes received when analyzing posting frequency.

The lack of significant correlation between behavioral sensitivity to likes and ADHD, contrasted by the high sensitivity of individuals with depression and low sensitivity of individuals with anxiety, may be explained by the distinct symptom profiles characterizing each condition. People with depression broadly report engaging in fewer social activities and receiving less social support (Steger & Kashdan, 2009). The social reward provided by likes on social media, however, is evidenced to provide perceived emotional gratification ("feeling of happiness and self-worth") and social gratification ("developing or enhancing interpersonal relationships") (Shabahang et al, 2022; Hayes et al., 2016). Thus, likes on social media may partially compensate for the emotional and social reward that individuals with depression often feel they lack. Interestingly, however, individuals with anxiety similarly report engaging in fewer social activities and receiving less social support in their daily lives (Saris et al., 2017). This would predict an effect similar to that found with depression, contrary to our actual findings. This discrepancy may be attributed to the unreliable nature of social media likes. Perhaps a "successful" post, a post that has received a lot of likes, generates a desire to produce an equally successful subsequent post, and users with anxiety may be more averse to the risk of a post that does not receive as many likes. Moreover, the GAD-7 scale assesses specifically generalized anxiety and not other types of anxiety that may be particularly related to social media reward sensitivity—namely, social anxiety. Users with social anxiety may be expected to demonstrate the opposite effect of what we found, demonstrating higher sensitivity to social media likes. Future studies may employ a scale specifically assessing social anxiety to distinguish between types of anxiety.

Our finding that ADHD is positively associated with self-reported social media sensitivity and addiction is in line with our hypothesis that users with ADHD will overreport problematic social media activity and sensitivity compared to actual logged activity (Section 1.4.3). Furthermore, previous literature suggests that individuals with depression, anxiety, and of older age self-report lower sensitivity to reward (Kasch et al., 2002; Potsch & Rief, 2023; Cardoso Melo et al., 2023), providing a possible explanation for the incongruity between behavioral and self-reported sensitivity for each group. These findings stress the importance of the use of behavioral data in addition to, or in place of, self-reported data in the study of social media use and/or reward sensitivity.

Paramountly, all of our findings are limited by our small sample size and the placement of the ASRS scale in the screener questionnaire. Although we recruited a large number of participants, the filters applied to preserve the quality of the data markedly reduced the sample size. It is possible that the marginal significance we found across analyses can be attributed to this lack of power, as other such studies use larger sample sizes (e.g., Guntuku et al., 2017). As aforementioned, data collection for this study is ongoing, and future studies may also seek to replicate our results with a larger sample size. Furthermore, the ASRS questionnaire we chose to employ was brief, and was the sole mental health scale placed in the screener questionnaire as opposed to the main study questionnaire. As we were offering compensation of $20 for a relatively brief study, participants may have been incentivized to submit dishonest responses on the screener questionnaire to gain eligibility and earn the promised sum. It is possible that this contributed to the discrepancies between ADHD diagnosis and symptom results, or was a generally insufficient measure of ADHD symptomatology. Future studies may employ a longer ASRS scale, included within the main study questionnaire, in order to 1) avoid the impression that ADHD symptom severity is being used to screen for the study and therefore bias results and 2) collect data from participants who have committed to further participation in the study.

It is important to consider why the findings from analyses categorized by diagnosis (e.g., ADHD) differed from those categorized by symptoms (e.g., ASRS-5). This may be attributed to any of four primary factors: 1) continuous data, as opposed to discrete, yield higher statistical power, 2) individuals with severe symptoms of any given condition may go undiagnosed, 3) self-report measures are, as previously stated, unreliable, and individuals may overestimate or underestimate their symptoms, and 4) individuals may be diagnosed but have lesser symptoms because they take prescribed medication or are in psychotherapy. Although we collected data on medication and psychotherapy, due to the small size of our dataset, we did not have sufficient data for meaningful analysis of the potential mitigating effect of medication. However, medication and psychotherapy may be significant moderators of the interaction between mental health and social media behavior. Future research might therefore consider these factors to clarify the distinction between diagnoses and symptoms.

In addition to the aforementioned, a number of other notable limitations may have influenced our findings. First, we did not collect IP addresses. Although our X/Twitter ads were targeted towards users based in the U.S., and ResearchMatch exclusively enrolls verifiable U.S. residents, we were unable to verify location and therefore filter for participants who may have been dishonest regarding their stated location. Relatedly, Qualtrics fraud detection devices are not infallible. Some seemingly authentic participants were flagged as bots and/or duplicates in one or both questionnaires, and were subsequently excluded from analysis. Other seemingly inauthentic participants were not flagged in either questionnaire and were only identified as bots or duplicates through inspection of their donated data. Furthermore, a demographic question assessing race was added to the main questionnaire only partway into data collection. Thus, we did not have enough data to include race as a control variable in our analyses. However, prior research suggests that race interacts significantly with social media behavior and particularly moderates the interaction between mental health and social media behavior (Rai et al., 2024). Future research, therefore, might include race as a central control variable.

Future research may also investigate sensitivity to other forms of reinforcement, e.g., reposts or replies, or seek to explore or replicate results on other social media platforms, e.g., Instagram, Facebook, Reddit, TikTok. The aforementioned factors of ADHD hypothesized to be relevant to addiction (i.e., impulsivity, anxiety sensitivity, high sensation-seeking) may also be differentially relevant to other components of the social media experience, such as the design of the platform (e.g., scrolling design), algorithm, types of content, sharing capabilities, expected length of engagement with each post, etc. Therefore, future research may also investigate the interaction between ADHD and similar components.

In summary, our results found that increased reward sensitivity is associated with depression, anxiety, and age, but did not find evidence for a relationship with ADHD. Self-reported measures of social media usage, reward sensitivity, and addiction were associated with ADHD and age, but not with depression or anxiety. Future studies should employ a more comprehensive ADHD symptom scale and collect a larger sample to investigate these hypotheses conclusively. These results underscore the value of using behavioral data in addition to, or in place of, self-reported data. More importantly, they highlight the heightened potential risk of social media use for people with pre-existing mental health conditions. Ultimately, these findings contribute to an understanding of the bidirectional relationship between social media usage and mental health, as well as to an understanding of ADHD and response to reward as a function of ADHD symptoms.

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Appendix

A. Honor Code

I pledge my honor that this thesis represents my own work in accordance with University regulations.

Katherine Belilty

Katherine Belilty

B. Twitter Advertisement

C. Screener Questionnaire

Attention check questions are colored in orange and bolded for clarity. Near the end of data collection, the attention check question was changed to "If you're paying attention to this question, please select 'Often' as your answer." in an attempt to identify and exclude straightliners.

Thank you for your interest in our study.

The following questionnaire will take approximately 2 minutes to complete.

Our study is investigating the relationship between social media and mental health. We are interested in all levels of mental health, so please answer as honestly and accurately as possible.

If we find that our study is right for you, you will be invited to complete a second, brief questionnaire and to donate your public Twitter/X data (information on your public posts and likes) via a secure platform. Following this, you will be compensated $20 for your participation.

Thank you for contributing to science! Please continue to the consent form.

…

In which country do you currently reside?

In which state do you currently reside?

How old are you?

On average, how often do you post (including reposts and replies to other people's posts) on Twitter/X?

- ☐ More than once a day
- ☐ Once a day
- ☐ A few times a week
- ☐ Once a week
- ☐ A few times a month
- ☐ Once a month
- ☐ A few times a year
- ☐ Never

ASRS-5:
How often do you have difficulty concentrating on what people are saying to you even when they are speaking to you directly?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often

- ☐ Very often

How often do you have difficulty concentrating on what people are saying to you even when they are speaking to you directly?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

How often do you leave your seat in meetings or other situations in which you are expected to remain seated?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

How often do you have difficulty unwinding and relaxing when you have time to yourself?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

When you're in a conversation, how often do you find yourself finishing the sentences of the people you are talking to before they can finish them themselves?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

How often do you put things off until the last minute?

- ☐ Never
- ☐ Rarely
- ☐ Sometimes
- ☐ Often
- ☐ Very often

How often do you find yourself remembering a time when you traveled to the moon?

- ☐ Never
- ☐ Rarely

☐ Sometimes
☐ Often
☐ Very often

How often do you depend on others to keep your life in order and attend to details?

☐ Never
☐ Rarely
☐ Sometimes
☐ Often
☐ Very often

What is the best email address at which to reach you if this study is right for you?

***Please continue to the final page of the survey*.**

D. Main Study Questionnaire

Attention check questions are colored in orange and bolded for clarity. The questions within each questionnaire (i.e. PHQ-9, GAD-7, Sensitivity to Social Media Likes Scale, SMD Scale) were presented to each participant in randomized order.

Thank you for your interest in our study.

The following questionnaire will take approximately 10-15 minutes to complete. At its conclusion, you will be invited to request and upload your public social media data via a secure platform. Upon donation of your data, you will be compensated $20 for your participation.

Our study is investigating the relationship between social media and mental health. Please answer as honestly and accurately as possible.

Please continue to the consent form.

…

Please verify your Subject ID:

Gender:

- ○ Woman
- ○ Man
- ○ I identify my gender as (please specify):

What is your race? (Choose all that apply.)

- ☐ American Indian/Alaska Native
- ☐ Asian
- ☐ Native Hawaiian or other Pacific Islander
- ☐ Black or African American
- ☐ White
- ☐ Other:
- ☐ ⊗ Rather not say

What is your ethnicity?

- ☐ Hispanic or Latino
- ☐ Not Hispanic or Latino
- ☐ Unknown
- ☐ ⊗ Rather not say

Have you ever been diagnosed with any of the following by a mental health professional?

- ☐ ADHD

- ☐ Major depressive disorder (depression)
- ☐ Generalized anxiety disorder (anxiety)
- ☐ Other:
- ☐ ⊗ I have not been diagnosed by a mental health professional.

Are you currently taking any prescribed medications to manage ADHD symptoms?
- ○ Yes
- ○ No

Are you currently taking any prescribed medications to manage other mental illness symptoms?
- ○ Yes
- ○ No

Are you currently in psychological therapy (psychotherapy)?
- ○ Yes
- ○ No

Have you received psychotherapy in the past?
- ○ Yes
- ○ No

PHQ-9:
Over the *last two weeks*, how often have you been bothered by any of the following problems?

Little interest or pleasure in doing things.
- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Feeling down, depressed, or hopeless.
- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Trouble falling or staying asleep, or sleeping too much.
- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Feeling tired or having little energy.
- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Poor appetite or overeating.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Feeling bad about yourself — or that you are a failure or have let yourself or your family down.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Trouble concentrating on things, such as reading the newspaper or watching television.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Moving or speaking so slowly that other people could have noticed, or so fidgety or restless that you have been moving a lot more than usual.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Thoughts that you would be better off dead, or thoughts of hurting yourself in some way.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Select 'More than half the days' for your answer to this question.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

GAD-7:

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

Feeling nervous, anxious, or on edge.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Not being able to stop or control worrying.

- ☐ Not at all

- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Worrying too much about different things.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Trouble relaxing.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Being so restless that it's hard to sit still.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Becoming easily annoyed or irritable.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Feeling afraid, as if something awful might happen.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Worrying about how you will never know what an insect feels.

- ☐ Not at all
- ☐ Several days
- ☐ More than half the days
- ☐ Nearly every day

Sensitivity to Social Media Likes Scale:
The statements below concern your feelings about receiving *likes from others on social media platforms*. Please read them carefully. Indicate the statement that most accurately defines your point of view. There are no right or wrong answers. All answers are valuable, provided they are sincere.

I feel happy when I receive likes.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree

- ☐ Agree
- ☐ Strongly agree

I feel ostracized when I don't receive enough likes.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

I get excited when I receive likes.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes makes me feel like I have a higher social status.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

I'm proud of myself when I receive likes.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes makes me feel as though I'm succeeding in climbing a social ladder.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes allows me to develop relationships with new people who like my social media posts.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes serves as an easy way to maintain relationships with my friends.

- ☐ Strongly disagree

- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes makes me feel closer to my social media friends/contacts.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Receiving likes enhances my social relationships.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

Select 'Strongly agree' for your answer to this question.

- ☐ Strongly disagree
- ☐ Disagree
- ☐ Neither agree nor disagree
- ☐ Agree
- ☐ Strongly agree

SMD Scale:

During the past year, have you…

… regularly found that you can't think of anything else but the moment that you will be able to use social media again?

- ○ No
- ○ Yes

… regularly felt dissatisfied because you wanted to spend more time on social media?

- ○ No
- ○ Yes

… often felt bad when you could not use social media?

- ○ No
- ○ Yes

… tried to spend less time on social media, but failed?

- ○ No
- ○ Yes

… regularly neglected other activities (e.g., hobbies, sports) because you wanted to use social media?

- ○ No
- ○ Yes

… regularly had arguments with others because of your social media use?

- No
- Yes

… regularly lied to your parents or friends about the amount of time you spend on social media?

- No
- Yes

… often used social media to escape from negative feelings?

- No
- Yes

… had serious conflict with your parents, brother(s) or sister(s) because of your social media use?

- No
- Yes

… often felt afraid that you would spontaneously turn into a potted plant?

- No
- Yes

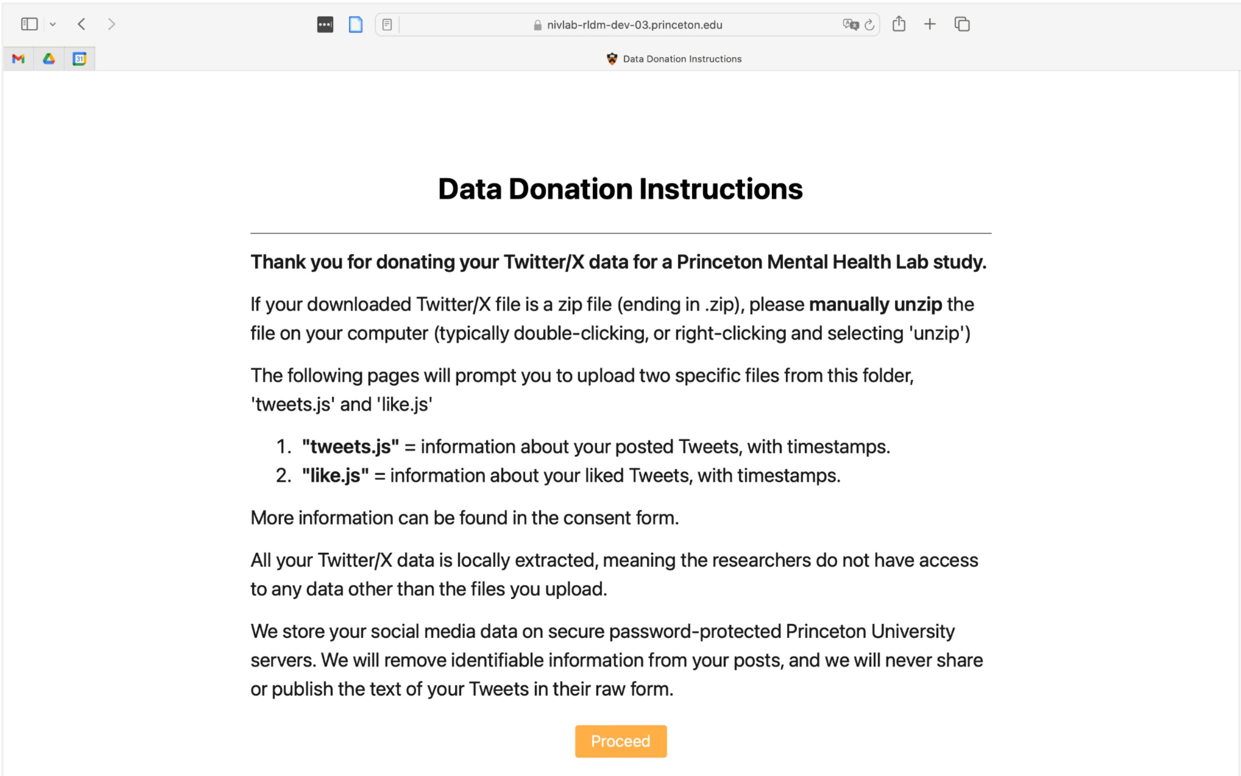
On average, how much time (in minutes) do you spend on social media on a given day?
If you are unsure, you can check the 'Screen Time' activity in your Settings app.

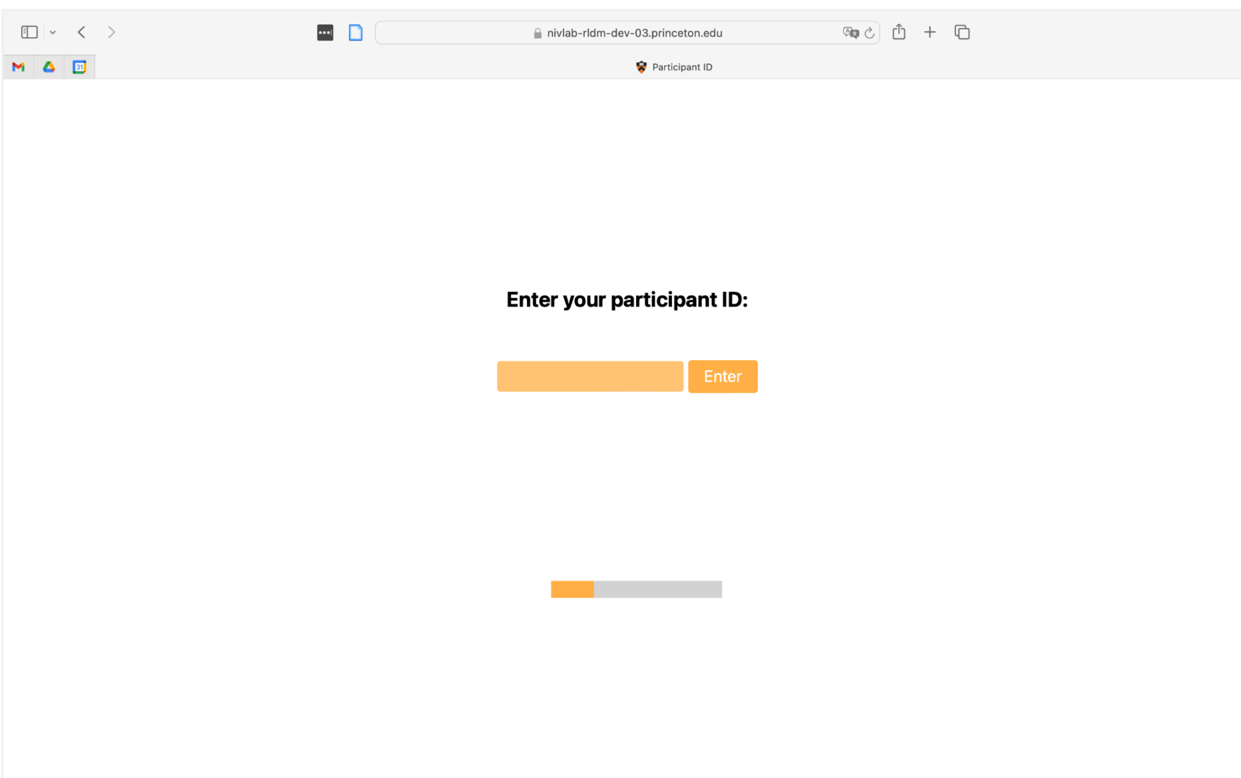
On average, how much time (in minutes) do you spend on Twitter/X on a given day?
If you are unsure, you can check the 'Screen Time' activity in your Settings app.

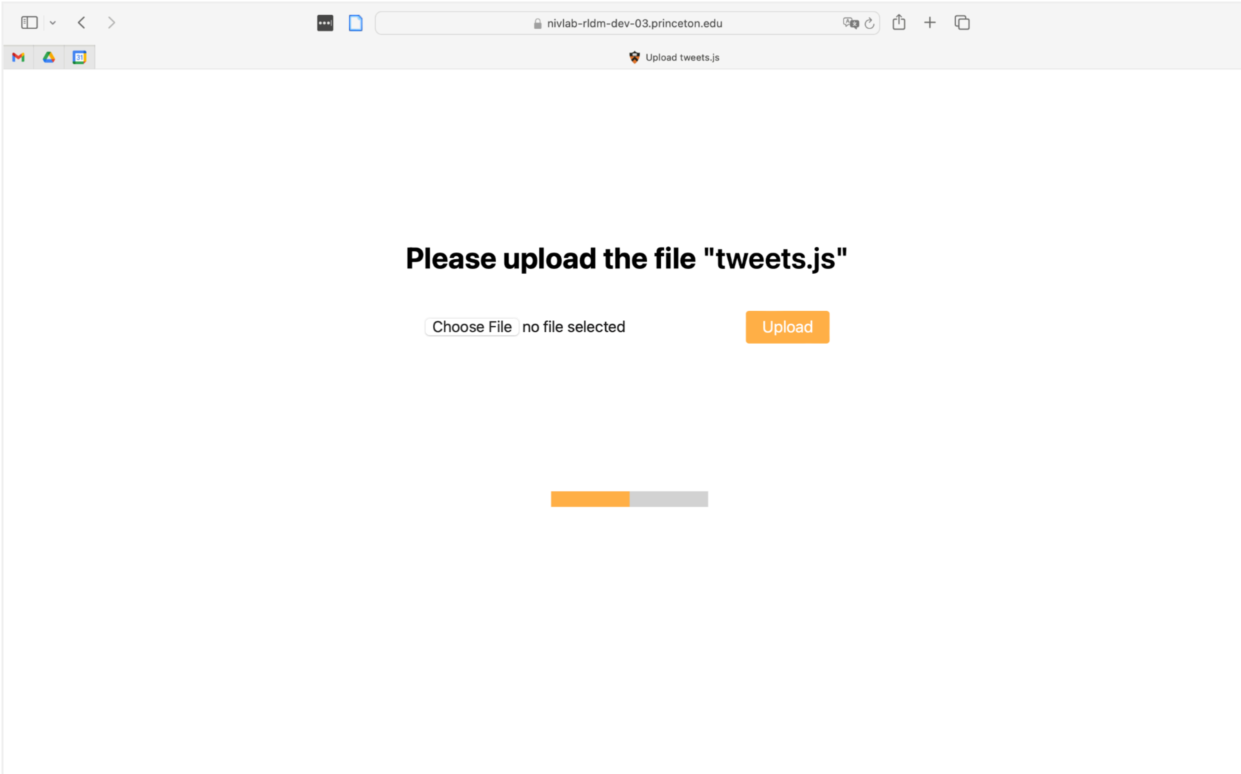
Thank you for participating in our survey. A list of mental health resources can be found at this link: https://nivlab.princeton.edu/mental-health-resources.

Please continue to the final page of the survey.

E. Data Upload Portal



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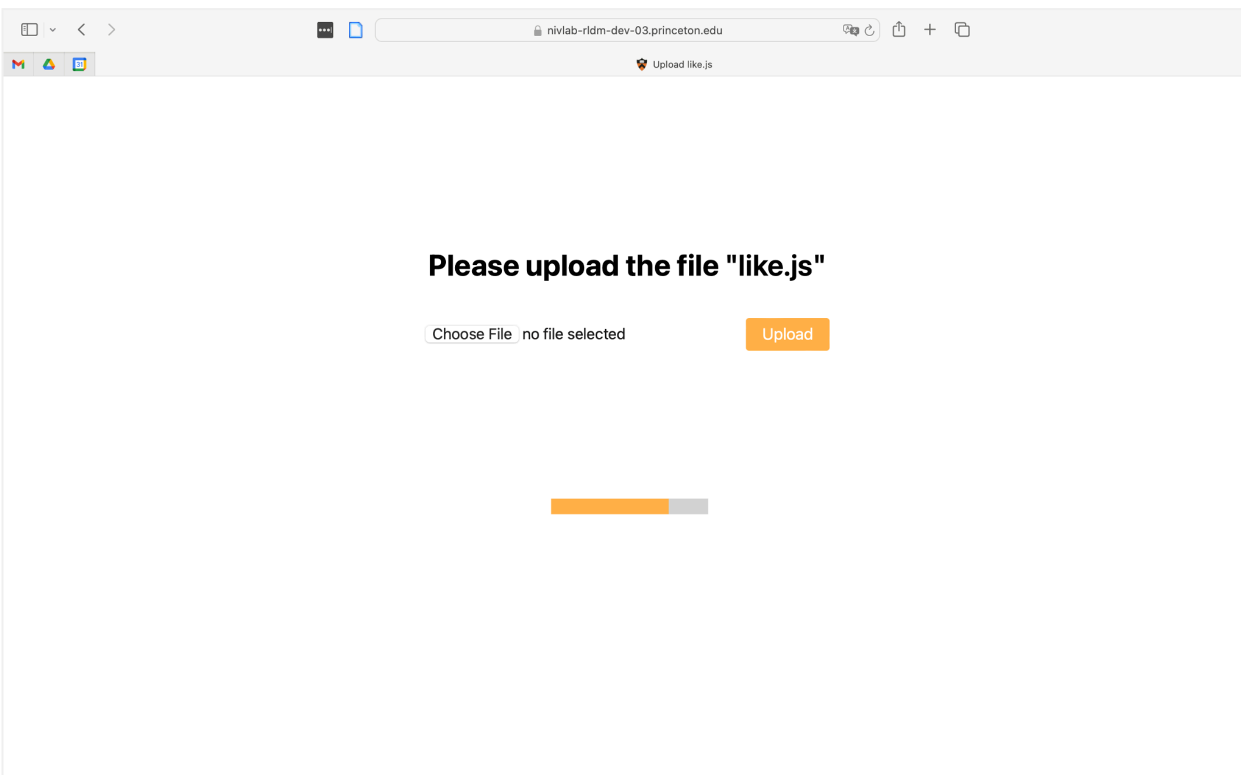
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Upload like.js
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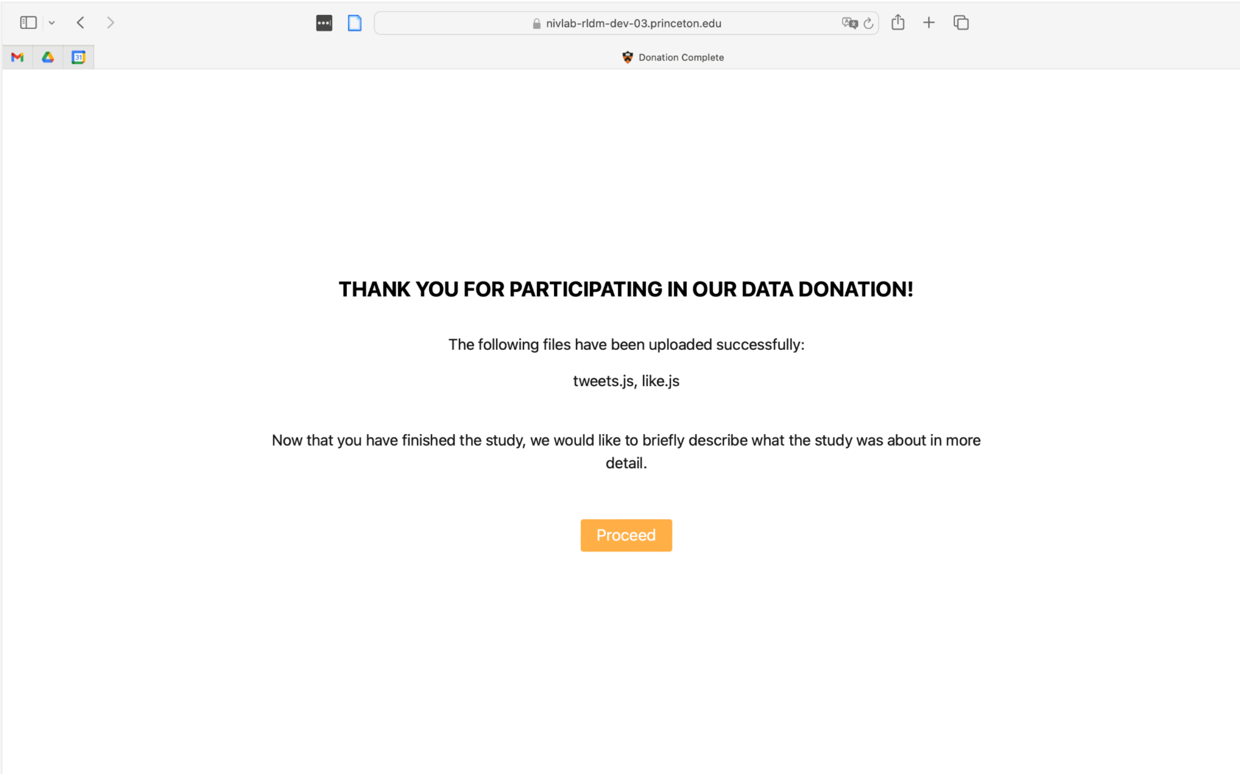
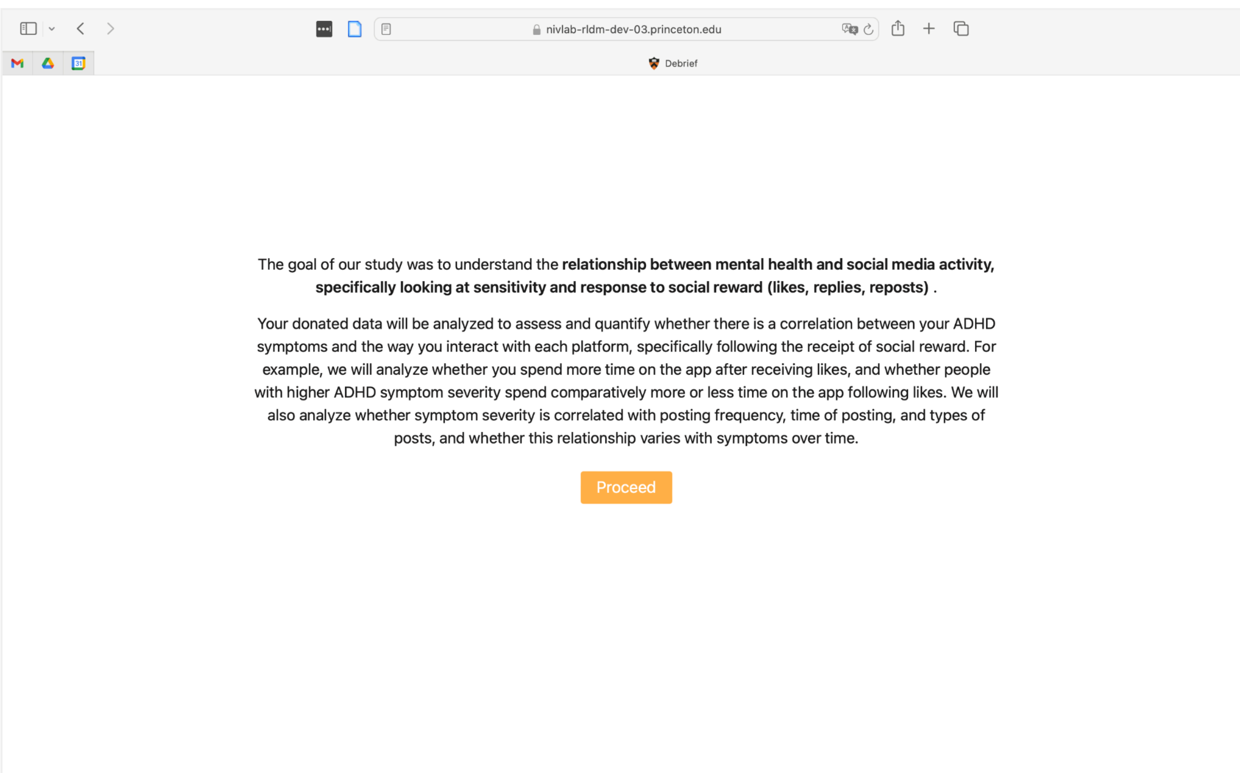
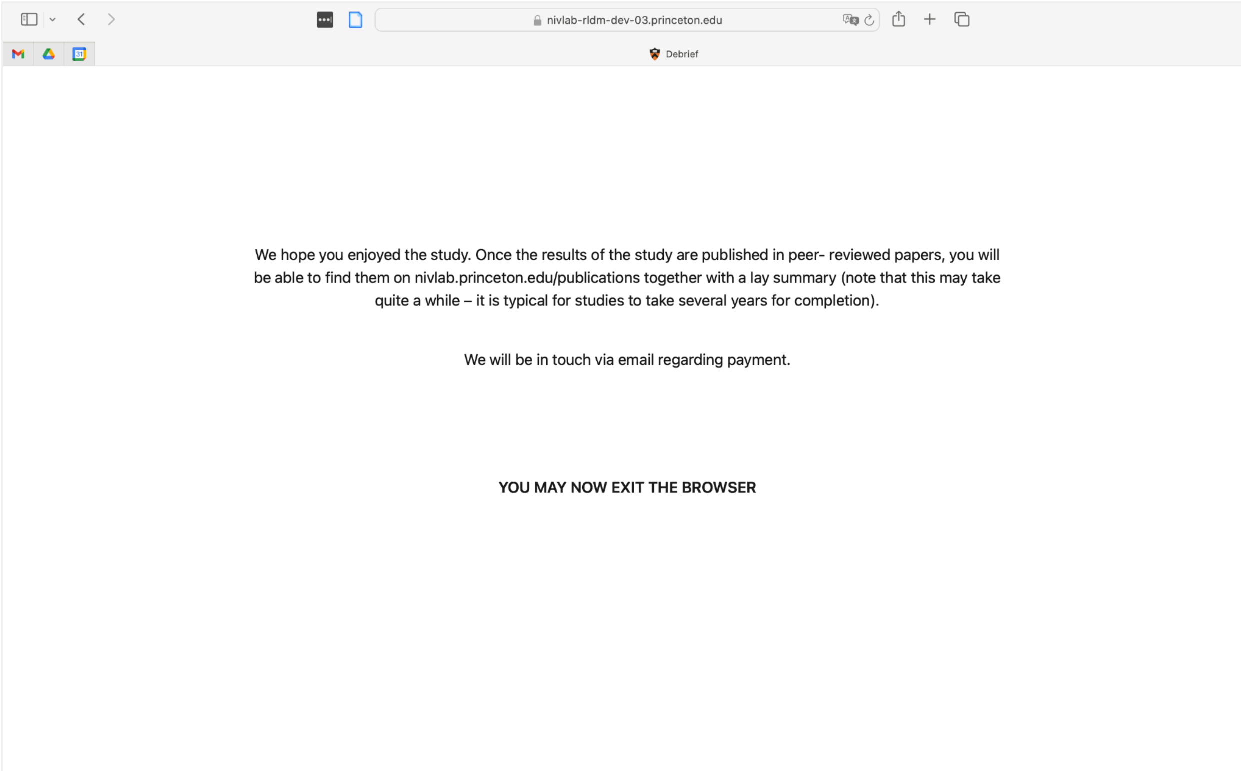

nivlab-rldm-dev-03.princeton.edu
Donation Complete
THANK YOU FOR PARTICIPATING IN OUR DATA DONATION!
The following files have been uploaded successfully:
tweets.js, like.js
Now that you have finished the study, we would like to briefly describe what the study was about in more detail.
Proceed


nivlab-rldm-dev-03.princeton.edu
Debrief
The goal of our study was to understand the **relationship between mental health and social media activity, specifically looking at sensitivity and response to social reward (likes, replies, reposts)** .
Your donated data will be analyzed to assess and quantify whether there is a correlation between your ADHD symptoms and the way you interact with each platform, specifically following the receipt of social reward. For example, we will analyze whether you spend more time on the app after receiving likes, and whether people with higher ADHD symptom severity spend comparatively more or less time on the app following likes. We will also analyze whether symptom severity is correlated with posting frequency, time of posting, and types of posts, and whether this relationship varies with symptoms over time.
Proceed


nivlab-rldm-dev-03.princeton.edu
Debrief
We hope you enjoyed the study. Once the results of the study are published in peer- reviewed papers, you will be able to find them on nivlab.princeton.edu/publications together with a lay summary (note that this may take quite a while – it is typical for studies to take several years for completion).
We will be in touch via email regarding payment.
YOU MAY NOW EXIT THE BROWSER