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Neurobiological sensitivity to popular peers moderates daily links between social media use and affect

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A B S T R A C T

Social media behaviors increase during adolescence, and quantifiable feedback metrics (e.g., likes, followers) may amplify the value of social status for teens. Social media's impact on adolescents' daily affect may be exacerbated given the neurodevelopmental changes that increase youths' sensitivity to socio-emotional information. This study examines whether neurobiological sensitivity to popularity moderates daily links between social media use and affect. Adolescents ($N = 91$, M_{age}=13.6 years, SD_{age}=0.6 years) completed an fMRI task in which they viewed faces of their high (>1 SD above the mean) and low (<1 SD below the mean) popular peers based on peer-nominated sociometric ratings from their school social networks. Two years later, adolescents reported their time spent on social media and affect daily for two weeks. Neural tracking of popularity in the ventromedial and dorsomedial prefrontal cortex moderated the association between time on social media and affect. Specifically, adolescents who tracked high popular peers in the vmPFC reported more positive affect on days when they used social media more. Adolescents who tracked low popular peers in the vmPFC and dmPFC reported more negative affect on days when they used social media more. Results suggest that links between social media and affect depend on individual differences in neural sensitivity to popularity.

1. Introduction

Social media behaviors increase during adolescence and are a primary platform by which youth engage in peer interactions (Rideout et al., 2022). Unique characteristics of social media may be augmenting the value of social status, particularly popularity, among adolescents (Nesi et al., 2018) at a time in which they are hypersensitive to social and emotional experiences (Blakemore and Mills, 2014; Somerville, 2013). While multiple studies have explored the association between time spent on social media and adolescents' emotions, such associations have been mixed in the literature (for reviews see Best et al., 2014; Orben, 2020). It may be that individual differences in neurobiological sensitivity to social cues determine the extent to which social media impacts adolescents' positive and negative affect. Thus, the current study explores the association between time spent on social media and daily positive and negative affect, and whether individual differences in adolescents' neural sensitivity to peer status moderates this link.

Social media platforms have become ubiquitous for adolescents worldwide, providing them with novel opportunities to explore, express themselves, and interact with others (Bhanderi et al., 2021; Rideout et al., 2022). Here, we define social media as a form of digital media that is often mobile, immersive, and offers a continuous form of engagement in social interaction, communication, and selective self-presentation (e.g., TikTok, Instagram, Youtube; Nesi et al., 2018). Distinct features of social media platforms have fundamentally transformed the landscape of adolescents' peer interactions. Characteristics such as the quantifiability of digital social interactions – the extent to which social media allows for numerical social metrics (e.g., likes, views, followers) – can impact adolescents' digital experiences and subsequent online behaviors, and may be altering the meaning of social status among adolescents (Dhir et al., 2018; Nesi and Prinstein, 2019). Social status is typically comprised of two distinct components. Popularity describes the extent to which an individual has prestige and influence in a group and is often associated with social dominance while social preference (i.e., likability) describes the extent to which an individual is considered as friendly and cooperative. Social media contexts have unique affordances such as quantifiable feedback metrics which emphasize the *number* of likes, retweets, comments on users' posts (i.e., how popular it was) over the

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content of those comments (i.e., how liked it was). As such, feedback metrics tend to represent the amount of influence an individual has over a group thus explaining why individuals that have a large number of followers and elicit high levels of engagement with their posts are often termed *influencers*. Thus, social media may be highlighting and augmenting the value of social influence in terms of popularity. For example, when using social media, adolescents can engage in digital status seeking behaviors to gain online indicators of peer status and approval (Nesi and Prinstein, 2019).

Greater social media use in adolescence coincides with an increased risk for the onset of depression and anxiety (Vuorre et al., 2021) which has sparked growing concerns among the public regarding how social media may be affecting adolescents' emotional well-being (Barry, 2023; Gordon and Brown, 2023). However, despite over 80 systematic reviews and metanalyses looking at a range of populations (Dickson et al., 2018), researchers have not reached a consensus on the impact of social media on the health of youth (for reviews see Best et al., 2014; Frith, 2017; Sarmiento et al., 2020; Orben, 2020). Indeed, studies have found positive, negative, and even null associations between social media use and affective well-being among adolescents (Banjanin et al., 2015; Orben and Przybylski, 2019; Verduyn et al., 2017). Discrepancies in research findings highlight complex and nuanced associations between social media use and adolescent emotional well-being.

It has been argued that the small associations and inconsistencies within research findings may arise from an attempt to identify overall trends within large datasets (Orben and Przybylski, 2019). This generalization may be obscuring important individual differences in how youth respond to digital social contexts. Indeed, past studies have primarily been cross-sectional, assessing variables at a single timepoint, and examine between-person associations to see if adolescents who use social media more or less than their peers report higher or lower levels of well-being (Orben, 2020). While valuable, these studies are unable to consider whether time spent on social media and mood can vary for an adolescent on a daily level. Indeed, social media can provide a variable source of both positive and negative emotions (Anderson and Jiang, 2018; Weinstein, 2018). As a result, researchers have begun exploring how social media behaviors may impact emotional well-being within adolescents rather than between them (Orben et al., 2019; Whitlock and Masur, 2019; Beyens et al., 2020). Measuring fluctuations of these behaviors using intensive longitudinal data such as daily diaries can increase the validity of self-report measures by taking into consideration the potential daily variance that can occur as well as decreasing recall bias of retrospective self-report (Jensen et al., 2019). However, even studies focused on within-person associations between social media and well-being have shown positive, negative, or null associations (Orben et al., 2019; Boers et al., 2019; Jensen et al., 2019; Coyne et al., 2020).

A potential explanation for the discrepancies in both between and within person associations of time spent on social media and emotional well-being may be explained by differences in neurobiological susceptibility to the social context (Schriber and Guyer, 2016). Adolescents experience significant restructuring of neural networks associated with social and affective processing (Blakemore and Mills, 2014; Crone and Dahl, 2012; Somerville et al., 2013), which heightens their sensitivity to social information within their environments. Indeed, such changes in the brain's neural circuity may explain why adolescents become increasingly motivated to connect with peers, acquire social status, and seek high-intensity affective experiences with the hope of gaining peer admiration (Crone and Dahl, 2012; Nelson et al., 2005, 2016). As such, heightened neurobiological sensitivity – particularly in regions that encode peer status – may determine the extent to which social media impacts adolescents' positive and negative affect.

The current preregistered (https://osf.io/skxvp) study offers insight into how adolescents' social media use and affective well-being vary daily and may be moderated by neural sensitivity to peer status. Using an intensive 14-day daily diary approach, we explored the association between youths' daily time spent on social media and their positive and negative affect. Based on mixed prior literature showing discrepant links between social media and affect, we hypothesized that associations between time on social media and positive and negative affect would be small or null. Capitalizing on neuroimaging methods, and a novel, ecologically valid fMRI task designed to measure the neural correlates of viewing high popular and low popular peers within their own social networks, we examined whether adolescents' neural sensitivity to popularity moderates links between social media use and daily affect. We separately defined high popularity and low popularity for a couple of reasons. First, to date, most studies in the extant literature have focused on the effect of high social status peer on others' social behaviors, relatively less attention has been paid to low social status peers. Second, literature suggests that these two types of peers constitute two important social signals in adolescents' social worlds – such that high social status peers provide avenue for teenagers to maintain or further improve their social status (Dijkstra et al., 2013), and low social status peers is often associated with social isolation and relational aggression that teenagers want to avoid (e.g., Prinstein and Cillessen, 2003). Therefore, investigating the specific neural activation in response to high and low social status peers may be important for understanding adolescents' social development.

We explored brain regions that are involved in valuation (i.e., ventromedial prefrontal cortex; vmPFC) and social cognition (i.e., dorsomedial prefrontal cortex; dmPFC and temporoparietal junction; TPJ) systems given the potential importance of these systems in navigating social context such as social media. The vmPFC has been consistently associated with processing the affective value and motivational significance of social stimuli (Doré et al., 2015; Güroğlu et al., 2008) and has been found to track group members' sociometric popularity among adults (Zerubavel et al., 2015). Exploring the activation of valuation-related brain regions may be particularly important among adolescents using social media given that digital quantitative feedback metrics may augment the value of peers. The dmPFC and the TPJ are both activated when making judgments about others' mental states and intentions (Adolphs, 2003; Doré et al., 2015) and have shown neural tracking of social status among adults (Zerubavel et al., 2015). Social media allows for near-constant access to social interactions which require understanding others' mental states and thus the recruitment of social cognition brain regions is important for understanding others' intentions and identifying status in peers' online behaviors. Since social media platforms highlight and amplify popularity, we preregistered our hypothesis that individuals who showed greater neural sensitivity to their highest- or lowest- popular peers in these regions of interest (ROI) would show a stronger association between their daily time spent on social media and their daily affect. In contrast, adolescents with low neural sensitivity to popularity would show a weaker or null association between social media and affect. Additionally, we preregistered an exploratory whole-brain analysis to determine if other brain regions may be involved in moderating the association between social media use and daily affect.

2. Material and methods

2.1. Participants

Data for the current study were collected across 3 waves when participants were in the 6th and 7th grade (wave 1, 2016–2017 academic year), 7th and 8th grade (wave 2, 2017–2018 academic year), and 9th and 10th grade (wave 4, 2019–2020 academic year). Note that data were also collected during wave 3 but are not included in the current study. For the purposes of this study, demographic information and sociometric nominations were obtained during school-based testing at waves 1 and 2, fMRI data were collected at wave 2, and daily diaries were completed at wave 4. All study procedures were approved by the University's Institutional Review Board and adolescents and their parents provided written assent and consent.

Participants were recruited from three rural middle schools in the southeast United States as part of a 5-year longitudinal study. A total of 873 adolescents participated in school-based data collection at wave 1. Letters of consent were mailed to the caregivers and students who returned a signed parental permission consent form, regardless of whether consent was granted or denied by the caregiver, were compensated \$5. Adolescent assent was obtained using a computer by trained research staff in school. School-based assessments were collected annually. At each wave, adolescents used computer-assisted self-interviews to report sociometric peer nominations among other self-report measures and were compensated \$5 for their participation.

A subset of participants who met eligibility criteria (i.e., no MRI contraindications, head trauma, history of seizures, or learning disabilities) participated in a longitudinal fMRI study. Adolescent participants completed an fMRI scan annually. A sample of 148 adolescents were recruited for the first wave of data collection. To account for attrition, an additional 30 participants were recruited for the neuroimaging sample at wave 2. At wave 2 of data collection, adolescents completed a 1.5-hour fMRI scan, which included the Classmates task, as well as behavioral tasks and self-report questionnaires which were not the focus of this manuscript. Participants were compensated \$90, a \$20 gift card for performing well in the scanner (e.g., minimum motion), an extra \$25 as a bonus for returning to our study for wave 2, snacks during the visit, and a meal. The participating caregiver was compensated \$50 as well as a meal and reimbursed for parking and gas. Of the original 178 participants, 26 did not participate in the second wave, eight were unable to complete the scan due to braces, six were excluded due to technical errors during scanning, one quit the scanning session early, two were not from the school district and so did not have social network data, and three participants were excluded from analyses for excessive head motion (> 2 mm in any direction on more than 20% of TRs). Of these 132 participants, 15 participants were excluded due to sociometric data calculation errors (see “fMRI Task” subsection).

During wave 4, participants completed a two-week daily diary survey via the ExpiWell application (https://app.expiwell.com). Participants were sent a notification via an app downloaded on their smartphone with the daily survey. The survey was sent at 8 p.m. and participants had until 12 a.m. to complete it. Each daily survey took approximately 10 min to complete. The application recorded the date and time of completion for each questionnaire. Concurrently, participants completed an ecological momentary assessment (EMA) three times per day and were jointly compensated for the EMA and daily diaries, \$25 for completing fewer than 50% of the surveys, \$35 for completing between 50–70% of the surveys, and \$50 for completing 70% or more of the surveys. The EMA data were not used in the current study. Participants (n = 115) completed the daily diary at wave 4 and reported their affect and amount of time they spent on social media (56% female, M_{age} = 15.88 years, SD_{age} = 0.59, Age Range = 14.64 – 17.68 years; 38% Hispanic, 25% White, 24% Black, 11% multi-racial, 1% Native American). On average, participants completed 77% of the daily diaries over the two-week period. No minimum percentage of surveys were needed to be included in the analysis. Our final sample, which included adolescents with both daily diary and fMRI data, was comprised of 91 participants (54% female, M_{age}=15.80 years, SD_{age} = 0.60; Age Range = 14.64 – 17.68 years; 38% Hispanic, 24% Black, 24% White, 11% multi-racial, 1% Native American).

2.2. Measures

The current study included sociometric ratings of peer status collected at waves 1 and 2, the Classmates fMRI task data collected at wave 2, and daily diary data of time spent on social media and affect collected at wave 4.

2.2.1. Sociometric peer ratings

As part of the larger study, participants completed a sociometric survey to assess peer social status within their own school networks. Participants were provided a full list of their peers within their school and grade level and were asked to report 1) who they liked the most, 2) who they liked the least, 3) who they thought was the most popular, and 4) who they thought was the least popular. Students were not given a limit to the number of peers they could nominate for each. For each student in the school, we used these peer nominations to calculate *social preference* (z-score of “liked the most” minus their z-score of “liked the least”) and reputation-based *popularity* (z-score of “most popular” minus their z-score of “least popular”). Z-scores for each sociometric index were based on participants’ rating relative to other students within their same school and grade. Peer nominations collected during wave 1 were used to create the stimuli in the fMRI task, which was administered at wave 2. Peer nominations were also collected during wave 2, which were used to control for participants’ own popularity in the analyses. Social preference and popularity were highly stable across wave 1 and wave 2 (see Supplementary material).

2.2.2. Classmates fMRI task

During wave 2, participants completed the Classmates fMRI task adapted from the social network position task (Parkinson et al., 2017). Participants viewed yearbook photos of peers from their school. Yearbook photos (i.e., targets) used in the task were selected based on the sociometric data from the previous year (wave 1). Peers selected as target images for the task had to have a sociometric z-score between 1 and 5 (representing 1–5 SD above the mean on popularity/social preference in their school and grade) or between − 1 and − 5 (representing 1–5 SD below the mean on popularity/social preference in their school and grade). Given the school- and grade- specific target images, a version of the task was created for each grade level within each school for a total of six versions. The task had four conditions: High social preference (i.e., z-score between 1 and 5 on social preference), low social preference (i.e., z-score between −1 and −5 on social preference), high popularity (i.e., z-score between 1 and 5 on popularity), and low popularity (i.e., z-score between −1 and −5 on popularity). In each condition, participants saw 10 target images, with roughly an equal number of boys and girls. Due to an error in data management, z-scores for the target images in two of the six task versions were miscalculated. We recalculated popularity and social preference scores for the target images for both task versions. For one group of participants (n = 20), there were enough target images that still fit the criteria for each condition (high popularity = 9, low popularity = 8, high likability = 8, low likability = 10) so we included them in the analyses. The other group of participants (n = 15) did not have enough number of target images in each condition (e.g., as few as 5) so these participants were excluded in the analyses. The absolute value of the average z-score within each condition was approximately 2 across all versions of the task. Each target image was assigned to only one sociometric category and appeared in one condition to avoid any overlap between conditions. The study participants were excluded as stimuli so they would not see their own image. Target images were collected from the previous year’s school yearbook picture, which was the same year sociometric ratings were collected. All yearbook photos were digitized into JPEG images.

The task was programmed in E-Prime and presented across two runs. Each run consisted of eight blocks, two blocks per condition, each with 10 faces. The eight blocks were presented in a randomized order in each run. The order in which the target images were shown was fixed within each block and pre-selected based on a randomization algorithm. To ensure participants were paying attention, the task had a built-in N-back design such that each block contained one stimulus that appeared twice in a row (Parkinson et al., 2017). Participants were asked to press with their right pointer finger when they saw the target image repeated to ensure they were paying attention. Button presses were monitored, and on average participants accurately pressed on 95% of the trials (range: 63–100%). Thus, no participants were excluded based on noncompliance with the attention checks during the task. Repeated targets were fixed in the task and balanced so that no target was shown more than another (i.e., if a target was seen twice in one block, it would be absent from the next block). Participants saw each face 4 times total (twice in each run), with each condition having 40 trials each. Stimuli were presented for 1750 ms and separated by a jittered inter-trial interval (*M* = 2300 ms).

2.2.3. Daily social media use.

During wave 4, participants completed daily diaries in the evenings in which they were asked if they had used social media (e.g., Instagram, TikTok, Twitter, Facebook, YouTube, Reddit, or other sites) that day. If they answered yes, they were asked to report how much total time they had spent on social media that day, with answers grouped into 14 categories (none, <1 h, 1 h, 2 h, 3 h, 4 h, 5 h, 6 h, 7 h, 8 h, 9 h, 10 h, 11 h, 12 + hours). These values were recoded into total minutes spent on social media to create an interval scale. As such "none" was recoded to 0 min, "less than 1 h" was recoded to 30 min, answers between "1 h" and "11 h" were recoded to the equivalent value in minutes (i.e., "1 h" became 60 min), and "12 + hours" was recoded to 720 min.

2.2.4. Daily affect

Daily affect was assessed every evening via daily diaries. Participants used a 5-point scale (1 = very little or not at all, 2 = a little, 3 = some, 4 = quite a bit, 5 = very strongly) to rate to what extent they felt 12 different emotions that day. We took the average of all negatively valanced emotions (anxious, fearful, embarrassed, awkward, stressed, tense, irritated, mad, sad, lonely) and all positively valanced emotions (happy and calm) to create one index of daily negative affect and daily positive affect, respectively. Note, there were two deviations from the preregistered study associated with the daily affect variable. First, we chose to average all negatively-valenced emotions rather than focusing solely on sadness, loneliness, anxiety, and fearfulness. Second, we explored associations between time spent on social media and both positive and negative affect instead of just examining negative affect. Deviations and justifications for these are described in detail in the supplementary materials.

2.3. MRI data acquisition and preprocessing

Imaging data were collected using a 3 Tesla Siemens Prisma MRI scanner. The Classmates Task was presented on a computer screen and projected through a mirror. A high-resolution structural T2 * -weighted echo-planar imaging (EPI) volume (TR = 2000 ms; TE = 25 ms; matrix = 92 ×92; FOV = 230 mm; 37 slices; slice thickness = 3 mm; voxel size 2.5 ×2.5 ×3 mm3) was acquired coplanar with a T2 * -weighted structural matched-bandwidth (MBW), high-resolution, anatomical scan (TR = 5700 ms; TE = 65 ms; matrix = 192 ×192; FOV = 230 mm; 38 slices; slice thickness = 3 mm). In addition, a T1 * magnetization-prepared rapid-acquisition gradient echo (MPRAGE; TR = 2400 ms; TE = 2.22 ms; matrix = 256 ×256; FOV = 256 mm; sagittal plane; slice thickness = 0.8 mm; 208 slices) was acquired. The orientation for the EPI and MBW scans was oblique axial to maximize brain coverage and to reduce signal dropout.

Preprocessing was conducted using FSL (FMRIB's Software Library, version 6.0; www.fmrib.ox.ac.uk/fsl) and included the following steps: Skull stripping using BET (Smith, 2002); motion correction with MCFLIRT (Jenkinson et al., 2002); spatial smoothing with Gaussian kernel of full width at half maximum (FWHM) 6 mm; high-pass temporal filtering with a filter width of 128 s (Gaussian-weighted least-squares straight line fitting, with sigma=64.0 s); grand-mean intensity normalization of the entire 4D dataset by a single multiplicative factor; and individual level ICA denoising for motion and physiological noise using MELODIC (version 3.15; Beckmann and Smith, 2004), combined with an automated signal classifier (Tohka et al., 2008; Neyman-Pearson threshold =.3). For the spatial normalization, the EPI data were registered to the T1 image with a linear transformation, followed by a white-matter boundary-based transformation (BBR; Greve and Fischl, 2009) using FLIRT, linear and non-linear transformations to standard Montreal Neurological Institute (MNI) 2-mm brain were performed using Advanced Neuroimaging Tools (ANTs; Avants et al., 2011), and then spatial normalization of the EPI image to the MNI. Quality check during preprocessing and analyses ensured adequate signal coverage.

2.4. fMRI data analysis

For the Classmates Task, individual level, fixed-effects analyses were estimated using the general linear model convolved with a canonical hemodynamic response function using SPM12. The data were modeled as event-related using four separate conditions: high popularity, low popularity, high social preference, and low social preference. Low popularity and social preference scores were originally negative (i.e., −1 SD below the mean) and high popularity and social preference scores were positive (i.e., +1 SD above the mean). We took the absolute value of the sociometric rating for the target (i.e., the social preference score for the high and low social preference conditions and the popularity score for the high and low popularity conditions) and used it as a parametric modulator at the trial level. Within each condition, the sociometric ratings therefore ranged from low to high scores so we could examine how adolescents track high popularity and low popularity at the neural level. For example, within the high popular condition, the parametric modulator allows us to examine if brain regions show linear increases in BOLD signal as the absolute value of popularity increases. Within the low popular condition, the parametric modulator allows us to examine if brain regions show linear increases in BOLD signal as the absolute value of 'unpopularity' increases. The repeated target within each block that served as an attention check was treated as a separate condition and modeled as a condition of no interest. TRs with motion greater than 0.5 FD were modeled as a nuisance regressor. Given the primary aim of this study was to examine neural sensitivity to popularity specifically, analyses focused solely on the high popularity and low popularity conditions.

From each individual's first level models, we extracted parameter estimates of signal intensity from each of the ROIs (bilateral vmPFC, dmPFC, and TPJ) for each condition of interest: high popular peers with the absolute value of high popularity as a parametric modulator at the trial level and low popular peers with the absolute value of low popularity as a parametric modulator at the trial level. Because of the parametric modulator, these parameter estimates of signal intensity in each ROI represent BOLD signal that increases linearly with increases in high popularity and low popularity, respectively. We defined each ROI using a distinct atlas built to highlight unique functional networks, a common analytical approach (McCormick et al., 2018). We defined the vmPFC using the Harvard-Oxford atlas. We defined the TPJ using the Saxe Lab social brain ROIs (Dufour et al., 2013) and the dmPFC was defined using the union of Brodman's areas 8 and 9, between and including the sagittal plane at MNI = 12 and − 12, superior to and including the axial plane at MNI z = 24, and anterior to and including the coronal plane at MNI y = 30 (Telzer et al., 2011). Additionally, we conducted a preregistered, exploratory whole-brain analysis to determine whether other brain regions that tracked peer popularity, not accounted for in the ROI analysis, moderated the association social media use and daily affect (See supplement).

2.5. Analysis plan

We conducted an unconditional multilevel model to examine links between daily reported time spent on social media and daily positive and negative affect. Models were estimated in R. Full information maximum likelihood was used to account for missing data due to nonnormality in the negative affect variable (similarly used in the positive affect models for consistency). Time spent on social media in minutes was included as a predictor and daily positive and negative affect indexes were included as outcome variables, each modeled separately. For the predictor, we person-centered time spent on social media, in which the aggregated person-level variable was subtracted from the raw variables, and we included on the intercept group-mean values for each of our daily predictors (Curran and Bauer, 2011). This approach helps to parse out within-subject (i.e., SMT w/in) vs between-subject (i.e., SMT b/w) effects. The models included 1075 observations across 115 participants. We included sex (dummy coded 0 = female, 1 = male), race/ethnicity (with dummy codes representing Hispanic, Black, Multiracial, and Native American; White race was the reference group), participants' own sociometric popularity, and age at time of scan (mean centered) as between-person covariates in the model and day of the week (dummy coded 0 = weekday, 1 = weekend) as a within-person covariate given prior literature showing differences in social media use in these categories (Rideout et al., 2022). We estimated the following equation (for simplicity, covariates are not shown in the equation):

Level 1:

$$Affect_{ij} = \beta_{0j} + \beta_{1j} SMT \quad w/in_{ij} + r_{ij}$$

Level 2:

$$\beta_{0j} = \gamma_{00} + \gamma_{01} SMT \quad b/w_{0j} + u_{0j}$$

$$\beta_{1j} = \gamma_{10}$$

Reduced-Form:

$$Affect_{ij} = \left(\gamma_{00} + \gamma_{01} SMT \quad b/w_{0j} + \gamma_{10} SMT \quad w/in_{ij}\right) + (u_{0j} + r_{ij})$$

At Level 1, affect for day *j*, and person *k* was modeled as a function of the intercept term (β_{0j}), daily social media time, and the residual. Level 2 included person-average social media time as a predictor of the intercept.

Subsequently, we explored whether neural sensitivity to popularity moderated the association between daily time spent on social media and daily affect. To this end, we used conditional multilevel models to see if neural tracking of popularity in the vmPFC, dmPFC, and TPJ moderated the daily association between time on social media and affect (nlme::lme package in R; Pinheiro et al., 2023). For each of the 3 ROIs, we ran separate models for neural tracking of high- and low- popular peers. Models were run separately for positive and negative affect, for a total of 4 models for each ROI. We employed a Benjamini Hochberg False Discovery Rate procedure to correct for the number of tests within each ROI. Each model included 830 observations across 91 participants. In the same level 2 equation above, cross-level interactions between neural tracking and daily time spent on social media were included. To explore significant interactions between time spent on social media and affect, we categorized neural sensitivity into those 0.25 SD above and below the mean and conducted post hoc models of each group to plot the interaction. We used a Benjamini Hochberg False Discovery Rate procedure to correct for the number of post hoc tests within each ROI.

3. Results

Descriptive statistics and correlations between continuous variables of interest are shown in Table 1. Daily measures were averaged across the 14 days for descriptive purposes. Significant differences by sex in variables of interest are shown in Table 2. There were no significant differences by racial or ethnic groups.

3.1. Daily level associations between social media use and affect

To examine the association between time spent on social media and affect, we first conducted an unconditional multilevel model including sex as a covariate in the model (Table 3). Results show that on days where adolescents spent more time on social media than their average, they reported more negative affect. We did not find significant between-

Table 2
Descriptive Statistics for Continuous Study Variables by Sex.

	Female		Male		Sex		
	M	SD	M	SD	t	DoF	p
1. SMT	256.61	169.53	263.09	166.73	0.65	113	0.518
2. PA	3.46	0.85	3.64	1.06	-0.99	113	0.326
3. NA	**1.55**	**0.53**	**1.28**	**0.46**	**2.92**	**113**	**0.004**
4. H Pop vmPFC	-0.07	0.36	0.01	0.45	-0.98	89	0.328
5. L Pop vmPFC	**-0.09**	**0.43**	**0.10**	**0.52**	**-1.99**	**89**	**0.049**
6. H Pop dmPFC	-0.02	0.42	-0.01	0.61	-0.09	89	0.927
7. L Pop dmPFC	-0.15	0.51	0.04	0.42	-1.92	89	0.058
8. H Pop TPJ	-0.01	0.40	0.00	0.65	-0.04	89	0.970
9. L Pop TPJ	**-0.07**	**0.39**	**0.14**	**0.45**	**-2.42**	**89**	**0.018**
10. Pop W2	-0.12	1.22	-0.31	1.51	0.70	103	0.488
11. Age at scan	13.67	0.59	13.69	0.59	0.19	112	0.853

Note. SMT = social media time. PA = positive affect. NA = negative affect. H Pop = neural tracking of high popular peers. L Pop = neural tracking of low popular peers.

Table 1
Correlations and Descriptive Statistics for Continuous Study Variables.

	1	2	3	4	5	6	7	8	9	10	11
1. SMT	–	–	–	–	–	–	–	–	–	–	–
2. PA	0.04	–	–	–	–	–	–	–	–	–	–
3. NA	0.12	-0.42 * *	–	–	–	–	–	–	–	–	–
4. H Pop vmPFC	-0.03	0.11	-0.15	–	–	–	–	–	–	–	–
5. L Pop vmPFC	0.13	0.09	-0.04	-0.23 *	–	–	–	–	–	–	–
6. H Pop dmPFC	-0.02	0.13	-0.1	0.41 * *	0.00	–	–	–	–	–	–
7. L Pop dmPFC	0.03	0.03	-0.08	-0.08	0.62 * *	0.17	–	–	–	–	–
8. H Pop TPJ	0.01	0.08 * *	-0.03	0.45 * *	0.01	0.84 * *	0.12 * *	–	–	–	–
9. L Pop TPJ	0.01	0.14 * *	-0.11 * *	0.01	0.41 * *	0.05	0.54 * *	0.09 * *	–	–	–
10. Popularity W2	0.00	0.02	-0.09	0.00	-0.05	-0.13	0.1	-0.08 *	0.02 * *	–	–
11. Age at scan	0.1	-0.03	-0.09	0.09	-0.04	-0.02	0.18	0.00	0.00	0.16	–
M	247.52	3.54	1.43	-0.03	-0.003	-0.02	-0.06	-0.006	0.03	-0.21	13.68
SD	167.15	0.95	0.52	0.40	0.48	0.51	0.48	0.53	0.43	1.35	0.58
Min	30	1	1	-1.15	-1.27	-1.89	-2.67	-1.83	-0.94	-6.02	12.42
Max	720	5	3.79	1.56	1.28	2.13	1.06	2.96	1.57	3.50	15.40

Note. SMT = social media time. PA = positive affect. NA = negative affect. H Pop = neural tracking of high popular peers. L Pop = neural tracking of low popular peers. Computed correlations of all continuous variables of interest using the Person-method. * $p < 0.05$, * * $p < 0.01$. Means and standard deviations are presented for all variables.

Table 3
Multilevel model with social media time predicting daily negative and positive affect.

	Negative Affect *b* [95% CI]	*SE*	*p*	Positive Affect *b* [95% CI]	*SE*	*p*
Intercept	**1.55 [1.42, 1.67]**	**.06**	**.000**	**3.47 [3.25, 3.68]**	**.11**	**.000**
SMT w/in	**0.0003 [.00003,.0005]**	**.0001**	**.028**	0.0003 [− .0002,.0008]	.0003	.323
SMT b/w	0.0003 [− .0003,.0008]	.0003	.370	0.0002 [− .0008,.001]	.0005	.637
Male	**-0.26 [− .46, − .07]**	**.09**	**.007**	0.22 [− .11,.55]	.17	.199

Note. SMT w/in = social media time within-person. SMT b/w = social media time between-people.

person or within-person associations between time spent on social media and positive affect. We also ran the model including adolescents' own popularity, race, school day, and age as covariates and found the findings remained and there were no significant differences in fit between the models, so we continued with the simpler model for parsimony.

3.2. *Moderating role of neural tracking of popularity*

To examine whether adolescents' neural sensitivity to popularity moderated links between social media use and daily affect we conducted a conditional multilevel model and included neural tracking in each ROI for the high popularity condition (i.e., when viewing peers whose popularity was > 1 SD above the mean) as a moderator. In separate models, we included neural tracking in each ROI for the low popularity condition (i.e., when viewing peers whose popularity was < 1 SD below the mean) as a moderator. Results are shown in Table 4. Results from the secondary, exploratory whole-brain analysis are describe in the supplement and are publicly available at https://identifiers.org/neurovault.collection:15670. Notably, no regions were identified at the whole brain level.

3.2.1. *Positive affect*

We found that neural tracking of high- but not low- popular peers within the vmPFC significantly moderated the association between daily time spent on social media and positive affect. Sensitivity to high or low popularity in the dmPFC and TPJ did not moderate associations between social media use and positive affect.

We decomposed the significant interaction between time spent on social media and positive affect by running post hoc models to compare individuals with vmPFC activation 0.25 SD above and below the mean. Those with vmPFC activation 0.25 SD above the mean were positively tracking highly *popular* peers (i.e., neural sensitivity increased as peers became more popular) and those with vmPFC activation 0.25 SD below the mean were negatively tracking highly *popular* peers (i.e., neural sensitivity decreased as peers became more popular). We controlled for sex in all the post hoc analyses. As shown in Fig. 1, adolescents who were positively tracking high popularity in the vmPFC reported greater positive affect on days when they spent more time on social media (b = 0.002, 95% CI [0.0009, 0.003], p < 0.001). However, adolescents who were negatively tracking popularity in the vmPFC showed no significant association at the daily level between time spent on social media and positive affect (b = 0.0002, 95% CI [−0.001, 0.002], p = 0.723).

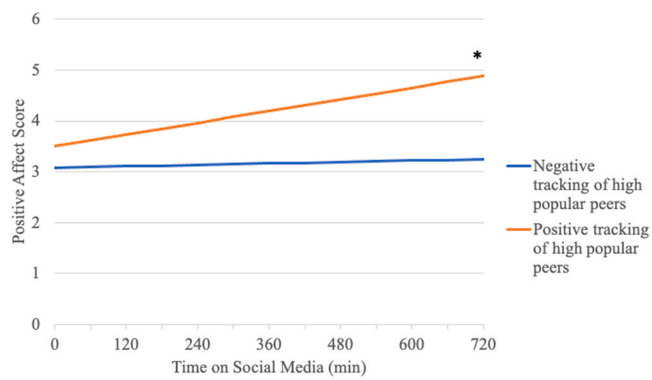

Fig. 1. Neural tracking of high popularity in the vmPFC. Negative tracking (i.e.,.25 SD below the mean, representing neural sensitivity that decreases as peers become more popular) shown in blue. Positive tracking (i.e.,.25 SD above the mean, representing neural sensitivity that increases as peers become more popular) shown in orange. Neural Sensitivity of High Popularity in the vmPFC Moderating Associations Between Time on Social Media and Positive Affect.

3.2.2. *Negative affect*

We found that neural tracking of low popular peers within the vmPFC and dmPFC, but not TPJ, significantly moderated the association between daily time spent on social media and negative affect. Neural sensitivity to high popular peers in the vmPFC, dmPFC, or TPJ did not moderate the association between time spent on social media and negative affect.

We unpacked the significant interactions between time spent on social media and negative affect by running post hoc models to compare individuals with vmPFC and dmPFC activation 0.25 SD above and below the mean. Adolescents who were negatively tracking highly *unpopular* peers (i.e., neural sensitivity decreased as peers became more unpopular) in the vmPFC (Fig. 2) and dmPFC (Fig. 3) reported greater negative affect on days when they spent more time on social media (vmPFC: b = 0.0007, 95% CI [0.0002, 0.001], p = 0.003; dmPFC: b = 0.0008, 95% CI [0.0003, 0.001], p = 0.002). However, adolescents who were positively

Table 4
Neural Sensitivity to Popularity Moderates Associations Between Time on Social Media and Affect.

	Negative Affect *b* [95% CI]	*SE*	*p*	Positive Affect *b* [95% CI]	*SE*	*p*
vmPFC						
High Popularity*SM	0.0003 [− .0007,.001]	.0005	.579	**0.003 [.001,.005]**	**.0009**	**.001**
Low Popularity*SM	**-0.001 [− .002, − .0001]**	**.0004**	**.022**	0.0002 [− .002,.002]	.0009	.844
dmPFC						
High Popularity*SM	-0.0004 [− .001,.0007]	.0005	.494	0.002 [− .0003,.003]	.001	.107
Low Popularity*SM	**-0.001 [− .002, − .0004]**	**.0005**	**.008**	-0.0004 [− .002,.002]	.001	.723
TPJ						
High Popularity*SM	0.00004 [− .001,.001]	.0005	.945	0.001 [− .0004,.003]	.001	.140
Low Popularity*SM	-0.0009 [− .002,.0002]	.0005	.094	0.0004 [− .002,.003]	.001	.707

Note. Participants' sex was controlled for in the models. *p*-values were corrected using the Benjamini Hochberg FDR procedure for multiple comparisons within each ROI. Significant values are bolded.

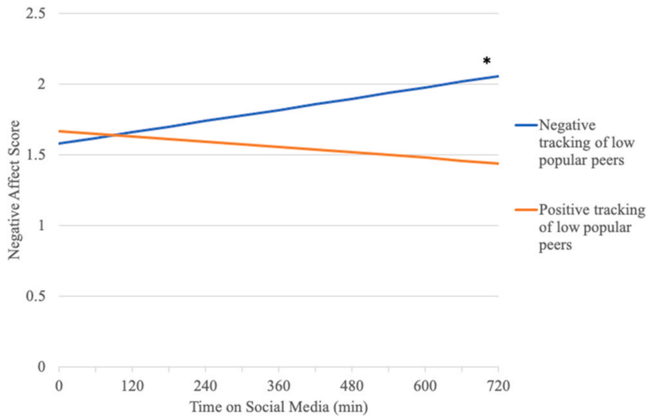

Fig. 2. Neural tracking of low popularity in the vmPFC. Negative tracking (i.e.,.25 SD below the mean, representing neural sensitivity that decreases as peers become more unpopular) shown in blue. Positive tracking (i.e.,.25 above the mean, representing neural sensitivity that increases as peers become more unpopular) shown in orange. Neural Sensitivity of Low Popularity in the vmPFC Moderating Associations Between Time on Social Media and Negative Affect.

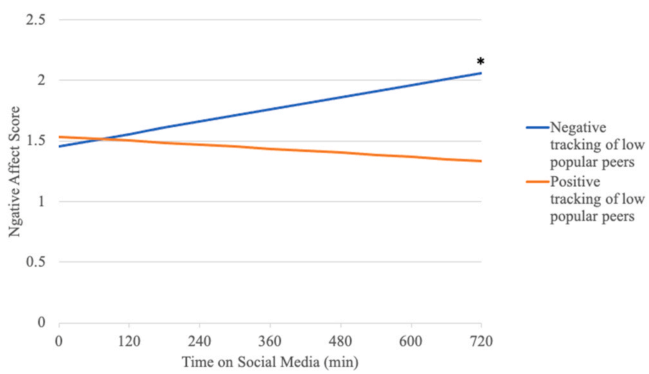

Fig. 3. Neural tracking of low popularity in the dmPFC. Negative tracking (i.e.,.25 SD below the mean, representing neural sensitivity that decreases as peers become more unpopular) shown in blue. Positive tracking (i.e.,.25 SD above the mean, representing neural sensitivity that increases as peers become more unpopular) shown in orange. Neural Sensitivity of Low Popularity in the dmPFC Moderating Associations Between Time on Social Media and Negative Affect.

tracking highly *unpopular* peers (i.e., neural sensitivity increased as peers became more unpopular) showed no significant association at the daily level between time spent on social media and negative affect (vmPFC: $b = -0.0003$, 95% CI [−0.0007, 0.00006], $p = 0.107$; dmPFC: $b = -0.0003$, 95% CI [−0.0009, 0.0004], $p = 0.392$).

4. Discussion

Social media contexts that magnify social status are omnipresent in modern adolescents' everyday lives. Indeed, we found that on average, adolescents reported spending 4.1 h a day on social media. Furthermore, we found that individual differences in neural sensitivity to popularity within the vmPFC and dmPFC moderated associations between time spent on social media and affect at the daily level. Results suggest that differences in neural sensitivity to popularity may serve as both a risk and protective factor in the association between social media use and adolescents' daily emotional wellbeing.

Our primary analyses examined whether individuals who were more neurally sensitive to their popular and unpopular peers in the vmPFC, dmPFC, and TPJ would show a stronger association between time spent on social media and positive affect, whereas those who were less sensitive would be buffered. Indeed, we found that adolescents who positively tracked high popular peers in the vmPFC (i.e., neural sensitivity increased as peers became more popular) reported more positive affect on days when they spent more time on social media than their own average, and adolescents who negatively tracked low popular peers in the vmPFC and dmPFC (i.e., neural sensitivity decreased as peers became more unpopular) reported more negative affect on days where they spent more time on social media than their own average.

While the vmPFC is implicated in various psychological proceses, it is well known for its role in the processing of affective value and motivational significance of stimuli, including social stimuli (Güroğlu et al., 2008), and its recruitment scales with perceived value (Hare et al., 2009; Kable and Glimcher, 2007; Zerubavel et al., 2015). One potential explanation for our results is that adolescents who positively track highly popular peers in the vmPFC are perceiving greater value in these more popular peers. For adolescents with this greater vmPFC activation to popularity, more time on social media is linked to greater positive affect. Importantly, we do not know the direction of the association. On the one hand, since social media platforms highlight and amplify the popularity of individuals via visible quantifiable cues (e.g., likes, retweets, followers; Nesi et al., 2018), adolescents who are more sensitive to high popularity may find social media platforms more rewarding and thus may feel more positive affect on days they spend more time online. In other words, these adolescents are more sensitized to the positive, rewarding features of social media. Indeed, studies have found that greater sensitivity to social rewards may increase the intensity and duration of positive emotional experiences (Heller et al., 2013) and thereby enhance positive affect and well-being (Morelli et al., 2018). Alternatively, on days where adolescents experience more positive affect, adolescents who are highly sensitive to popular peers may seek out positive rewards by spending more time on social media. Indeed, researchers have posited that adolescent mental health and affect may both impact and be impacted by social media use and have called for future work to examine the bidirectional relationship (Flannery et al., 2023; Luo and Hancock, 2020).

For neural tracking of low popular peers, we found the opposite effect in the vmPFC, such that adolescents whose vmPFC activity decreased as peers became more unpopular experienced more negative affect on days where they spent more time on social media. In line with the argument that vmPFC activation scales with perceived value, adolescents who are negatively tracking low popularity may especially devalue unpopular peers. As a result, they may experience social media - which highlights both high and low popularity – as less rewarding. As such, on days where they use social media more than their average, adolescents who show dampened vmPFC activation to unpopular peers may experience more negative affect. It is also possible that adolescents who are experiencing more negative affect may also be using social media as a coping mechanism (Maftei et al., 2023) and thus spend more time on social media. It is critical to note that while we focused on the role of the vmPFC for reward representation, this brain region has also been associated with other functions such as the generation and regulation of negative emotions and facial emotion recognition (Hiser and Koenigs, 2018). Future work is needed to narrow down the specific psychological process moderating the association between daily social media use and affect.

We found a similar pattern in the dmPFC, a brain region involved in making judgements about others' characteristics, mental states, and intentions (Blakemore, 2008; Blakemore and Mills, 2014) and processing information about the self with respect to others, among other functions. Mentalizing is often used by adolescents to navigate complex social contexts such as social hierarchies among peers (Brown and Larson, 2009). This is particularly important in digital contexts where fewer interpersonal cues (i.e., facial expression, tone of voice, or gestures) are available during social interactions (Nesi et al., 2018). While speculative, one possible explanation for the current results may be that adolescents who are negatively tracking low popularity in the dmPFC engage in less mentalizing when viewing unpopular peers. This, in turn, may complicate adolescents' ability to navigate social media contexts, such that on days where they spend more time on social media, they experience more negative affect. On the other hand, mentalizing has also been shown to impact adolescent well-being (Guazzelli Williamson and Mills, 2023) such that lower mentalizing is associated with higher self-reported symptoms of depression (Poznyak et al., 2019) and anxiety (Pile et al., 2017). In this case, when experiencing more negative affect, adolescents may be using social media more to avoid navigating complex in-person social contexts. Again, it is vital to acknowledge that the dmPFC is also involved in a variety of functions beyond mentalizing such as modulating and regulating emotional responses thus more work is necessitated to ascertain how this may be impacting daily associations between social media use and affective states.

Interestingly, neural sensitivity for high or low popular peers in the TPJ did not moderate the association between time spent on social media and negative or positive affect. Several studies have found that functional connectivity between both valuation and social cognition regions in the brain, particularly between the vmPFC and TPJ, can predict individual differences in social valuation (for review see Li et al., 2014; Smith et al., 2014). Moreover, prior work has found that when tracking popularity, activation of the social cognition system is mediated by the extent that valuation brain regions signal their motivational significance (Zerubavel et al., 2015). This suggests that exploring the interaction between the TPJ, vmPFC, and dmPFC, rather than the activation within each brain region, will be important in future work.

4.1. Contributions, limitations, and future directions

The current study contributes to the growing literature on adolescent social media use and emotional well-being by assessing daily-level associations between time spent on social media and positive and negative affect and showing that these may be moderated by neural sensitivity to popularity. Using two-week daily dairies and an ecologically valid fMRI task that used adolescents' real-world peers as stimuli allowed us to capture individual differences in how adolescents use social media and how this may impact their affective well-being. Results from the current study reiterate that social media can present both risks and opportunities thereby serving as a 'double-edged sword' for adolescent development. This parallels research showing that social media use may be associated with both positive and negative subjective well-being (for reviews see ; Choukas-Bradley et al., 2023; Verduyn et al., 2017). Additionally, our study shows that some adolescents do not experience significant associations between social media use and affect, underscoring that adolescents may be differentially impacted by social media contexts, and some adolescents are impervious to these effects. This finding is supported by prior literature showing that the association between social media use and affective well-being differs strongly across adolescents (Beyens et al., 2020).

Despite the novelty and strengths of the current study, several limitations should be acknowledged. The study relied on adolescents' self-reported estimates of time spent on social media which researchers have criticized for not being a reliable and accurate measure of social media use (Sewall et al., 2020; Parry et al., 2021). However, by using a repeated longitudinal design and centering participants' daily time spent on social media on their own average, this study overcomes the between-person factors that may differentially affect individuals' ability to accurately estimate social media use. To build on the current findings, future work should not only examine *how much time* is spent on social media but also on *how* and *why* adolescents are using social media to better understand how it may be differentially impacting individuals. Additionally, daily diary data were collected during the COVID-19 pandemic when social distancing restrictions significantly disrupted youth's typical social media use patterns and general affect (for meta-analysis see Marciano et al., 2022; Zhang et al., 2021). While modeling within-person differences may control for how the pandemic differentially impacted teens, findings should be replicated among a non-socially isolated sample of adolescents in future work. Finally, the fMRI task involved the passive viewing of their own peers and while this was designed to elicit responses when viewing highly popular or unpopular peers, activation may have been impacted by other factors that were not accounted for including familiarity, trustworthiness, or attractiveness of the peer. Indeed, popularity is strongly correlated with attractiveness (Gordon et al., 2013) and trustworthiness (Rotenberg et al., 2004) among adolescents. Furthermore, the vmPFC is sensitive to positive ratings of facial attractiveness (Mende-Siedlecki et al., 2013) and has been associated with decisions involving trustworthiness (Zheng et al., 2016). Moreover, the task was completed two years prior to EMA data collection and sensitivity to popularity may have changed in that time. Future studies could use longitudinal fMRI studies to examine how stable neural responsivity to popularity among adolescents.

5. Conclusion

The nearly ubiquitous presence of social media in adolescents' daily lives may have important consequences for their emotional well-being. Findings suggest that individual differences in adolescents' neural sensitivity to popularity may be a risk or protective factor in the daily association between time spent on social media and affective well-being. The current study contributes important insights that may further our understanding of how social media is impacting adolescents differently and what this could mean for their subsequent development.

CRediT authorship contribution statement

Maria Maza: Conceptualization, Data curation, Formal analysis, Writing – original draft, **Seh-Joo Kwon:** Formal analysis, Writing – review & editing **Nathan Jorgensen:** Data curation, Writing – review & editing **Jimmy Capella:** Data curation, Writing – review & editing **Mitchell Prinstein:** Writing – review & editing, Funding acquisition **Kristen Lindquist:** Writing – review & editing, Funding acquisition **Eva Telzer:** Conceptualization, Supervision, Writing – review & editing, Funding acquisition.

Declaration of Competing Interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Dr. Telzer and Dr. Prinstein reported receiving private research funds from the Winston Family Foundation during the conduct of the study. The Winston Family Foundation had no role in the design and conduct of the study; collection, management, analysis, and interpretation of the data; preparation, review or approval of the manuscript; and decision to submit the manuscript for publication.

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Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.dcn.2023.101335.

References

Adolphs, R., 2003. Cognitive neuroscience of human social behaviour. Nat. Rev. Neurosci. 4 (3), 165–178. https://doi.org/10.1038/nrn1056.

Anderson, M. & Jiang, J., 2018, May 31. *Teens, Social Media and Technology 2018*. Pew Research Center. 〈https://www.pewresearch.org/internet/2018/05/31/teens-social-media-technology-2018/〉.

Avants, B.B., Tustison, N.J., Song, G., Cook, P.A., Klein, A., Gee, J.C., 2011. A reproducible evaluation of ANTs similarity metric performance in brain image registration. NeuroImage 54 (3), 2033–2044. https://doi.org/10.1016/j.neuroimage.2010.09.025.

Banjanin, N., Banjanin, N., Dimitrijevic, I., Pantic, I., 2015. Relationship between internet use and depression: focus on physiological mood oscillations, social networking and online addictive behavior. Comput. Hum. Behav. 43, 308–312. https://doi.org/10.1016/j.chb.2014.11.013.

Barry, E. , 2023; January 3. *Social Media Use Is Linked to Brain Changes in Teens, Research Finds*. New York Times. 〈https://www.nytimes.com/2023/01/03/health/social-media-brain-adolescents.html〉.

Beckmann, C.F., Smith, S.M., 2004. Probabilistic independent component analysis for functional magnetic resonance imaging. IEEE Trans. Med. Imaging 23 (2), 137–152. https://doi.org/10.1109/TMI.2003.822821.

Best, P., Manktelow, R., Taylor, B., 2014. Online communication, social media and adolescent wellbeing: a systematic narrative review. Child. Youth Serv. Rev. 41, 27–36. https://doi.org/10.1016/j.childyouth.2014.03.001.

Beyens, I., Pouwels, J.L., van Driel, I.I., Keijsers, L., Valkenburg, P.M., 2020. The effect of social media on well-being differs from adolescent to adolescent. Sci. Rep. 10 (1), 1. https://doi.org/10.1038/s41598-020-67727-7.

Bhanderi, D.J., Pandya, Y.P., Sharma, D.B., 2021. Smartphone use and its addiction among adolescents in the age group of 16–19 years. Indian J. Community Med.: Off. Publ. Indian Assoc. Prev. Soc. Med. 46 (1), 88–92. https://doi.org/10.4103/ijcm.IJCM_263_20.

Blakemore, S.J., 2008. The social brain in adolescence. Nat. Rev. Neurosci. 9, 267–277. https://doi.org/10.1038/nrn2353.

Blakemore, S.J., Mills, K.L., 2014. Is adolescence a sensitive period for sociocultural processing? Annu. Rev. Psychol. 65, 187–207. https://doi.org/10.1146/annurev-psych-010213-115202.

Boers, E., Afzali, M.H., Newton, N., Conrod, P., 2019. Association of screen time and depression in adolescence. JAMA Pediatr. 173 (9), 853–859. https://doi.org/10.1001/jamapediatrics.2019.1759.

Brown, B.B., Larson, J., 2009. Peer relationships in adolescence. Handbook of Adolescent Psychology. American Cancer Society. https://doi.org/10.1002/9780470479193.adlpsy002004.

Choukas-Bradley, S., Kilic, Z., Stout, C.D., Roberts, S.R., 2023. Perfect Storms and Double-Edged Swords: Recent Advances in Research on Adolescent Social Media Use and Mental Health. Advances in Psychiatry and Behavioral Health 3, 149–157. https://doi.org/10.1016/j.ypsc.2023.03.007.

Coyne, S.M., Rogers, A.A., Zurcher, J.D., Stockdale, L., Booth, M., 2020. Does time spent using social media impact mental health?: an eight year longitudinal study. Comput. Hum. Behav. 104, 106160 https://doi.org/10.1016/j.chb.2019.106160.

Crone, E.A., Dahl, R.E., 2012. Understanding adolescence as a period of social–affective engagement and goal flexibility. Article 9 Nat. Rev. Neurosci. 13 (9). https://doi.org/10.1038/nrn3313.

Curran, P.J., Bauer, D.J., 2011. The disaggregation of within-person and between-person effects in longitudinal models of change. Annu. Rev. Psychol. 62, 583–619. https://doi.org/10.1146/annurev.psych.093008.100356.

Dhir, A., Yossatorn, Y., Kaur, P., Chen, S., 2018. Online social media fatigue and psychological wellbeing—a study of compulsive use, fear of missing out, fatigue, anxiety and depression. Int. J. Inf. Manag. 40, 141–152. https://doi.org/10.1016/j.ijinfomgt.2018.01.012.

Dickson, K., Richardson, M., Kwan, I., MacDowall, W., Burchett, H., Stansfield, C., Brunton, G., Sutcliffe, K., Thomas, J., 2018. Screen-Based Activities and Children and Young People's Mental Health: A Systematic Map of Reviews. EPPI-Centre, Social Science Research Unit, UCL Institute of Education, University College London,, London.

Dijkstra, J.K., Cillessen, A.H.N., Borch, C., 2013. Popularity and adolescent friendship networks: selection and influence dynamics. Dev. Psychol. 49 (7), 1242–1252. https://doi.org/10.1037/a0030098.

Doré, B.P., Zerubavel, N., Ochsner, K.N., 2015. Social cognitive neuroscience: a review of core systems. In: Mikulincer, M., Shaver, P.R., Borgida, E., Bargh, J.A. (Eds.), APA handbook of personality and social psychology, Vol. 1. Attitudes and social cognition. American Psychological Association, pp. 693–720. https://doi.org/10.1037/14341-022.

Dufour, N., Redcay, E., Young, L., Mavros, P.L., Moran, J.M., Triantafyllou, C., Gabrieli, J.D., Saxe, R., 2013. Similar brain activation during false belief tasks in a large sample of adults with and without autism. PloS One 8 (9), e75468. https://doi.org/10.1371/journal.pone.0075468.

Flannery, J.S., Maza, M.T., Kilic, Z., Telzer, E.H., 2023. Cascading bidirectional influences of digital media use and mental health in adolescence. Adv. Child Dev. Behav. 64, 255–287. https://doi.org/10.1016/bs.acdb.2022.10.003.

Frith, E., 2017. Social Media and Children's Mental Health: A Review of the Evidence. Education Policy Institute, London, UK.

Gordon, A. & Brown, P.2023, January 29. Surgeon General says 13 is 'too early' to join social media. CNN. 〈https://www.cnn.com/2023/01/29/health/surgeon-general-social-media/index.html〉.

Gordon, R.A., Crosnoe, R., Wang, X., 2013. Physical attractiveness and the accumulation of social and human capital in adolescence and young adulthood: assets and distractions. Monogr. Soc. Res. Child Dev. 78 (6), 1–137. https://doi.org/10.1002/mono.12060.

Greve, D.N., Fischl, B., 2009. Accurate and robust brain image alignment using boundary-based registration. NeuroImage 48 (1), 63–72. https://doi.org/10.1016/j.neuroimage.2009.06.060.

Guazzelli Williamson, V., Mills, K.L., 2023. Mentalizing strategies for navigating the social world in adolescence. Infant Child Dev. 32 (1), e2374 https://doi.org/10.1002/icd.2374.

Güroğlu, B., Haselager, G.J.T., van Lieshout, C.F.M., Takashima, A., Rijpkema, M., Fernández, G., 2008. Why are friends special? Implementing a social interaction simulation task to probe the neural correlates of friendship. NeuroImage 39 (2), 903–910. https://doi.org/10.1016/j.neuroimage.2007.09.007.

Hare, T.A., Camerer, C.F., Rangel, A., 2009. Self-control in decision-making involves modulation of the vmPFC valuation system. Science 324 (5927), 646–648. https://doi.org/10.1126/science.1168450.

Heller, A.S., van Reekum, C.M., Schaefer, S.M., Lapate, R.C., Radler, B.T., Ryff, C.D., Davidson, R.J., 2013. Sustained striatal activity predicts eudaimonic well-being and cortisol output. Psychol. Sci. 24 (11) https://doi.org/10.1177/0956797613490744.

Hiser, J., Koenigs, M., 2018. The multifaceted role of the ventromedial prefrontal cortex in emotion, decision making, social cognition, and psychopathology. Biol. Psychiatry 83 (8), 638–647. https://doi.org/10.1016/j.biopsych.2017.10.030.

Jenkinson, M., Bannister, P., Brady, M., Smith, S., 2002. Improved optimization for the robust and accurate linear registration and motion correction of brain images. NeuroImage 17 (2), 825–841. https://doi.org/10.1016/s1053-8119(02)91132-8.

Jensen, M., George, M.J., Russell, M.R., Odgers, C.L., 2019. Young adolescents' digital technology use and mental health symptoms: Little evidence of longitudinal or daily linkages. Clin. Psychol. Sci. 7 (6), 1416–1433. https://doi.org/10.1177/2167702619859336.

Kable, J.W., Glimcher, P.W., 2007. The neural correlates of subjective value during intertemporal choice. Nat. Neurosci. 10 (12), 1625–1633. https://doi.org/10.1038/nn2007.

Li, W., Mai, X., Liu, C., 2014. The default mode network and social understanding of others: what do brain connectivity studies tell us. Front. Hum. Neurosci. 8, 74. https://doi.org/10.3389/fnhum.2014.00074.

Luo, M., Hancock, J.T., 2020. Self-disclosure and social media: Motivations, mechanisms and psychological well-being. Curr. Opin. Psychol. 31, 110–115. https://doi.org/10.1016/j.copsyc.2019.08.019.

Maftei, A., Merlici, I.A., Dănilă, O., 2023. Social media use as a coping mechanism during the COVID-19 pandemic: a multidimensional perspective on adolescents' well-being. Front. Public Health 10, 1062688. https://doi.org/10.3389/fpubh.2022.1062688.

Marciano, L., Ostroumova, M., Schulz, P.J., Camerini, A.L., 2022. Digital media use and adolescents' mental health during the covid-19 pandemic: a systematic review and meta-analysis. Front. Public Health 9, 793868. https://doi.org/10.3389/fpubh.2021.793868.

Mende-Siedlecki, P., Said, C.P., Todorov, A., 2013. The social evaluation of faces: a meta-analysis of functional neuroimaging studies. Soc. Cogn. Affect. Neurosci. 8 (3), 285–299. https://doi.org/10.1093/scan/nsr090.

Morelli, S.A., Leong, Y.C., Carlson, R.W., Kullar, M., Zaki, J., 2018. Neural detection of socially valued community members. Proc. Natl. Acad. Sci. 115 (32), 8149–8154. https://doi.org/10.1073/pnas.1712811115.

Nelson, E.E., Leibenluft, E., McClure, E.B., Pine, D.S., 2005. The social re-orientation of adolescence: a neuroscience perspective on the process and its relation to psychopathology. Psychol. Med. 35 (2), 163–174. https://doi.org/10.1017/s0033291704003915.

Nelson, E.E., Jarcho, J.M., Guyer, A.E., 2016. Social re-orientation and brain development: an expanded and updated view. Dev. Cogn. Neurosci. 17, 118–127. https://doi.org/10.1016/j.dcn.2015.12.008.

Nesi, J., Prinstein, M.J., 2019. In search of likes: Longitudinal associations between adolescents' digital status seeking and health-risk behaviors. J. Clin. Child Adolesc. Psychol. 48 (5), 740–748. https://doi.org/10.1080/15374416.2018.1437733.

Nesi, J., Choukas-Bradley, S., Prinstein, M.J., 2018. Transformation of adolescent peer relations in the social media context: Part 1—a theoretical framework and application to dyadic peer relationships. Clin. Child Fam. Psychol. Rev. 21 (3), 267–294. https://doi.org/10.1007/s10567-018-0261-x.

Orben, A., 2020. Teenagers, screens and social media: a narrative review of reviews and key studies. Soc. Psychiatry Psychiatr. Epidemiol. 55 (4), 407–414. https://doi.org/10.1007/s00127-019-01825-4.

Orben, A., Przybylski, A.K., 2019. The association between adolescent well-being and digital technology use. Nat. Hum. Behav. 3 (2), 173–182. https://doi.org/10.1038/s41562-018-0506-1.

Orben, A., Dienlin, T., Przybylski, A.K., 2019. Social media's enduring effect on adolescent life satisfaction. Proc. Natl. Acad. Sci. 116 (21), 10226–10228. https://doi.org/10.1073/pnas.1902058116.

Parkinson, C., Kleinbaum, A.M., Wheatley, T., 2017. Spontaneous neural encoding of social network position. Nat. Hum. Behav. 1 (5), 1–7. https://doi.org/10.1038/s41562-017-0072.

Parry, D.A., Davidson, B.I., Sewall, C.J., Fisher, J.T., Mieczkowski, H., Quintana, D.S., 2021. A systematic review and meta-analysis of discrepancies between logged and self-reported digital media use. Nat. Hum. Behav. 5 (11), 1535–1547. https://doi.org/10.17605/OSF.IO/JS6YE.

Pile, V., Haller, S.P.W., Hiu, C.F., Lau, J.Y.F., 2017. Young people with higher social anxiety are less likely to adopt the perspective of another: Data from the director task. J. Behav. Ther. Exp. Psychiatry 55, 41–48. https://doi.org/10.1016/j.jbtep.2016.11.002.

Pinheiro, J., Bates, D., & R Core Team. , 2023. nlme: Linear and nonlinear mixed effects models (R package version 3.1–162). ⟨https://CRAN.R-project.org/package=nlme⟩.

Poznyak, E., Morosan, L., Perroud, N., Speranza, M., Badoud, D., Debbané, M., 2019. Roles of age, gender, and psychological difficulties in adolescent mentalizing. J. Adolesc. 74, 120–129. https://doi.org/10.1016/j.adolescence.2019.06.0.

Prinstein, M.J., Cillessen, A.H.N., 2003. Forms and functions of adolescent peer aggression associated with high levels of peer status. Merrill-Palmer Q. 49 (3), 310–342. https://doi.org/10.1353/mpq.2003.0015.

Rideout, V., Peebles, A., Mann, S., Robb, M.B., 2022. Common Sense Census: Media Use by Tweens and Teens, 2021. Common Sense,, San Francisco, CA.

Rotenberg, K.J., McDougall, P., Boulton, M.J., Vaillancourt, T., Fox, C., Hymel, S., 2004. Cross-sectional and longitudinal relations among peer-reported trustworthiness, social relationships, and psychological adjustment in children and early adolescents from the United Kingdom and Canada. J. Exp. Child Psychol. 88 (1), 46–67. https://doi.org/10.1016/j.jecp.2004.01.005.

Sarmiento, I.G., Olson, C., Yeo, G., Chen, Y.A., Toma, C.L., Brown, B.B., Bellmore, A., Mares, M.-L., 2020. How does social media use relate to adolescents' internalizing symptoms? conclusions from a systematic narrative review. Adolesc. Res. Rev. 5 (4), 381–404. https://doi.org/10.1007/s40894-018-0095-2.

Schriber, R.A., Guyer, A.E., 2016. Adolescent neurobiological susceptibility to social context. Dev. Cogn. Neurosci. 19, 1–18. https://doi.org/10.1016/j.dcn.2015.12.009.

Sewall, C.J., Bear, T.M., Merranko, J., Rosen, D., 2020. How psychosocial well-being and usage amount predict inaccuracies in retrospective estimates of digital technology use. Mob. Media Commun. 8 (3), 379–399. https://doi.org/10.1177/2050157920902830.

Smith, D.V., Clithero, J.A., Boltuck, S.E., Huettel, S.A., 2014. Functional connectivity with ventromedial prefrontal cortex reflects subjective value for social rewards. Soc. Cogn. Affect. Neurosci. 9 (12), 2017–2025. https://doi.org/10.1093/scan/nsu005.

Smith, S.M., 2002. Fast robust automated brain extraction. Hum. brain Mapp. 17 (3), 143–155. https://doi.org/10.1002/hbm.10062.

Somerville, L.H., 2013. The teenage brain: sensitivity to social evaluation. Curr. Dir. Psychol. Sci. 22 (2), 121–127. https://doi.org/10.1177/0963721413476512.

Telzer, E.H., Masten, C.L., Berkman, E.T., Lieberman, M.D., Fuligni, A.J., 2011. Neural regions associated with self control and mentalizing are recruited during prosocial behaviors towards the family. NeuroImage 58 (1), 242–249. https://doi.org/10.1016/j.neuroimage.2011.06.013.

Tohka, J., Foerde, K., Aron, A.R., Tom, S.M., Toga, A.W., Poldrack, R.A., 2008. Automatic independent component labeling for artifact removal in fMRI. NeuroImage 39 (3), 1227–1245. https://doi.org/10.1016/j.neuroimage.2007.10.013.

Verduyn, P., Ybarra, O., Résibois, M., Jonides, J., Kross, E., 2017. Do social network sites enhance or undermine subjective well-being? A critical review. Soc. Issues Policy Rev. 11 (1), 274–302. https://doi.org/10.1111/sipr.12033.

Vuorre, M., Orben, A., Przybylski, A.K., 2021. There is no evidence that associations between adolescents' digital technology engagement and mental health problems have increased. Clin. Psychol. Sci. 9 (5), 823–835. https://doi.org/10.1177/2167702621994549.

Weinstein, E., 2018. The social media see-saw: positive and negative influences on adolescents' affective well-being. N. Media Soc. 20 (10), 3597–3623. https://doi.org/10.1177/1461444818755634.

Whitlock, J., Masur, P.K., 2019. Disentangling the association of screen time with developmental outcomes and well-being: problems, challenges, and opportunities. JAMA Pediatr. 173 (11), 1021–1022. https://doi.org/10.1001/jamapediatrics.2019.3191.

Zerubavel, N., Bearman, P.S., Weber, J., Ochsner, K.N., 2015. Neural mechanisms tracking popularity in real-world social networks. Proc. Natl. Acad. Sci. 112 (49), 15072. https://doi.org/10.1073/pnas.1511477112.

Zhang, S., Liu, M., Li, Y., Chung, J.E., 2021. Teens' social media engagement during the covid-19 pandemic: a time series examination of posting and emotion on reddit. Int. J. Environ. Res. Public Health 18 (19), 10079. https://doi.org/10.3390/ijerph181910079.

Zheng, H., Huang, D., Chen, S., Wang, S., Guo, W., Luo, J., Ye, H., Chen, Y., 2016. Modulating the activity of ventromedial prefrontal cortex by anodal tDCS enhances the trustee's repayment through altruism. Front. Psychol. 7, 1437. https://doi.org/10.3389/fpsyg.2016.01437.