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Full-length Research Article

The link between social media browsing and emerging adults' momentary affective well-being: unraveling levels of analysis, underlying reasons, and content valence

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Abstract

Social media browsing has been linked to both declines and improvements in affective well-being, with recent research suggesting its effects depend on key factors. This experience sampling study among emerging adults ($N = 108$, $M_{age} = 22.29$, 61 female) examines three such factors: levels of analysis, underlying reasons, and content valence. Results reveal no significant between-person associations, but a small average within-person association, suggesting that, on average, social media browsing slightly reduces positive affect. However, this effect was only statistically significant in one model, and person-specific analyses showed no significant individual-level effects, underscoring the high statistical uncertainty. Additionally, when examining the underlying factors, browsing was modestly linked to lower affective well-being when driven by habit and when individuals encountered positive content. This study contributes to a deeper understanding of the complex relationship between social media browsing and well-being, emphasizing the importance of considering key underlying factors when interpreting these effects.

Lay Summary

Social media browsing, such as scrolling through TikTok or Instagram, is often linked to reduced well-being among emerging adults due to social comparison processes. However, research indicates that not everyone is equally affected as the impact likely depends on varying factors, such as why individuals are browsing (i.e., underlying reasons) and what they are seeing while browsing (i.e., valence of content). This study explored these factors through an experience sampling method with 108 emerging adults aged 18–26. Three key findings emerged: First, when emerging adults browsed social media more than usual, they tended to feel a little less happy. However, this finding only appeared in one analysis, and when we looked at the individual data, it was too uncertain to say if any specific person was truly affected. Second, the impact of browsing seemed to depend on its purpose and content—habitual browsing and exposure to positive content were particularly linked to feeling slightly less happy. In summary, the link between social media browsing and emerging adults' affective well-being is complex, with important factors being at play.

Keywords: social media, experience sampling method, media effects, well-being, youth

Social media plays a significant role in the daily lives of emerging adults, with 64% of 18- to 24-year-olds in Belgium using more than four platforms daily, particularly Instagram and TikTok (De Marez et al., 2024). These platforms are often used for passive content browsing—such as scrolling through TikTok's "For You" page or Instagram feeds—without direct interaction (Frison & Eggermont, 2016; Verduyn et al., 2017). This passive social media use has raised societal concerns due to its potential impact on well-being. Research following social comparison processes (Festinger, 1954) has shown that it can trigger upward social comparisons, envy, and fear of missing out, which can subsequently harm one's well-being (Frison & Eggermont, 2016; Karsay et al., 2023; Yang et al., 2021). These effects may be especially pronounced during emerging adulthood—a period marked by identity exploration and relational challenges (Arnett, 2000)—as browsing and comparing oneself to others' content can reinforce perceptions of failing to meet societal expectations and amplify feelings of exclusion (Spitzer et al., 2023).

However, despite prior research, the "passive social media use hypothesis" has been criticized for being empirically unverifiable, as inconsistent findings make it difficult to conclude that passive use is inherently negative (Valkenburg, Beyens et al., 2022). For example, Beyens et al. (2020) found that passive social media use did not affect adolescents' well-being on average. However, a deeper analysis of the average within-person effect revealed substantial heterogeneity: only 10% felt worse, 44% experienced no change, and 46% felt better. These findings suggest that the impact of passive browsing on well-being varies depending on the level of analysis. Additionally, the hypothesis has also been challenged theoretically, as users exercise autonomy in selecting and interpreting content (Valkenburg, Beyens et al., 2022). Building on the uses and gratifications theory (Katz et al., 1974), individuals, for example, actively engage with social media to fulfill specific needs (e.g., entertainment and escapism). As such, browsing behavior may also be influenced by underlying motives that shape its effects, as suggested by limited research (Sheldon & Titova, 2023; Yang et al., 2021). Finally, building on the interpretation of content, the way individuals perceive and interpret the content they encounter while browsing may also shape its impact (Valkenburg, van Driel et al., 2022). Still, despite

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emerging evidence, our understanding of the factors potentially explaining the link between social media browsing and well-being remain incomplete.

This study, therefore, aims to enhance the literature by investigating three specific factors. First, we provide a comprehensive understanding of how social media browsing relates to emerging adults' affective well-being by analyzing associations at multiple levels—between-person, average within-person, and person-specific. To do so, we conducted an experience sampling method study. Second, we explored whether underlying motives for social media browsing (i.e., entertainment, escapism, information, relationship maintenance, and social monitoring) moderate the relationship between browsing and affective well-being. Lastly, we assessed whether the perceived valence of the content (negative, positive, or neutral) impacted these outcomes.

The association between social media browsing and emerging adults' well-being

Given the extensive use of social media in emerging adults' daily lives (De Marez et al., 2024), numerous studies have examined its potential impact on their overall well-being (Karsay et al., 2023; Rasmussen et al., 2020; Yang et al., 2021). Emerging adulthood is, for example, a period characterized by increased susceptibility to well-being challenges as individuals need to navigate new life paths (e.g., pursuing education or careers), build new social connections, and maintain existing ones, all while moving away from supportive home environments (Brito & Soares, 2023; Matud et al., 2023). To cope with these challenges, emerging adults may turn to social media as they allow to form/maintain social connections and unwind (García-Manglano et al., 2024; Griffioen et al., 2021). However, the question of whether social media benefits emerging adults remains contested. Research often yields mixed results, with studies reporting positive, negative, or negligible effects, fueling ongoing debate among media scholars. Specifically, scholars attempted to explain these discrepancies by discussing variations in methodological approaches, operational definitions of media use, and time intervals examined (Meier & Reinecke, 2021; Valkenburg, Meier et al., 2022; Vandenbosch et al., 2025).

Here, significant attention has been given to the level of analysis in media effects research. Most studies rely on cross-sectional designs, primarily examining between-person associations—how individuals who browse more frequently report lower well-being than infrequent browsers (Burnell et al., 2020; Yang et al., 2021). In fact, 64% of the 141 studies in a recent meta-analysis discussing passive social media use implemented this approach (Godard & Holtzman, 2024). While these comparisons offer valuable insights, they may not fully capture media effects, as such effects are likely driven by within-person fluctuations—how changes in an individual's own media use impact their well-being (Aalbers et al., 2023; Valkenburg, van Driel et al., 2022). In response, research has started to focus on within-person associations, but findings remain mixed (Godard & Holtzman, 2024). Some studies, for example, suggest that browsing more than usual is linked to lower affective well-being (Ferguson et al., 2024; Godard & Holtzman, 2024), while most report negligible effects (Godard & Holtzman, 2024; Karsay et al., 2023) or even positive effects (Beyens et al., 2020). A likely explanation is the possibility of a third level of analysis: the person-specific level. That is, even when within-person analyses show a specific effect, this effect may still obscure substantial individual differences. For instance, Beyens et al. (2020) found no average within-person effect of social media browsing on affective well-being, yet deeper analysis revealed striking variability—44% of participants experienced no effect, 46% felt better, and only 10% felt worse. This thus shows that aggregate effects can potentially conceal heterogeneity, underscoring the necessity of analyzing multiple levels to fully understand the relationship between social media browsing and well-being (Valkenburg et al., 2024).

This has, however, not been done frequently as most research focuses on one or two levels of analysis (e.g., only between-person, within- and between-person, but not person-specific) (Burnell et al., 2020; Ferguson et al., 2024; Karsay et al., 2023), with the notable exception of Beyens et al. (2020). However, that study focuses on adolescents, leaving a gap in our understanding of how these effects may differ among emerging adults. The qualitative findings of Griffioen et al. (2021) suggest heterogeneity in effects based on emerging adults' narratives, but this has yet to be confirmed quantitatively. To address this gap, the present study therefore investigates how the relationship between social media browsing and emerging adults' well-being unfolds across three levels of analysis: between-person, average within-person, and person-specific. Specifically, the following hypotheses and research questions are posed:

> H1a (between-level): Emerging adults who, on average, engage in more social media browsing experience lower affective well-being compared to their peers who browse less.
> H1b (within-level): If emerging adults engage in more social media browsing (compared to their own mean), they will also experience lower affective well-being.
> RQ1 (person-specific level): To what extent does the association between social media browsing and emerging adults' affective well-being differ on a person-specific level?

Importantly, in this study, the focus is on affective well-being, characterized by high positive affect and low negative affect, for three reasons. First, according to the extended two-continua model of mental health (Meier & Reinecke, 2021), affective well-being is a critical indicator of psychological well-being. Second, it has been studied extensively in the context of social media use (Beyens et al., 2020; Griffioen et al., 2023; Karsay et al., 2023), thus ensuring comparability across studies. Finally, research indicates that affective well-being can fluctuate over short periods (Luhmann et al., 2021), highlighting the importance of understanding whether some of these fluctuations are influenced by social media browsing.

Underlying motives for social media browsing

As noted earlier, individuals' underlying motives for engaging in social media browsing may play a crucial role in explaining differences in its effects. According to the uses and gratifications theory (Katz et al., 1974), motivations are critical, as individuals actively select media to fulfill specific needs. Originally developed for traditional media like radio and television, the uses and gratifications theory has since been adapted to study social media usage, including browsing behaviors (Lai, 2019; Smock et al., 2011; Yang et al., 2021). In this context, common motivations for social media use include entertainment, relationship maintenance, information seeking, social monitoring, and escapism (Brailovskaia et al., 2020; Lai, 2019; Pertegal et al., 2019; Smock et al., 2011; Yang et al., 2021). In their multidimensional model of social media use, Yang et al. (2021) discuss these motives and highlight that while they are frequently studied, their connection to well-being remains poorly understood due to limited research and conflicting findings:

Entertainment involves using social media for fun and relaxation. While studies suggest it can reduce depressive symptoms and increase positive mood (Apaolaza et al., 2014; Brailovskaia et al., 2020), it has also been linked to problematic usage (Kircaburun et al., 2020; Thorell et al., 2024), which subsequently contributed to negative emotions (e.g., sadness and loneliness, Lin et al., 2017).

Relationship maintenance focuses on fostering social connections and improving relationships. While it can yield positive outcomes, such as a positive mood and a larger perceived social network with close ties (Apaolaza et al., 2014; Lai, 2019), it may also lead to negative effects like depressive symptoms, loneliness, and anxiety (Bonsaksen et al., 2023; Brailovskaia et al., 2020), especially when interacting with new friends (Yang et al., 2021).

Information seeking, which is the desire to stay updated on news and topics of interest, has been linked to benefits like higher life satisfaction and positive mood (Apaolaza et al., 2014; Pertegal et al., 2019). However, excessive engagement in behaviors such as doomscrolling—persistently focusing on negative information—can also negatively impact well-being (Sharma et al., 2022; Thorell et al., 2024).

Social monitoring, or observing others' activities to stay informed, has shown positive associations with life satisfaction and peer support (Pertegal et al., 2019). Yet, it can also result in loneliness or depressive symptoms, particularly when users perceive themselves as left out of social events (Vanherle et al., 2023).

Finally, *escapism*, using social media to temporarily avoid daily responsibilities, shows more consistent results as it has mostly been linked to poorer well-being (e.g., more stress, less satisfied with life) due to its maladaptive nature (e.g., avoidant behavior; Brailovskaia et al., 2020; Jarman et al., 2021; Thorell et al., 2024; Yang et al., 2021).

In addition to these motives, the literature identifies "killing time" as another reason for using social media, though its classification remains debated. Smock et al. (2011) consider it a form of habituation, while Pertegal et al. (2019) categorize it under entertainment, and Lai (2019) argues that it constitutes a distinct motive. Aligning with Lai (2019), we view "killing time" as a separate motive, as it differs from engaging in social media purely for fun. Moreover, the concept of habituation has faced criticism in the literature for not qualifying as a true motive (LaRose, 2010).

Social media browsing: motive or habit

Specifically, although "habituation" has been previously classified as a social media motive (Lai, 2019; Smock et al., 2011), research suggests this classification conflicts with the emphasis on active, goal-driven behavior in uses and gratifications theory (LaRose, 2010). Unlike goal-oriented behaviors, social media habits develop through repeated associations between specific actions—such as opening an app or browsing—and the rewards these actions provide, such as feeling entertained or connected (Bayer et al., 2022; Tokunaga, 2020). Over time, these associations result in automatic behaviors that require little conscious thought or deliberate decision-making (Meier et al., 2023). Social media habits are thus primarily driven by learned cues and past experiences rather than intentional goals (Bayer et al., 2022; LaRose, 2010). This suggests that, in addition to users actively engaging with social media to fulfill specific needs (e.g., seeking information), much of their browsing may occur habitually, without conscious awareness. Supporting this view, Griffioen et al. (2021) found that although users often reported having a clear goal when browsing, they largely engaged in passive social media use out of habit.

This habitual use has also raised concerns in the literature regarding its impact on well-being, with research highlighting both positive and negative effects (Bayer et al., 2022; Tokunaga, 2020). For example, positive habits, such as automatically responding to a text, can enhance social connectivity and relationship success (Bayer et al., 2022). In contrast, negative habits, such as poorly controlled or problematic media consumption, may lead to relational failures, academic challenges, or occupational difficulties (Tokunaga, 2020). Meier et al. (2023), for example, already found that increased automatic social media use is associated with greater task procrastination.

However, despite these insights, it remains unclear what drives emerging adults' social media browsing behaviors—whether they are predominantly motivated by specific goals or driven by habitual tendencies—and how these underlying factors influence their well-being. To address this gap, this study poses two exploratory research questions. First, it examines whether underlying social media motives amplify or mitigate the relationship between social media browsing and well-being. Second, it seeks to clarify the role of habitual use in shaping this relationship.

> RQ2: Do social media motives (i.e., escapism, killing time, entertainment, information seeking, relationship maintenance, and social monitoring) moderate the between-and within-person associations between social media browsing and affective well-being?
>
> RQ3: Does habitual use moderate the between-and within-person associations between social media browsing and affective well-being?

Social media browsing and content valence

Another factor that might possibly explain the inconsistent associations between social media browsing and individuals' well-being is the content encountered, as discussed in Verduyn et al.'s (2021) extension of the active-passive model. Specifically, while browsing, individuals encounter a diverse array of content with varying emotional tones, potentially triggering different social comparison processes (Valkenburg, van Driel et al., 2022; Verduyn et al., 2021). To illustrate, building on social comparison theory (Festinger, 1954), previous research has primarily hypothesized that exposure to content on social media instigates upward comparison processes (i.e., comparing to someone superior) and feelings of envy, as people mostly display idealized content, leading individuals to believe that others are more successful or better off (Frison & Eggermont, 2016; Karsay et al., 2023; Schreurs et al., 2023). However, Verduyn et al. (2021) also state that social media can be used to share failures, which may instigate downward comparison (i.e., comparing to someone worse off), leading individuals to feel better off.

Still, despite both comparison processes, individuals do not necessarily always feel worse when viewing others' idealized content or better when viewing failures. For example, Meier et al. (2020) found that "insta-worthy" nature and travel images can also inspire users through social comparison. Similarly, Verduyn et al. (2021) indicate that exposure to others' failures may also lead to empathy, and that both negative and positive responses may even occur simultaneously. For instance, someone might view a friend's holiday picture, feeling a bit jealous but still glad for the friend. Whether someone feels better or worse after seeing content may thus depend on the emotional valence attributed to the post. According to the appraisal theory (Scherer et al., 2001), individuals' emotions, or affective responses, are namely based on their appraisal of certain events (e.g., a social media post), with one event often resulting in different emotional appraisals among people. Building on these insights, one person may thus evaluate a post as positive, leading them to feel better, while another may evaluate it as negative, leading them to feel worse. Valkenburg, van Driel et al. (2022), for example, already reflect on how uplifting messages may enhance well-being, whereas disturbing messages may have the opposite effect. Still, this remains unclear because little research so far has examined the impact of perceived content valence in the relationship between social media browsing and affective well-being. As follows, we propose the following hypotheses, tested at both the between-and within-person level.

H2a: The between-person association between social media browsing and emerging adults' affective well-being will be moderated by the perceived valence of content, in that positively perceived content will be associated with higher well-being and negatively perceived content with lower well-being.

H2b: The within-person association between social media browsing and emerging adults' affective well-being will be moderated by the perceived valence of content, in that positively perceived content will be associated with higher well-being and negatively perceived content with lower well-being.

Method

This experience sampling method study is part of the DIGIPAW project investigating the relationships between youth's digital media use and their psychosocial well-being. Please see the Open Science Framework for more information on the entire project and other papers written on this data (OSF: https://osf.io/z2bnv/). Additionally, the study was preregistered and the report, including detailed information on the methodology and analyses, can be found on OSF (https://osf.io/m5nk4). Importantly, several deviations from the original pre-registration were made and we encourage readers to have a look at the *Deviations from Pre-Registration* document on OSF for a complete overview (https://osf.io/fdv2s/). For instance, the hypothesis at the between-person level was added during the manuscript revision process, following a review of relevant literature (Johannes et al., 2024; Valkenburg et al., 2024). Additionally, the exploratory research questions were initially framed as hypotheses based on prior findings linking motives to well-being (Yang et al., 2021). However, after reevaluating the evidence, we found insufficient justification to retain them as hypotheses, leading to their reformulation as research questions.

Study procedure

This experience sampling method study, approved by the university's ethics committee (IRB number: G-2023-6844-R6 (AMD)), had two main parts. First, participants completed a 10-15 minute background survey on their smartphones in March 2024. This survey included a consent form and questions about their demographics, personality, and well-being. Participants received the survey via the m-Path application (Mestdagh et al., 2023), an application specifically designed for real-time monitoring of individuals.

Two days later, participants enrolled in the actual experience sampling study, in which participants received four surveys per day via the app for 14 consecutive days (14 days*4 prompts = ideally 56 observations per participant). The surveys were sent out at fixed times via the m-Path app (12:30 pm, 3:30 pm, 6:30 pm, and 9:30 pm) and contained a maximum of 32 items. After receiving the surveys, participants had a one-hour timeslot to respond and were automatically reminded after 30 min. Additionally, the researchers engaged in real-time monitoring and motivated participants throughout the study in case of non-compliance. On the last day, participants received some additional questions about the study procedure and their experiences (i.e., post-test). Finally, they were rewarded with monetary vouchers based on their survey completion: €10 for at least 50% completion, €15 for 75%, and €20 for 100%.

Recruitment procedure

Given that the paper is part of a bigger project, one recruitment procedure was used. Specifically, the process involved collaboration with two master's students and unfolded through two main approaches. Initially, we selected a representative sample of colleges/universities from the Department of Education's list in Belgium, but due to a low response rate, we expanded our recruitment with alternative methods. For instance, we utilized social media platforms (e.g., Facebook and Instagram) and shared information through posts and stories, thereby partly sampling within our own personal network. Additionally, we also engaged in location sampling by distributing information brochures at busy areas (e.g., campus facilities). All interested participants received comprehensive details about the study's objectives, practical aspects (e.g., installment of app), incentives, and data management procedures.

Sample

Based on a priori power analyses using PowerAnalysisIL (see OSF for more information, Lafit et al., 2021), we aimed to sample 90 participants but the final sample was slightly bigger because of a higher study interest. Specifically, 113 participants initially started the study but five participants were removed based on three criteria: no background survey, inaccurate answers, and consistently filling out surveys outside the 1-hour timeslot. The final sample thus consisted of 108

Belgian participants between the ages of 18 and 26 ($M = 22.29$, $SD = 1.66$). From this sample, 46 individuals identified as male, 61 as female, and 1 as "other." Additionally, 74% were enrolled in college, 22% were employed, and the remaining participants were either unemployed or balancing work and study.

In total, the participants provided 4,221 assessments, but after removing responses based on response time (i.e., outside 1-h timeslot) and duplicates, 3,853 assessments were retained. This resulted in a 64% compliance rate, with participants completing an average of 36 assessments ($SD = 14.40$) and taking on average 96 s ($SD = 66.64$) to complete each daily survey.

Measurements

An entire overview of the background and daily surveys can be found on OSF (https://osf.io/fdv2s/). Both surveys were pre-tested for clarity in a pilot study (see pre-registration for more information).

Social media browsing frequency

Social media browsing was measured at each beep by asking participants the following item "In the past 3 hours, how often have you looked at other people's photos and/or videos on social media? (e.g., scrolling through videos on TikTok foryou page, photos on Instagram feed/stories)." Based on the study of Karsay et al. (2023), this could be answered on a 5-point scale: 1 (never), 2 (one time), 3 (a couple of times), 4 (multiple times), and 5 (the whole time).

Motives and habitual social media browsing

If participants reported browsing social media in the past three hours, they were asked: "Why did you look at others' photos and/or videos on social media?" Rather than focusing on motives tied to a specific browsing episode—which participants might struggle to recall—we used the prompt "Indicate which is most applicable" to capture the motive most salient or top of mind during that period. Answer options included six motives derived from prior research (Lai, 2019; Pertegal et al., 2019; Smock et al., 2011; Yang et al., 2021): "To entertain myself," "To kill time," "To be aware of what others are doing," "To maintain relationships with existing friends," "To escape from school, work, or other obligations," and "To find information on topics I like and am interested in." Participants were also given the option "Out of habit" to assess their habitual social media browsing. This item was included with the other motive items in the dropdown list, following prior research (Lai, 2019; Smock et al., 2011), and to facilitate comparisons with other motives. In the interest of full transparency, we initially classified habitual use as a motive based on prior research (Lai, 2019; Smock et al., 2011). However, after reevaluating the literature (Bayer et al., 2022; LaRose, 2010; Meier et al., 2023), we reclassified it as a distinct construct. The complete motives scale is available on OSF.

Perceived valence of social media content

Participants who reported browsing were also questioned about the tone of the posts that they viewed: "What was the tone of most of the photos and/or videos you remember?" Similarly, we did not assess the valence of a specific post, as this would likely be difficult for participants to recall. Instead, we focused on the overall valence of most posts from the past three hours. This item was adapted from Wolfers et al. (2023) and could be rated on a VAS scale from 1 (negative) to 7 (positive). The responses were recoded into a categorical variable with three categories: (1) negative valence (VAS scale points 1–3), (2) neutral valence (point 4), and (3) positive valence (VAS scale points 5–7).

Momentary affective well-being

To assess affective well-being, we measured both positive and negative affect. Drawing on the studies by Eisele et al. (2021) and Griffioen et al. (2023), participants were asked about their current feelings (i.e., how … .do you feel right now?) using four items for positive affect (i.e., happy, relaxed, energetic, satisfied) and four for negative affect (i.e., anxious, stressed, irritated, sad). Each item was rated on a VAS scale ranging from 1 (not … at all) to 7 (very …). Guided by Eisele et al. (2021), we then conducted a multilevel confirmatory factor analysis and formulated two factors containing the positive and negative affect items. Both showed high reliability (positive affect: $\alpha = .81$ and negative affect: $\alpha = .85$) and were used as dependent variables in our models.

Control variables

In our models, we controlled for participants' gender and age, which were measured at baseline, to ensure that these variables do not introduce any unintended bias in interpreting the associations (Prinstein et al., 2020). Gender was assessed by asking participants to identify as 1 (man), 2 (woman), 3 (transgender), 4 (genderfluid), or 5 (other, specifically …). Since the 'other' category had only one response and the 'genderfluid' and 'transgender' categories no responses, we opted to proceed with a binary gender variable (man and woman) to protect participant anonymity.

Additionally, we also controlled for the observation number and whether it was a week (1) vs. weekend day (2) to account for possible time trends.

Analyses

The analysis description is similar to the following preregistered paper within the bigger project (https://osf.io/bxzmg/). First, missing data were checked using the mice package in R and descriptive statistics were calculated (e.g., between-and within-level correlations, plotting of variables). Then, random effects models were formulated using the nlme package in R (Pinheiro et al., 2012). Following our preregistration, we initially tested two-level models to accommodate the data's hierarchical structure (observations nested within participants). However, contrary to our preregistration, we also explored three-level models (observations nested within days per participant), which demonstrated significantly better fit compared to the two-level models. Consequently, we adopted the three-level structure for further analysis. In total, three models were created with part A predicting positive affect and part B predicting negative affect.

First, we calculated the intraclass correlation coefficient (ICC) by testing an intercept-only model. Then, control variables (i.e., age, gender, observation number, and week vs. weekend) were added. In the next step, social media browsing was added as a fixed effect on both the between- (H1a) and within-level (H1b) to predict positive (Model 1a) and negative affect (Model 1b). Additionally, to examine the heterogeneity of within-person associations (RQ1), we allowed the

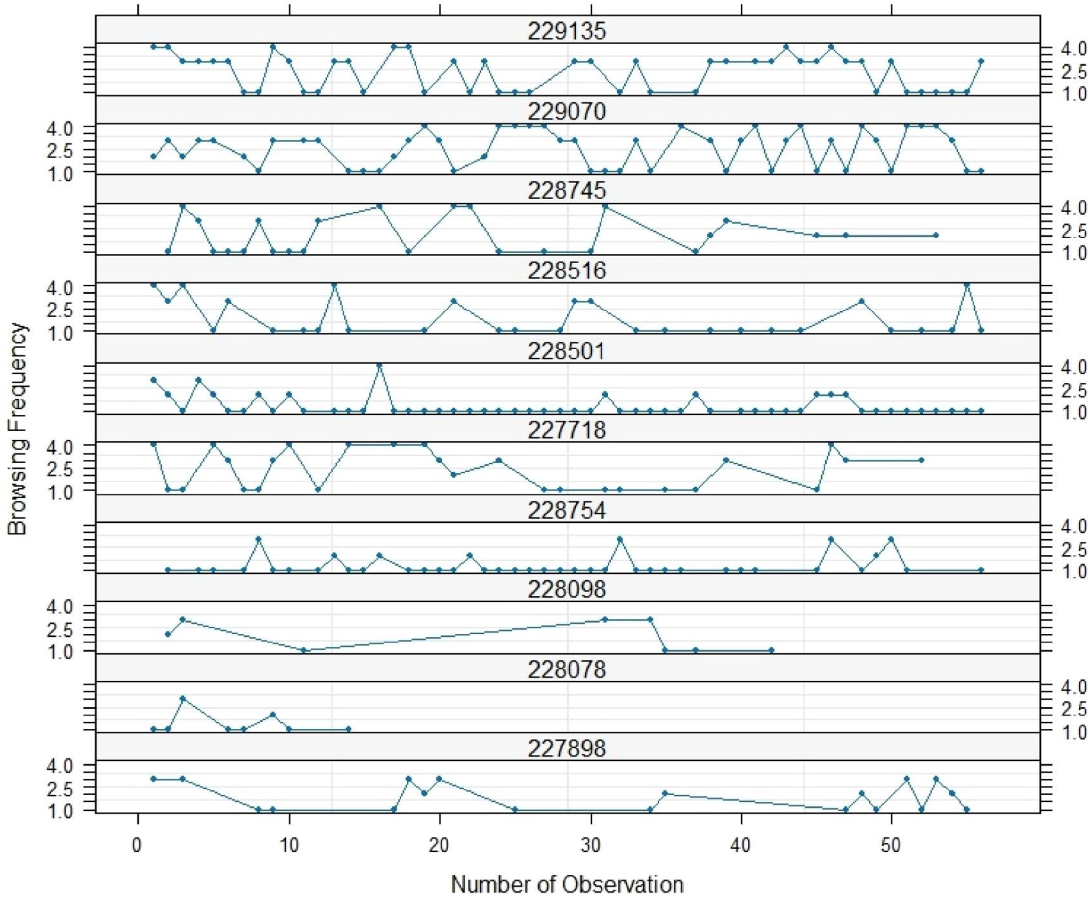

Figure 1. Social media browsing plotted over observations.

Note. The X-axis displays the observation number and consists of 56-times points. The Y-axis displays a person's reported social media browsing frequency of the past three hours. The numbers in the yellow bar provided above the graphs represent the ID numbers of 10 random participants.

slope of social media browsing to vary across individuals. Following the approach outlined by Johannes et al. (2024), we estimated heterogeneity intervals and calculated confidence intervals for each person-specific slope. These confidence intervals were first derived from the nlme models using the group-level standard deviation of the random slope. However, since this approach assumes constant variance across individuals and does not account for individual-level uncertainty, we conducted supplementary Bayesian multilevel analyses to provide more accurate estimates of the person-specific effects and their credible intervals (see OSF for full code and model outputs). In interpreting these slopes, and consistent with Siebers et al. (2021), we classified effects below –.05 as negative, above .05 as positive, and between –.05 and .05 as minimal or negligible. Finally, to test our moderations, we added an interaction term between social media browsing and browsing motives/habitual use (Models 2a and 2b, RQ2 and RQ3) as well as content valence (Models 3a and 3b, H2a and H2b) on both the between-and within-level. Importantly, given the multiple comparisons in our research questions, there was a risk of alpha error inflation and we therefore applied false discovery rate (FDR) corrections to address this (Benjamini & Hochberg, 1995). While this deviates from our pre-registration, it was necessary to ensure more reliable results (see FDR-corrected *p*-values in Tables).

In our models, we centered social media browsing on both the between- and within-person level (Masur, 2018). Specifically, we calculated each participant's mean score across all observations to enable between-person comparisons and assessed how individuals deviate from their own mean at specific time points to facilitate within-person comparisons. Additionally, we accounted for auto-correlation between residuals and tested the model fit using Maximum Likelihood estimation and the obtained Akaike information criterion (AIC), Bayesian information criterion (BIC), and Likelihood ratio test. Finally, we also tested model assumptions for multilevel modeling. More information on the analyses, including the script, used packages, and extra visualizations, can be found on OSF (https://osf.io/fdv2s/).

Results

Descriptives

Participants predominantly reported never browsing (60%), followed by browsing a couple of times (21%), once (11%), multiple times (7%), or continuously (1%) over the past three hours. They mostly did this on Instagram (in 45% of the cases) or TikTok (36%). However, this frequency showed variability within individuals across observations, as depicted in Figure 1 and supported by the low ICC value (.14), indicating substantial within-level variance. When engaging in browsing, the most common motives for browsing were entertainment (32%) and killing time (32%), followed by escaping from school or work (9%), seeking information (4%), and keeping track of others' whereabouts (3%). Notably, the motive of "maintaining social relationships with existing friends" was rarely mentioned (0.7%), so we excluded it from the analyses to ensure more robust comparisons. Habitual browsing accounted for 20%. Regarding content valence, participants primarily encountered positive content (79%), followed by neutral content (18%), and negative content (3%).

Regarding affective well-being, participants on average reported agreeing with experiencing positive feelings ($M = 4.71$, $SD = 1.05$) and disagreeing with experiencing negative feelings ($M = 2.39$, $SD = 1.22$). However, also these variables showed variability within individuals, as illustrated by the ICC values (positive affect: .34 and negative affect: .49). For more information on the ICC's and within/between-person correlations, please see Table A (see online supplementary material).

Social media browsing predicting positive and negative affect

In models 1a and 1b (Table B, see online supplementary material), we tested the direct between- and within-person associations between social media browsing and both positive and negative affect (H1a and b). The results of the nlme model showed no significant associations between social media browsing and negative affect at either level (within: $\beta = -.01$, $p = .637$; between: $\beta = .04$, $p = .648$). However, social media browsing was significantly associated with positive affect at the within-level ($\beta = -.05$, $p = .005$) but not between-level ($\beta = -.06$, $p = .335$). This means that, on average, when an individual browses social media more than they typically do (relative to their own mean), their positive affect slightly decreases.[1]

Building on the average within-person association, we further explored heterogeneity in this effect (RQ1) by adding random slopes to our models and comparing them with the fixed-slope models. For the positive affect model, both the likelihood ratio test and AIC values indicated a significantly better fit for the random slope model. However, the higher BIC value raised concerns about added model complexity (Table C, see online supplementary material). Given these conflicting model fit indices, we further explored person-specific variation by summing the fixed and random effects from the nlme model and plotted them (Figure A, see online supplementary material). The estimated variance of the slopes was small ($\sigma^2 = .004$), with within-person associations ranging from –.17 to .07. Specifically, 59 participants had slopes close to zero ($-.05 < \beta < .05$), 48 had negative slopes ($\beta < -.05$), and none had positive slopes ($\beta > .05$). However, when we calculated person-specific confidence intervals and p-values based on the group-level random slope standard deviation, none of the individual effects were statistically significant (Figure C, see online supplementary material). Additionally, to further refine our understanding, we conducted a supplementary Bayesian multilevel analysis, which provided person-specific standard deviations (see OSF for full details). While the Bayesian analysis offered slightly more precise estimates, the credible intervals for all individual effects still included zero, confirming the absence of statistically meaningful variation across individuals. Importantly, the average within-person association was no longer significant in the Bayesian model, likely because this model better accounts for uncertainty. In conclusion, the results from both the nlme and Bayesian models suggest that observed patterns—whether at the average or person-specific level—should be interpreted with caution. The findings indicate that any apparent effects are likely to reflect noise or measurement variability rather than true, consistent associations.

For negative affect, the random slope model showed slight improvements in AIC and log-likelihood, but the p-value (.061) suggests that the difference is not statistically significant (Table C, see online supplementary material). Additionally, the random slope model had a higher BIC, indicating that the added complexity of the random slope may not be justified. This is further supported by the negligible variability in random slopes (Figure B, see online supplementary material). The heterogeneity interval ranged from −.008 to −.007, with all participants showing minimal or no effects, suggesting that the fixed slope model may be more appropriate for negative affect.

Moderation of browsing motives and habitual use

In Models 2a and 2b (see Table 1), we examined whether the between- and within-person associations between social media browsing and positive affect or negative affect were moderated by browsing motives (RQ2) and habitual use (RQ3). The addition of browsing motives, including habitual use, to the models increased the marginal R-squared (the proportion of variance explained by the fixed effects) from 1% to 5% for positive affect, indicating that browsing reasons explain more variance in positive affect than browsing frequency alone. For negative affect, the increase was smaller, from 4% to 6%.

For positive affect, the results showed that for users who browsed out of habit, increased browsing was associated with a small decrease in positive affect at the average within-person level ($\beta = -.21$, $p < .001$, see Figure 2). Interestingly, the significant interaction terms suggested that the association between browsing and positive affect might vary based on the browsing motives "To kill time" and "To entertain myself" (Table 1). However, after examining the simple slopes for these motives, we found no significant associations between browsing to kill time, to entertain oneself, and positive affect (Table 2).

Regarding negative affect, notable interaction effects were observed at the average within-person level (but not the between-person level). Specifically, while Model 1b, which did not account for browsing motives, showed no significant association between browsing and negative affect, the current model revealed that browsing was associated with a small increase in negative affect for users who browsed out of habit ($\beta = .17$, $p = .001$, see Figure 3). Although significant interaction terms were again found for browsing to entertain oneself and to kill time (Table 1), the simple slopes were not significant (Table 2).

Overall, our findings suggest that only habitual browsing was significantly linked to a small decrease in positive affect and a small increase in negative affect, while the browsing motives showed no direct associations.

Moderation of content valence

In Models 3a and 3b, we tested whether the between-and within-level associations between social media browsing and positive affect or negative affect were moderated by the valence of content, with negative content as the reference category. The initial analysis showed no significant interaction

Table 1. Social media browsing predicting positive affect and negative affect: interaction with browsing motives and habitual use (Models 2a and 2b).

Variable	Positive affect					Negative affect				
	β	*SE*	*T*	*p*	*p* (FDR)	β	*SE*	*T*	*p*	*p* (FDR)
Fixed part										
Between-person										
(Intercept)	**4.83**	**.25**	**19.43**	**.000**	**.000**	**2.30**	**.32**	**7.14**	**.000**	**.000**
Weekend vs week	.08	.07	1.23	.221	.485	−.02	.07	−.28	.777	.883
Gender	−.18	.14	−1.31	.192	.468	.23	.18	1.25	.213	.427
Age	.03	.07	.50	.617	.862	−.14	.09	−1.56	.123	.300
Observation	−.00004	.002	−.02	.982	.998	**−.01**	**.002**	**−4.17**	**.000**	**.000**
Social media browsing	−.10	.09	−1.14	.256	.511	−.04	.10	−.38	.708	.865
Motive 2: To kill time	.0002	.07	.003	.998	.998	−.03	.07	−.40	.687	.865
Motive 3: To entertain myself	.15	.07	2.03	.043	.156	−.17	.08	−2.24	.026	.081
Motive 4: To know what others are doing	.07	.16	.44	.660	.862	−.12	.16	−.72	.470	.690
Motive 5: To escape work or school	**−.28**	**.10**	**−2.77**	**.006**	**.032**	.13	.11	1.26	.208	.427
Motive 6: To look for information	.04	.13	.27	.788	.932	−.02	.13	−.15	.883	.883
Social media browsing *Motive 2	.03	.07	.43	.666	.862	.18	.08	2.32	.021	.077
Social media browsing *Motive 3	.07	.08	.92	.358	.606	.01	.08	.16	.871	.883
Social media browsing *Motive 4	.16	.16	1.02	.307	.563	−.13	.17	−.77	.444	.690
Social media browsing *Motive 5	−.02	.10	−.25	.805	.932	.11	.10	1.03	.303	.512
Social media browsing *Motive 6	.06	.13	.50	.618	.862	−.02	.13	−.16	.877	.883
Within-person										
Social media browsing	**−.21**	**.05**	**−4.33**	**.000**	**.000**	**.17**	**.05**	**3.25**	**.001**	**.007**
Social media browsing *Motive 2	**.18**	**.06**	**2.76**	**.006**	**.032**	**−.18**	**.07**	**−2.72**	**.007**	**.030**
Social media browsing *Motive 3	**.17**	**.06**	**2.70**	**.007**	**.032**	**−.24**	**.06**	**−3.78**	**.000**	**.001**
Social media browsing *Motive 4	−.01	.15	−.04	.964	.998	−.26	.15	−1.68	.093	.256
Social media browsing *Motive 5	.13	.08	1.61	.108	.339	−.05	.08	−.60	.546	.751
Social media browsing *Motive 6	.16	.12	1.39	.164	.451	−.13	.12	−1.09	.277	.507
Random part	σ^2	*SD*				σ^2	*SD*			
Participant ID										
Intercept	.36	.60				.71	.84			
Day of study in participant ID										
Intercept	.08	.28				.12	.35			
Residual	.56	.74				.55	.74			
	Phi1 .28					Phi1 .20				

Note. Phi1 = estimated autocorrelation (how residuals that are one lag apart are correlated), σ^2, Variance component. The reference category is "out of habit." FDR, False Discovery Rate corrected *p*-value. The numbers in bold are those that can be considered significant based on both the raw *p*-value and the FDR corrected *p*-value.

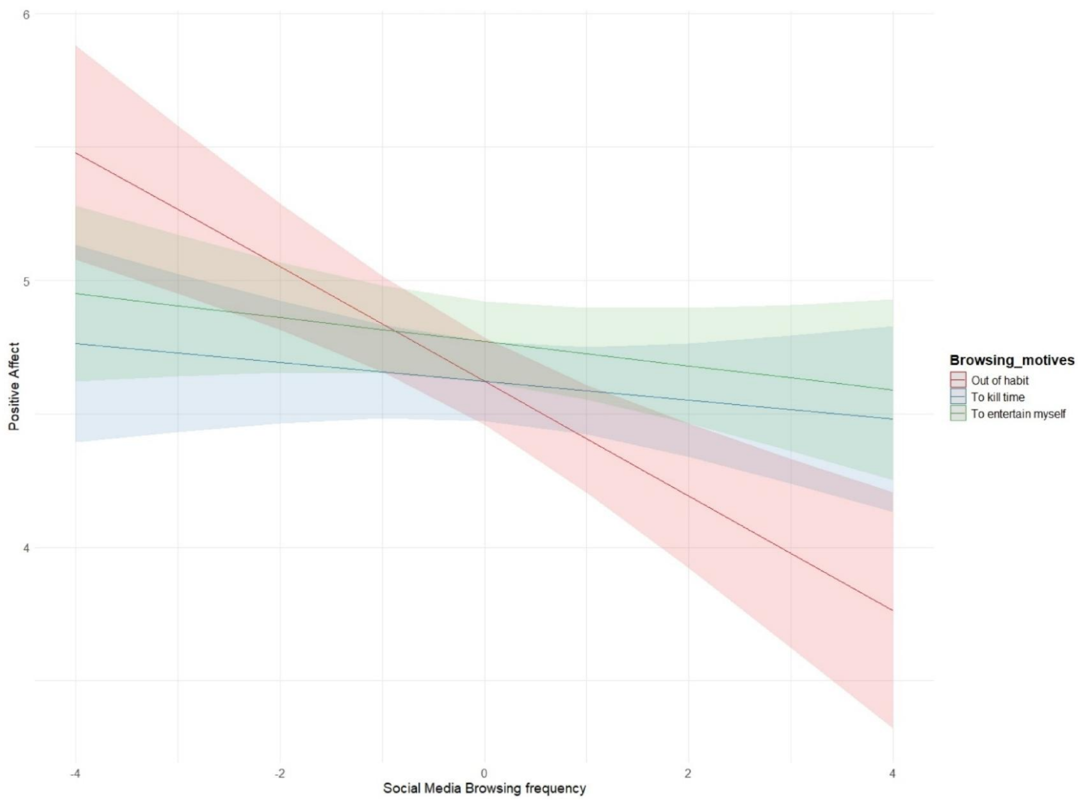

Figure 2. Interaction of social media browsing, browsing motives, and habitual use on positive affect (within-person level).

Note. This figure displays the interaction between social media browsing, browsing motives, and habitual use on positive affect (within-level). Only the line for "Out of habit" (red line) is significant.

effects between social media browsing, content valence, and both positive and negative affect (Table D, see online supplementary material). However, upon conducting simple slopes analyses for each content type (Table 2), a significant association emerged for positive content on the within-person level. Specifically, for users who reported seeing positive content, an increase in browsing (relative to their own mean) was significantly associated with a small decrease in positive affect ($\beta = -.13$, $p < .001$, see also Figure 4). No significant effects were found for the other content categories. This lack of significant (interaction) effects may be due to the insufficient variability in content valence across the sample, as the majority of participants reported seeing positive content (79%).

Discussion

In this study, we disentangled the complex relationship between social media browsing and emerging adults' affective well-being by shedding light on different (a) levels of analysis, (b) browsing motives, and (c) content valence. Three important reflections can be made.

First, this study provides a comprehensive overview of how social media browsing relates to emerging adults' affective well-being by analyzing associations at multiple levels, allowing for a more nuanced understanding of potential differences. At the between-person level, we found no significant relationship between average social media browsing and affective well-being. This aligns with findings from Godard and Holtzman's (2024) meta-analysis, which reported no significant between-person effects between passive social media use, positive affect, and negative affect across 141 studies. In contrast, at the within-person level, our initial nlme model revealed a small but statistically significant negative association between social media browsing and positive affect ($\beta = -.05$, $p = .005$), suggesting that individuals tended to report slightly lower positive affect when they browsed more than their personal average. However, this effect did not reach significance in our supplementary Bayesian analysis, thus highlighting the need for caution when interpreting the robustness of the average within-person association as it may be driven by noise rather than true effects. Further reinforcing this caution, our analysis of person-specific slopes showed no significant individual effects. One plausible explanation for this lies in the number of repeated observations per participant. Although the average number of assessments was 36, some individuals contributed as few as four, potentially limiting the reliability of their estimated slopes. Future studies would, therefore, benefit from collecting a higher number of repeated assessments per participant to more accurately capture intraindividual variability and enable more robust estimation of person-specific effects (Rohrer et al., 2024).

Additionally, the directionality of the relationship between browsing and affective well-being warrants further investigation. While our study assessed social media browsing within the past three hours and momentary affective well-being, both measures were collected simultaneously, leaving open the possibility of a reversed causal relationship. It is plausible, for instance, that mood influences social media browsing behavior, which in turn affects subsequent affect, potentially creating a reinforcing spiral (Slater, 2007). Prior crosssectional and longitudinal studies have already shown that well-being can predict social media use (Reer et al., 2019; Scherr et al., 2019), but

Table 2. Simple slope tests for browsing motives and content valence.

Variable	Positive affect					Negative affect				
	β	SE	T	p	p (FDR)	β	SE	T	p	p (FDR)
Fixed part										
Between-person										
Browsing: Out of habit	−.10	.09	−1.14	.256	.511	−.04	.10	−.38	.708	.865
Browsing: To kill time	−.07	.07	−.93	.353	.894	.14	.09	1.57	.120	.225
Browsing: To entertain myself	−.02	.07	−.33	.741	.905	−.03	.09	−.27	.787	.866
Browsing: To know what others are doing	.07	.16	.41	.686	.794	−.17	.17	−.95	.346	.708
Browsing: To escape work or school	−.12	.09	−1.35	.182	.422	.07	.11	.63	.530	.572
Browsing: To look for information	−.03	.13	−.27	.787	.982	−.06	.14	−.42	.672	.912
Content valence: Positive	−.08	.06	−1.34	.183	.397	.07	.08	.81	.419	.544
Content valence: Negative	.01	.13	.06	.951	.982	−.12	.15	−.81	.420	.497
Content valence: Neutral	−.10	.08	−1.30	.198	.527	.08	.10	.76	.449	.649
Within-person										
Browsing: Out of habit	**−.21**	**.05**	**−4.33**	**.000**	**.000**	**.17**	**.05**	**3.25**	**.001**	**.007**
Browsing: To kill time	−.04	.04	−.85	.396	.894	−.02	.04	−.37	.711	.782
Browsing: To entertain myself	−.05	.04	−1.19	.235	.574	−.08	.04	−2.01	.045	.110
Browsing: To know what others are doing	−.22	.14	−1.58	.114	.699	−.09	.14	−.64	.521	.708
Browsing: To escape work or school	−.09	.06	−1.35	.179	.422	.12	.07	1.78	.076	.301
Browsing: To look for information	−.05	.11	−.47	.637	.982	.03	.11	.31	.760	.912
Content valence: Positive	**−.13**	**.02**	**−5.39**	**.000**	**.000**	.05	.03	1.85	.065	.212
Content valence: Negative	.07	.11	.58	.565	.982	−.10	.12	−.88	.379	.493
Content valence: Neutral	.06	.05	1.17	.243	.527	−.08	.06	−1.38	.167	.363

Note. FDR, False Discovery Rate corrected p-value. The numbers in bold are those that can be considered significant based on both the raw p-value and the FDR corrected p-value.

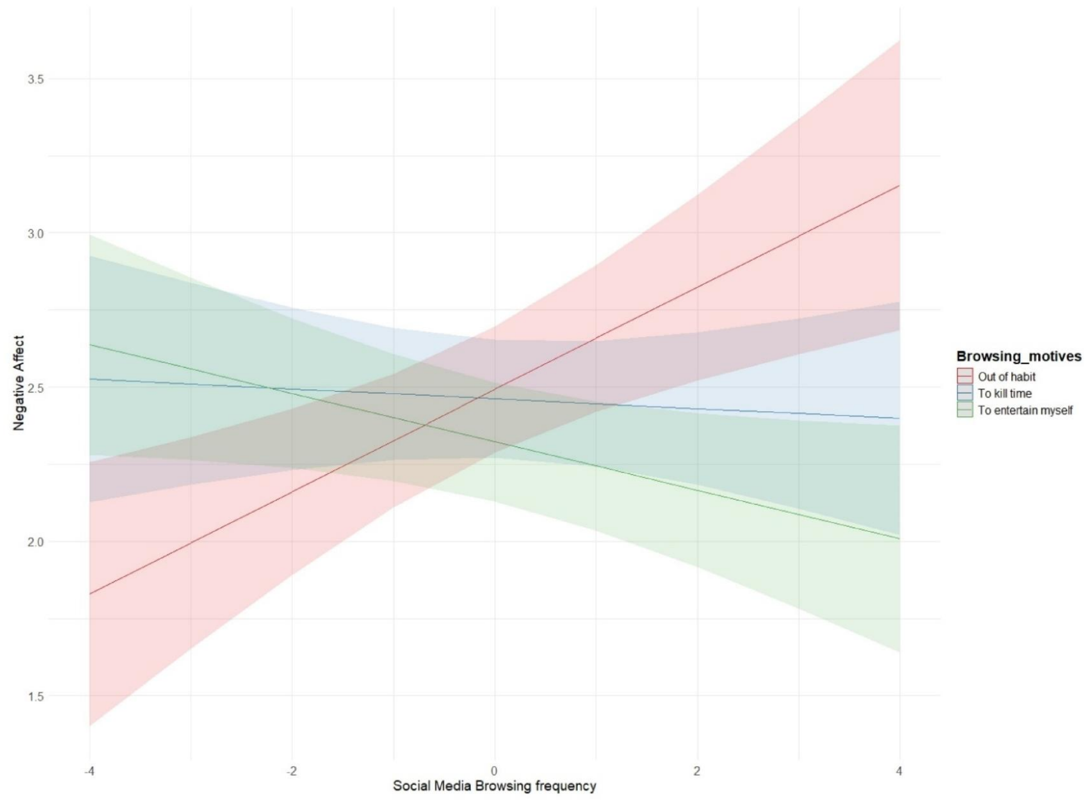

Figure 3. Interaction of social media browsing, browsing motives, and habitual use on negative affect (within-level).

Note. This figure displays the interaction between social media browsing, browsing motives, and habitual use on negative affect. Only the line for "Out of habit" (red line) is significant.

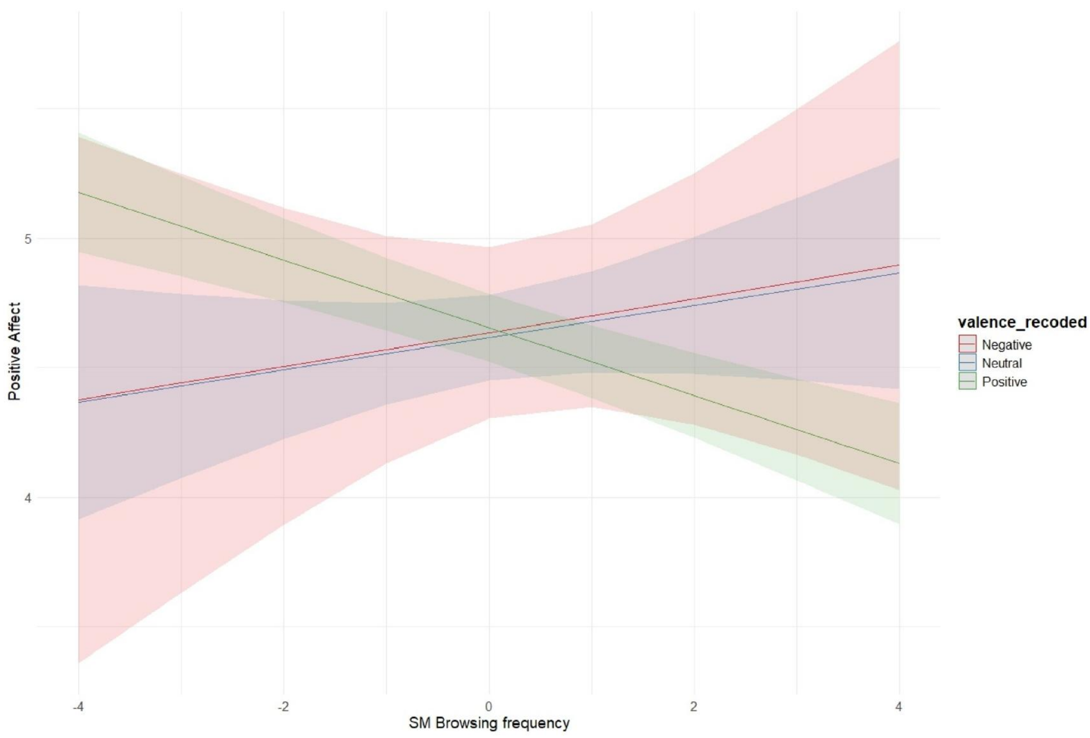

Figure 4. Interaction social media browsing and valence of content on positive affect (within-level).

Note. This figure displays the interaction between social media browsing and content valence on positive affect (within-level). Only the line of "positive content" (green line) is significant more research is needed to explore this transactional relationship over shorter time periods.

Second, this study underscores the critical role of the underlying factors behind social media use in explaining the inconsistent relationships with well-being, as highlighted by prior research (Sheldon & Titova, 2023; Yang et al., 2021). Specifically, we found that habitual social media browsing negatively impacted affective well-being in both positive affect and negative affect models. As such, building on habits literature, which indicates habits to be repeated expressions of earlier motivations (Bayer et al., 2022), it is crucial to prevent goal-driven browsing from turning into automatic routines, especially unhealthy routines (Tokunaga, 2020). For instance, someone who initially browses for relaxation might repeat this behavior until it becomes habitual, ultimately undermining its original purpose (e.g., no longer feeling relaxed; Tokunaga, 2020). Related research by Anderson and Wood (2023), albeit focused on social media posting, offers further evidence for this. In their study, occasional social media users adjusted their posting behavior in response to social recognition (e.g., likes and comments), while habitual posters—despite valuing such recognition—did not. This suggests that habitual posters' actions were no longer driven by goals (i.e., receiving social recognition) but instead triggered by contextual cues. Building on these insights and the results of the current study, it is thus crucial to ensure that users' underlying goals for social media use, including browsing, are not overshadowed by habitual tendencies. Sheldon and Titova (2023, p. 656), for example, rightly noted, "it matters why we do things; if we are doing what is enjoyable and meaningful, there is generally no problem." Drawing from this perspective, we emphasize the importance of future research in exploring users' reasons for engaging in social media use in the first place as this could lead to the expansion of theoretical models and provide clarity on the inconsistent findings in the existing literature.

Third, this study highlights the relevance of the content encountered during social media browsing. Notably, individuals who perceived the content encountered as positive reported slightly lower levels of positive affect. This contrast with appraisal theory, which suggests that positively perceived events, and thus perhaps also content, should lead to positive emotions (Scherer et al., 2001). This discrepancy may arise from the positivity bias common on social media, where users often showcase idealized versions of their lives through curated posts, such as social outings or picture-perfect holidays (Schreurs & Vandenbosch, 2021). While participants may have consciously labeled such posts as positive (e.g., based on societal norms: holiday is supposed to be fun, selfie is supposed to be pretty), these posts may have unconsciously triggered negative emotions like envy, upward social comparisons, or feelings of inferiority (Meier & Johnson, 2022; Schreurs et al., 2023). There may, thus, have been a discrepancy between how participants appraised the valence of content and how it emotionally impacted them. However, as indicated in the literature, individual differences likely exist in this discrepancy. Verduyn et al. (2021), for example, highlight key factors such as individuals' social comparison orientation (i.e., their tendency to compare with others), the personal relevance of the content, and whether it showcases others' accomplishments. Future research should thus further investigate these factors alongside content valence to better understand their complex interactions. Additionally, future studies should critically reflect on how social media content is measured. Digital trace data methods—such as data donation, screen tracking, and APIs—provide objective insights into the content people share and view online (Ohme et al., 2023). However, these methods depend on researchers or algorithms to classify content, which may not align with users' subjective experiences. To address this, we recommend prioritizing subjective perceptions and incorporating mixed-method approaches, such as linkage analysis, to develop a more comprehensive understanding of individuals' media diets.

Practical implications

The results of this study contribute to the ongoing societal debate regarding social media use and its potential harm by indicating that the impact on individuals' well-being depends on the levels of analysis, the underlying reasons, and the perceived valence of content encountered. Three important reflections can be made for designing interventions aimed at stimulating digital flourishing among youth (Schreurs & Vandenbosch, 2021).

First, while the person-specific slopes suggested that only a subset of individuals experienced a slight decline in well-being after browsing, these estimates were marked by substantial statistical uncertainty, thus offering little practical value for making reliable person-level inferences. This has important implications for personalized interventions: Although such approaches are often promoted as offering tailored insights based on individual data, our findings caution against overinterpreting noisy estimates. If the uncertainty around a person's estimated effect is too large, any personalized advice derived from it may be no better—or potentially worse—than simply relying on the average effect (Rohrer, 2024). For instance, advising someone to reduce their social media browsing based on a negative individual slope could be misleading if that slope primarily reflects measurement error rather than a true effect. In such cases, the advice could not only be unhelpful but potentially harmful, particularly when browsing actually contributes to the person's sense of joy, connection, or relaxation.

Second, this study revealed that particularly habitual browsing was detrimental to users' well-being. Therefore, interventions could target this habitual use by, for instance, offering digital toolboxes (Bayer et al., 2022), encouraging users to reflect on their habits, and, when necessary, helping adjust their habits. Such tools could, for example, be especially valuable in situations where habits are spiraling out of control or are perceived as undermining personal goals.

Finally, regarding content, this study reinforces the growing body of literature on the negative impact of the positivity bias online (Schreurs et al., 2023; Weinstein, 2017). As Schreurs and Vandenbosch (2021) suggest, social media literacy interventions should therefore address this issue by improving individuals' cognitive structures (e.g., raising awareness that such overly positive content often distorts reality) and their affective structures (e.g., learning how to regulate emotional responses while viewing content).

Limitations

Despite the valuable contributions of this study, several limitations must be acknowledged. First, the generalizability of our findings is limited by the sample. While we based our study on power analyses, the sample was relatively small and homogenous in characteristics (e.g., predominantly students) and behaviors (e.g., low average browsing activity). This lack of diversity likely hindered the detection of true inter-individual heterogeneity, as most participants were similar and exhibited minimal or non-existent effects. To address these limitations, future research should aim to replicate this study with a larger and more diverse sample to better capture variance across individuals and enhance the generalizability of findings.

Second, our study did not examine motives specific to individual social media browsing episodes or the valence of specific content, which may have introduced recall bias or reduced precision. Future research should address this limitation by investigating these factors more closely, potentially through shorter time frames or event-contingent sampling designs (e.g., sending prompts immediately after browsing). Such methods could provide deeper insights into the dominant motives and content valence, their fluctuations, and their impact on outcomes.

Third, the self-reported browsing frequency in this study was relatively low, potentially due to recall bias or participants skipping questions to speed up survey completion. To mitigate this, future research could incorporate filler questions. Additionally, combining subjective self-reports with objective measures would offer a more comprehensive understanding of browsing behavior by allowing direct comparisons between perceived and actual usage.

Finally, to reduce respondent burden in line with experience sampling recommendations, we measured social media motives and habitual use with single-item measures. However, as these constructs have been assessed with multi-item scales in prior research (e.g., Anderson & Wood, 2023; Pertegal et al., 2019; Smock et al., 2011), it is important to validate our single-item measures in future research to ensure they perform comparably to their multi-item counterparts (Allen et al., 2022; Wolfers et al., 2023).

Supplementary material

Supplementary material is available at *Journal of Computer-Mediated Communication* online.

Data availability

The data underlying this article are available at https://osf.io/fdv2s/. Additionally, several deviations were made from our pre-registration throughout the revision process. For a full overview, please refer to the "Deviations from Pre-Registration" document on OSF.

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Conflict of interest

None declared.

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Open science framework badges

Open Materials

The components of the research methodology needed to reproduce the reported procedure and analysis are publicly available for this article.

Open Data

Digitally shareable data necessary to reproduce the reported results are publicly available for this article.

Preregistered

Research design was preregistered.

Note

1. Since our study examined social media browsing and momentary affective well-being within the same assessment, we conducted sensitivity analyses using lagged variables to explore causal direction. No lagged associations were found and caution is thus needed when interpreting the directionality of the associations (see also the RMarkdown file on OSF: https://osf.io/fdv2s/).

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