Social Media Sensitivity

Sumer S. Vaid*[1], Lara Kroencke[2], Mahnaz Roshanei[1], Sanaz Talaifar[3], Jeffrey T. Hancock[1], Mitja D. Back[2], Samuel D. Gosling [4,5], Nilam Ram[1] and Gabriella M. Harari[1]

[1] Stanford University

[2] University of Münster

[3] Imperial College Business School

[4] University of Texas at Austin

[5] Melbourne University

Author Note

This manuscript will undergo peer-review, copyediting, typesetting and reviewing of resulting proofs before it is published in final form. Code needed to reproduce all analyses reported in the paper and supplementary materials are publicly available at the Open Science Framework. Data needed to reproduce all analysis will be made available after peer-review of the manuscript is complete.

This research was supported in part by a Stanford IRISS Computational Social Science Fellowship awarded to SSV, a Stanford HAI Google Cloud Credit Award, a National Science Foundation Award (SES-1758835), and a German Research Foundation Award (BA 3731/11-1). The funders had no role in study design, data collection and analysis, decision to publish, or preparation of the manuscript. The authors did not report any conflict of interest.

Author contributions for this manuscript were as follows: Conceptualization: SSV, LK, ST, JTH, NR, GMH; Data Curation: SSV, LK, ST; Formal Analysis: SSV; Funding Acquisition: SSV, MD, SDG, GMH; Investigation/Data Collection: SSV, LK, ST, MB, SDG, GMH; Methodology: SSV, LK, MR, NR; Project Administration: SSV; Supervision: GMH; Validation: SSV, LK, MR; Visualization: SSV; Writing – Original Draft: SSV, ST, GMH; Writing – Review and Editing: SSV, LK, MR, ST, JTH, MD, SDG, NR, GMH.

Correspondence concerning this manuscript should be addressed to Sumer S. Vaid, Department of Communication, Stanford University, 450 Jane Stanford Way, Stanford, CA, 94305, USA. Email: sumer@stanford.edu.

Abstract

Research on the effects of social media on wellbeing has been equivocal. Social media impacts people's wellbeing indifferent ways, but relatively little is known about why this is the case. Here we introduce the construct of "Social Media Sensitivity" to understand how social media's effects on wellbeing differs across people and the contexts in which these platforms are used. In a month-long large-scale intensive longitudinal study (total n = 1,632; total number of observations = 120,599), we examined for whom and under which circumstances social media was associated with positive and negative changes in social and affective wellbeing. Applying a combination of frequentist and Bayesian multilevel models, we found that the effects of social media on wellbeing were heterogenous, but most people generally experienced a negative social media sensitivity in terms of changes to their loneliness, stress levels, affect and feelings of being accepted. People with psychologically vulnerable dispositions (e.g., those who were depressed, lonely, not satisfied with life) tended to experience a heightened negative social media sensitivity in comparison to people who were not psychologically vulnerable. People also experienced heightened negative social media sensitivities when in certain types of places (e.g., in social places, in nature) and while around certain types of people (e.g., around family members, close ties), as compared to using social media at home or when alone. Our results suggest that an understanding of the effects of social media on wellbeing should account for the psychological dispositions of social media users, and the physical and social contexts surrounding their use. We discuss theoretical and practical implications of social media sensitivity for scholars, policymakers, and those in the technology industry.

Keywords: social media, wellbeing, physical context, social context, personality

Introduction

How does social media impact wellbeing? This is an important question for a variety of stakeholders ranging from users to academic researchers to leaders of social media companies. In this paper, we introduce the construct of "Social Media Sensitivity" to understand how social media's effects on wellbeing differ across people (e.g., based on their psychological dispositions) and over time (e.g. based on the context in which use is occurring). We conceptualize social media sensitivity as the change in people's momentary feelings of wellness after they have used social media within a defined time period (e.g., during an hour, a day or over a week). People can have a negative social media sensitivity (e.g., a tendency to feel worse after using social media), a positive social media sensitivity (e.g., a tendency to feel better after using social media), or a neutral social media sensitivity (e.g., a tendency to feel to no better or worse after using social media). Since social media and wellbeing studies are routinely studied across time domains ranging from hours to years, specifying a specific time domain of social media use allows us to differentiate social media effects on wellbeing driven by the choice of time interval.

Using data from two month-long large-scale intensive longitudinal studies, we show that people's momentary social media sensitivity is shaped by their psychological dispositions (*who* they are) as well as the physical and social contexts in which they are using social media platforms (*where* and *around whom* use is occurring).

Multidisciplinary studies have focused on identifying the magnitude and valence of the effects of social media on wellbeing (Valkenburg, 2022), consistently finding that on average, there is a small and negative effect. For example, correlational research has generally found small negative effects of using social media on cognitive and social wellbeing (Orben et al., 2019b; Orben & Przybylski, 2019). Quasi-experimental evidence based on observational data suggests that the introduction of social media on college campuses led to small decreases in mental health indices and increases in depression symptomatology (Braghieri et al., 2022). Casual evidence has shown that decreased use is associated with improved subjective wellbeing (e.g., satisfaction with life, feelings of happiness, loneliness: Allcott et al., 2020; Asimovic et al., 2021; van Wezel et al., 2021). However, past studies have also found that there are considerable differences in social media sensitivity across people (e.g., Beyens et al., 2020). As a result, research in this area has generated questions about what drives the heterogeneity of these associations across different people (Johannes et al., 2021).

The last two decades have witnessed the transformation of social media platforms' userbase from a relatively small and homogenous group of tech-savvy enthusiasts to include millions of young adults, who have varying psychological dispositions that may make them sensitive to the effects of social media use. The expansion of social media's user base is consequential for understanding how they affect a range of outcomes across wellbeing domains (e.g., affective, social). Hence, one possible explanation for the heterogeneity in social media effects focuses on psychological dispositions to understand *who* is using social media, and whether some people are more psychologically vulnerable to the effects of social media use on wellbeing.

Indeed, research suggests that people's personality traits (e.g., extraversion) are systematically linked with their patterns of social media use (Vaid & Harari, 2020), and that psychological dispositions are closely linked to feelings of wellness (Steel et al., 2008). In particular, much of the past work has focused on whether people's dispositional wellbeing, such as their self-esteem (Valkenburg, Pouwels, Beyens, Driel, et al., 2021), loneliness (Yang, 2016), and attachment style (Young et al., 2020), explains the relationship between social media use and wellbeing. Cumulatively, the research on this topic suggests that people who are psychologically vulnerable (i.e., those who have a dispositional tendency towards worse wellbeing) tend to suffer greater declines in wellbeing outcomes after using social media, as compared to people who have better dispositional wellbeing. For example, people who are higher in dispositional loneliness tend to feel lonelier after using social media, compared with people who are lower in dispositional loneliness (e.g., Song et al., 2014). The converse is true as well for those who have more sociable dispositions: people who are higher in extraversion and have greater goal-driven behavior are less likely to suffer the negative psychological effects of using social media (Gerson et al., 2016; Weiß et al., 2022). Hence, people with greater psychological vulnerabilities tend to have negative social media sensitivities whereas people with lesser psychological vulnerabilities tend to have positive social media sensitivities.

When the first social media platforms were launched at the turn of the millennium, they were primarily desktop-based websites that were used in a limited number of places by a relatively small number of people. Over the course of the past two decades, revolutions in computing technologies have transformed social media websites into mobile platforms that are used *on-the-go* in the contexts of everyday life (e.g., Campbell, 2013; Humphreys et al., 2013). Compared to dispositional traits, relatively little research has examined the extent to which a person's surrounding context shapes social media sensitivity in the moment (Masur et al., 2022a). Some empirical evidence supports the idea that people's physical and social contexts (e.g., where they are and who they are with) can complement or interfere with their social media sensitivities. For instance, when using smartphones while engaging in social interactions, people tend to report lower feelings of enjoyment in comparison to engaging in social interactions without using their smartphones (Dwyer et al., 2018). To the best of our knowledge, only one study has investigated the extent to which places modify the impact of social media use on wellbeing outcomes. This study found that using Facebook while at home was linked to lower emotional arousal as compared to using Facebook at other locations (Bayer et al., 2018), suggesting that using social media outside of the home is favorable for wellbeing outcomes.

Cumulatively, past research on social media sensitivity has been subject to several key limitations. First, some of this past research focused on time domains that do not capture everyday social media sensitivity (e.g., instead studying trends aggregated over months and years: Orben et al., 2019b; Stavrova & Denissen, 2020). Second, past research into how the effect of social media differs from person to person has recruited participants that are not representative of the largest user base of social media platforms – young adults – focusing instead on adolescents (e.g., Valkenburg, Pouwels, Beyens, van Driel, et al., 2021). Third, a large subset of past research has either failed to capture within-person effects or routinely conflated between and within-person effects, leading to biased assessments of effect sizes (see Stavrova & Denissen, 2020 for more details). Fourth, even when between and within person effects are modelled separately, past studies have only controlled for a small number of variables (e.g., sex and age) that are correlated with both social media use and wellbeing. Typically, modelling complexity issues are cited for such modeling decisions (e.g., Song et al., 2014), but this can lead to an overestimation of the effect sizes and of the heterogeneity associated with social media use and wellbeing constructs. Fifth, the most recent research has operationalized wellbeing through a small (albeit still important) set of constructs (e.g., self-esteem, attachment style: Demircioğlu & Göncü Köse, 2018; Valkenburg, Pouwels, Beyens, van Driel, et al., 2021). And lastly and perhaps most importantly, the bulk of past research has ignored the role played by physical and social contexts in modifying the relationship between social media use and wellbeing (e.g., Goggin, 2014; Masur et al., 2022b; for an important exception, see Bayer et al., 2018).

In the present research, we build upon the past research in multiple ways. First, we focus on collecting data from people's everyday life, the most ecologically valid time domain for studying social media effects. Second, unlike recent research that has focused on adolescent populations, our target population of interest are young adults. To the best of our knowledge, our research is significantly larger in terms of sample size and study duration, compared to past studies about the effects of social media on wellbeing in daily life. Third we deploy a mixture of frequentist and Bayesian analytical strategies that allow us to decompose within and between person components of social media use. These strategies allow us to specify random slopes (i.e., a slope for each person is estimated) for the effects of social media use on wellbeing outcomes, which allows us to investigate how social media sensitivity differs across people. Fourth, the richness of our data (e.g., the number of observations per participant) allows us to include many control variables (e.g., sex, age, preceding wellbeing states, engagement in multitasking; see Table S41 for more details) without hindering model computation. Finally, in addition to examining person-level heterogeneity, we also examine how social media sensitivity varies along the physical and social contexts in which these platforms are used.

We structure our contributions using three research questions:

RQ 1: What is the relationship between social media use and subsequent wellbeing in daily life?

RQ 2: What is the relationship between psychological dispositions and social media sensitivity?

RQ 3: What is the relationship between context of use and social media sensitivity?

Results

Our data was collected from a large sample of young adults in the United States (n_{ppt} = 1,632; n_{obs}= 120,599) using a combination of cross-sectional surveys and four weeks of experience sampling surveys. We analyzed this data using multilevel models to examine the relationship between social media use and momentary affective and social wellbeing (*social media sensitivity)*, and to determine whether these associations were moderated by people's psychological dispositions and the context in which they used social media.

We operationalized social media use by collecting data about whether people used social media ("Social Media Use," defined as a binary variable of use vs. non-use in a given hour) and the degree of their usage if they had used social media ("Duration of Social Media Use," defined as the duration of social media use in 15-minute increments during the hour). For our affective and social wellbeing outcomes, we asked people to report their momentary stress, affect balance, loneliness, and feelings of being accepted. To assess psychological dispositions, we measured people's Big Five personality traits (i.e., their levels of openness, extraversion, neuroticism, conscientiousness, and agreeableness) (Soto & John, 2017) and dispositional measures of social, affective, and cognitive wellbeing (i.e., loneliness, depression, affect balance, satisfaction with life) (Diener et al., 1985; Radloff, 1977; Russell, 1996; Schimmack, 2009). To assess people's physical and social context at the time of social media use, we asked people to report the places they had been (e.g., if they were at home, the gym, in nature when they were using social media platforms) and the people they had spent time with in-person (e.g., if they were around close ties, distant ties, family ties).

To examine the construct of social media senstivity, we first conducted an exploratory analysis of data collected in the fall of 2020 from a sample of 920 participants (observations = 73,284). We used the exploratory findings to generate hypotheses that were then pre-registered for a confirmatory analysis of data collected in the spring of 2021 from a second sample of 764 participants (observations = 55, 903). Our anonymized pre-registration can be found on our project's OSF page.

In general, most of the exploratory findings observed in the Fall 2020 dataset did not replicate in the 2021 dataset. For RQ1, 80% of the exploratory findings were confirmed (4 of

5 pre-registered hypotheses replicated). For RQ2, 22% of the exploratory findings were confirmed (2 of 9 pre-registered hypotheses replicated). For RQ3, 33% of the exploratory findings (4 of 12 pre-registered hypotheses replicated).

We suspect that the lack of replication across the two datasets might be due, in part, to the macro-level differences in the experiences of our participants. Specifically, the first cohort of participants were living off-campus and experiencing the lockdown period of the COVID-19 pandemic, while the second cohort was back on campus and experiencing the lifting of restrictions on daily life activities. Given such macro-level differences across our two datasets, we subsequently performed a mega analysis (Eisenhauer, 2021), by pooling the exploratory and confirmatory datasets together. Our research questions and analytical approach (e.g., exclusion criteria for observations and participants, modeling strategy) did not change from the preregistration for the purposes of the pooled dataset analysis. Combining the datasets in a mega-analysis allowed us to control for sample-specific differences, permitting a more robust analysis of social media sensitivity.

What is the effect of using social media on social and affective wellbeing?

Social Media Use (vs Non-Use)

People reported lower feelings of being accepted, a negative affect balance, and greater feelings of loneliness after using social media, as compared to after not using social media (Figure 2a).

Duration of Use

People reported a negative affect balance, and greater feelings of loneliness after using social media for longer durations than their own average, as compared to after using social media for shorter durations than their own average (Figure 2b).

What is the relationship between psychological dispositions and social media sensitivity?

To examine whether between-person differences in psychological dispositions explain the within-person relationship between social media use and momentary wellbeing outcomes, we focus here on the significant cross-level interactions observed. Generally, we find that people who are psychologically vulnerable are more sensitive to the negative effects of using social media[1].

Loneliness. People who were higher in neuroticism (Figure 3a) and depression (Figure 3b) reported feeling lonelier in the moments after using social media platforms, as compared to after not using social media. Similarly, people who were lower in satisfaction with life (Figure 3c) and had a generally negative affect balance (Figure 3d) reported feeling lonelier in the moments after using social media platforms, as compared to after not using social media. In contrast, people who were not psychologically vulnerable (those who were low in neuroticism and depression, or had a generally positive affect balance and high satisfaction with life) did not report significant changes in their feelings of loneliness after using social media as compared to not using social media

Stress. People who were higher in depression (Figure 3e) reported feeling greater stress in the moments after using social media platforms, as compared to after not using social media. People who were lower in depression did not report significant changes in their stress in the moments after using social media.

Affect Balance. People who were higher in depression (Figure 3f) reported a greater negative affect balance in the moments after using social media, as compared to after not

[1] There were several significant findings at the between-person level (see supplementary materials). For the purposes of brevity and clarity we have chosen to only interpret the within-person findings in the main body of the text.

using social media. People who were lower in depression did not report significant changes in their affect balance in the moments after using social media.

What is the relationship between context of use and social media sensitivity?

People used social media platforms most frequently around family members and close ties (Figure 2a), and while in study places and in transit (Figure 2b). They were used least frequently when people were alone and around distant ties, and while in the gym and workplace. In terms of the degree of use, people used social media platforms for longer durations than their own average when they were alone and around family ties (Figure 2c), and while they were at home and in study places (Figure 2d). Similarly, people used social media for shorter durations than their own average when they were around close ties and distant ties, and while in transit and in nature.

Physical Context Moderators

Loneliness. People reported feeling lonelier after using social media while they were in transit (Figure 4a), as compared to using social media in other places. Similarly, people reported feeling lonelier after using social media for longer durations than their own average when they were in transit (Figure 5a), as compared to using social media for longer durations than their own average in other places.

Stress. People reported feeling greater stress after using social media when they were outside their homes (Figure 4b), especially when they were at the gym (Figure 4c) and in nature (Figure 4d), as compared to using social media in other places.

Affect Balance. People reported a greater negative affect balance after using social media when they were outside the home (Figure 4e), as compared to using social media when they were at home. Specifically, people reported a greater negative affect balance after using social media when they were at the gym (Figure 4f) and in nature (Figure 4g), as compared to using social media in other places. In terms of the degree of use, people reported a greater negative affect balance after using social media for longer durations than their own average outside their home (Figure 5b) as compared to using social media for longer durations than their own average while they were at home. Similarly, people reported a greater negative affect balance after using social media for longer durations than their own average when they were at the gym (Figure 5c) and in nature (Figure 5d), as compared to using social media for longer durations than their own average in other places.

Feelings of Being Accepted. People reported lower feelings of being accepted after using social media outside of their homes (Figure 4h), as compared to using social media at home. Specifically, people reported lower feelings of being accepted after using social media in nature (Figure 4i), social places (Figure 4j) and study places (Figure 4k), as compared to using social media in other places. In terms of the degree of use, People reported lower feelings of being accepted after using social media for longer durations than their own average when they were at their workplaces (Figure 5e), as compared to after using social media for longer durations than their own average in other places.

Social Context Moderators

Stress. People reported lower feelings of stress when using social media around family ties (Figure 6a), as compared to using social media around other people. Similarly, people reported lower feelings of stress when using social media around people that were not close ties (Figure 6b), as compared to using social media around people who were close ties.

Affect Balance. People reported a greater negative affect balance after using social media around others (Figure 6c), as compared to using social media alone. Specifically, people reported a greater negative affect balance after using social media around close ties (Figure 6d), as compared to after using social media around other people.

Feelings of Being Accepted. People reported lower feelings of being accepted after using social media around others (Figure 6e), as compared to using social media alone. Specifically, people reported lower feelings of being accepted after using social media around family ties (Figure 6f) and close ties (Figure 6g), as compared to after using social media around other people.

Discussion

Our primary goal in this research paper was to introduce and empirically investigate the construct of social media sensitivity. We hypothesized and found support for the idea that (1) people experience different social media sensitivities that are partly determined by their psychological dispositions, and (2) the physical and social contexts in which people use social media platforms partly explains their social media sensitivity in the moment. To examine how social media sensitivities varied across and within people, we analyzed a large experience sampling dataset collected from young adults over the course of a month using a mixture of frequentist and Bayesian multilevel modelling techniques. This analytic approach allowed us to comprehensively disaggregate between and within-person effects, and account for many different control variables to precisely estimate effect sizes for people's social media sensitivity.

We have three sets of findings that are consequential for the regulation of social media platforms and for research on the psychological effects of social media. First, we found evidence that supports the idea that there is generally a negative, but small, effect of social media use on social and affective wellbeing. That is, on average, people reported feeling greater negative affect, lower feelings of being accepted, greater stress, and greater feelings of loneliness after using social media, compared to after not using social media. A similar pattern of results was observed for the duration of social media use. When people used social media for longer durations than usual (in reference to their own average duration as a baseline), they reported lower social (e.g., feelings of being accepted, loneliness) and affective wellbeing (e.g., affect balance, stress), compared to when they used social media for shorter durations than usual. However, we also noticed considerable heterogeneity in people's social media sensitivities. Across each social and affective wellbeing outcome we examined, there were some people who displayed a sensitivity to social media that was negative, positive, or even neutral. Hence, we corroborate many recent findings that indicate that social media effects tend to differ from person to person (e.g., Beyens et al., 2020; Rodriguez et al., 2021).

Much of the past research has studied social media's effects on affective wellbeing in adolescents. We build upon this past work in two concrete ways. First, we investigated social media effects in large samples of young adults and found similar levels of heterogeneity as those observed in adolescents. Second, we investigated the heterogeneity of social media's effects on social wellbeing, which is particularly relevant for platforms meant to facilitate the formation and maintenance of social relationships (Keyes, 1998). We found comparable levels of heterogeneity in social media effects for both social and affective wellbeing, suggesting that social media's heterogenous effects on wellbeing are not limited to affective operationalizations of the construct. Hence, this set of findings addresses concerns raised by past scholars about how different operationalizations of psychological wellbeing might influence findings about social media effects (Hancock et al., 2022; Kross et al., 2021). These findings are also consequential for researchers studying social media and wellbeing – regardless of how the latter is operationalized, researchers should strive to collect longitudinal data such that within and between-person components can be disentangled.

Our results also revealed that people with dispositional psychological vulnerabilities (e.g., higher depression, lower satisfaction with life) experienced greater negative social media sensitivities across the social and affective wellbeing outcomes, in comparison to people who were less psychologically vulnerable. These findings corroborate recent research that has similarly found psychologically vulnerable people to asymmetrically suffer from poor mental health as a result of using social media (Allcott et al., 2020; Lee et al., 2023). We replicated this pattern of results using experience sampling methods, which is a different methodology as compared to most past research on this topic that has focused on panel data (e.g., Orben, 2020; Orben et al., 2019a). Hence the convergent findings are particularly noteworthy given that they suggest, for example, that people with psychological vulnerabilities might form a positive feedback loop with digital media platforms, wherein pre-existing vulnerabilities drive increased usage that subsequently result in lowered wellbeing and so on (e.g., Flannery et al., 2022; Hartanto et al., 2021; Orben, 2020)

Being in specific physical contexts (e.g., in social places and in nature) while using social media also resulted in greater negative social media sensitivity on average. Similarly, being in the company of certain people (e.g., close ties, family ties) resulted in greater negative social media sensitivity on average. In contrast, people were least sensitive to social media effects when they used social media platforms at home or while alone. These findings suggest that not all social media use results in negative wellbeing outcomes. By focusing on understanding the context in which social media use is occurring, researchers and policymakers can gain a better understand of *when, where* and *around whom* social media use is beneficial or not.

We further highlight two important observations: first, we failed to find specific dispositions that make people positively sensitive to social media use. That is, there were no dispositional traits (e.g., extraversion) that made people more likely to feel better after using social media platforms. Similarly, we did not find that certain physical contexts resulted in a positive social media sensitivity: using social media at home resulted in *no* social media sensitivity at all. These patterns of findings were also true for social context: there were no people around whom social media use resulted in positive effects on wellbeing. Second, the negative social media sensitivity effects that we did observe were small in terms of effect sizes (in the range of 0.02 to 0.08). It is possible that these small effects, and the absence of positive social media sensitivity findings are being driven by (a) idiosyncrasies of our data samples (collected primarily during the pandemic) and (b) by analytical decisions made about comparison groups (e.g., being in social places vs.other places as compared to being in social places vs. at home). An analysis of individual participants' data might reveal that certain people have positive social media sensitivities in certain contexts, however at the average level, these effects are masked. In any case, it is not particularly surprising that the observed effect sizes were small, given that affective and social wellbeing are psychological outcomes that are being independently affected by many different processes (Götz et al., 2021). Indeed, our findings corroborate a large body of research that finds small to near-zero effects of social media use on wellbeing, especially as examined in the temporal domain of everyday life (Johannes et al., 2022; Valkenburg, Beyens, Pouwels, Driel, et al., 2021; Valkenburg et al., 2017). Hence, the possibility remains that the true effect size of interest is truly in the range of small effect sizes – a possibility that is difficult to ignore given that our work has greater between-person power as compared to previous experience sampling research on social media use and wellbeing.

For public policy legislation, it is essential to accommodate the notion that *any* legislation will prioritize the wellbeing of certain people over others and will similarly prioritize certain types of wellbeing for certain people. Since effects are heterogenous across people and operationalizations of wellbeing, any universally applicable legislation (e.g., wherein social media use is discouraged) will be less effective for some people (e.g., those who have a positive social media sensitivity) and more effective for others (e.g., those who have a negative social media sensitivity). Hence, the conversation surrounding the legislation of social media should focus on determining which segments of the population would benefit from external regulation of social media platforms (e.g., those with psychologically vulnerable dispositions) instead of focusing overtly on the unrealistic end-goal of benefiting all segments of the population from the same underlying policy. Similarly, public policy initiatives can focus on increasing the data transparency of social media platforms to facilitate user's self-regulation, removing the need for implementation of blanket policies (Bertot et al., 2010; Heidi & Alicia, 2022)

One weakness of the current research is that we operationalize social media using self-report measures, which have been shown to weakly correlate with objective measures of social media use obtained from log data (e.g., Johannes et al., 2021; Parry et al., 2021). This weakness is caveated with newer literature that suggests that self-report measures of social media use have comparable predictive validity for psychological outcomes as compared to digital trace data. Hence, we expect that that many of our findings are likely to replicate with more objective measures of social media use (Verbeij et al., 2021). Nonetheless, future research should focus on investigating the heterogeneity of social media sensitivity using logged data. Importantly, future studies should focus on deriving social media sensitivity of different platforms by asking people about usage of different applications or by collecting digital media trace data (e.g., Parry et al., 2021).

Our research is also limited in that it overtly samples participants from highly industrialized Western settings. Social media platforms are used ubiquitously across the globe, which has led to recent calls for research examining their effects on wellbeing in diverse populations in the Global South (Ghai et al., 2022). Since we are interested in examining the moderating role of physical and social context on social media effects, we cannot ignore the role played by cultural differences in shaping people's patterns of social media use, their global feelings of wellness, as well as the plurality of physical and social contexts they inhabit. Even though we collect data from highly industrialized Westernized settings, our sample composition is quite ethnically diverse: over 50% of our sample is composed of people of color (see Methods sections). Future research could further alleviate these weaknesses by collecting data from representative panels of non-Western social media users to validate the concept of social media sensitivity in understudied populations.

These weaknesses aside, our paper makes a pivotal contribution to social media and wellbeing research. We formulate the concept of social media sensitivity to examine three dimensions along which media effects differ: *who* is using these platforms, *where* these platforms are being used, and *around whom* these platforms are being used. Our results suggest that each of these three dimensions introduce heterogeneity in social media sensitivity. Specifically, we find that the psychological effects of using social media platforms differ significantly across people and the contexts in which they use social media. Viewing the psychological effects of using social media platforms as dynamic and contingent on the person and the environment allows us to resolve several key debates. Psychologically vulnerable people are more likely to suffer from the negative repercussions of using social media. Social media use is not detrimental to wellbeing when used alone and at home but is associated with negative changes in wellbeing when used in social and natural places. As a result of our contribution, future research is better primed to understand the myriad factors that contribute to social media sensitivity, especially using combinations of novel methodologies (e.g., objective trace data) and causal designs (e.g., field-experiments).

Materials and Methods

Participants

Participants were college students recruited from an introductory psychology class at ANONYMIZED. The datasets analyzed in this paper were collected in Fall 2020 (exploratory sample: n=920, observations=73284) and Spring 2021 (confirmatory sample: n=764, observations=55903). Prior to data analysis, we followed an initial data procedure to ensure that only high-quality experience sampling occasions were retained in the final sample:

1. ESM surveys completed too quickly. We computed a threshold based on the number of questions completed in each ESM survey (by multiplying this number by 0.5 seconds). We subsequently filtered any reports that were completed faster than the threshold.
2. Participant-specific ESM surveys completed too close in time to each other (less than 60 minutes after the previous report).
3. ESM surveys that took too long to complete (more than 60 minutes).
4. Participants who indicated in the post-survey that they had not been truthful in the ESM surveys.

We then excluded participants who failed to complete more than 65% of the total required experience sampling reports to gain credit for the assignment. As a final step, we removed participants who were older than 24 years of age since our target population of interest was young adults.

Initial data cleaning procedures resulted in the removal of 32 participants corresponding to 5245 observations for the exploratory sample. Subsequently, we removed 18 participants corresponding to 1528 observations who were older than 24 years of age from the exploratory sample. Finally, we removed 49 participants corresponding to 577 observations because they failed to complete more than 65% of the total number of experience sampling questions required to gain credit for the assignment. Hence, the final sample size of the exploratory sample was 821 participants corresponding to 65934 observations.

Similarly, initial data cleaning procedures led to the removal of 20 participants corresponding to 3343 observations from the confirmatory sample. We additionally removed

10 participants corresponding to 837 observations who were older than 24 years of age from the confirmatory sample. Finally, we removed 53 participants corresponding to 837 observations because they failed to complete more than 65% of the total number of experience sampling questions required to gain credit for the assignment. Hence, the final size of the confirmatory sample was 681 participants corresponding to 51500 observations.

In the combined sample consisting of both the exploratory and confirmatory sample, most participants identified as female (69.1 %) with a mean age of 18.7 years and were enrolled in either their first (58.7%) or second year of college (26.1%). Most participants identified as Anglo/White (32.5%), Asian/Asian American (21.7%), Hispanic/Latino (25.6%) and African Americans (5.1%).

Procedure

Participants completed a demographic survey during the first week of the semester and a range of personality questionnaires during other weeks of the semester. Participants received seven daily ESM surveys for up to four weeks. Participants received full credit if they provided at-least fourteen days of data with at least four surveys on each of those days. Participants downloaded an application onto their smartphones which sent periodic push notifications to participants about pending surveys. The notifications were programmed to arrive at semi-random times within seven 120-minute blocks between 8 am and 10 pm, with a minimum time window of 60 minutes between each consecutive notification. Participants were permitted to complete surveys on their phones or computers, but notifications expired by the end of each block. Hence, the average time window between two consecutive surveys within the same day was 163 minutes. The surveys were distributed in the following pattern throughout the day: 22% during the morning, 24% during the midday, 27% during midday, 27% during afternoon and 24% during the evening. All participating students were compensated with class credit and personalized feedback reports that summarized their social media use trends and psychological wellbeing patterns over the course of the semester.

Momentary Measures

Wellbeing. Wellbeing was measured using seven adjectives: “happy”, “sad”, “valued and accepted by others”, “lonely”, “worried”, “angry” and “stressed”. Participants responded to each scale using a 1-4 Likert scale (ranging from “not at all” to “a great deal”). The question stem asked participants to indicate their feelings “right now”, explicitly capturing momentary wellbeing at the time of the ESM. The adjectives “angry”, “worried”, “happy”, and “sad” were borrowed directly from past work (Schimmack, 2009). Following past research (Schimmack, 2009; Schimmack & Kim, 2020), we computed momentary affect balance by subtracting the “happy” score from the arithmetic mean score of “sad”, “worried” and “angry”. We treated momentary affect balance and stress as indicators of affective wellbeing. Conversely, we treated momentary feelings of being accepted and loneliness as indicators of social wellbeing. We reverse scored stress and loneliness variables such that higher values on different wellbeing outcomes all indicated “positive wellbeing”. Hence, higher values of loneliness, stress, affect balance and feelings of being accepted all indicate *positive wellbeing.*

Social Media Use (vs Non-Use). During each ESM survey, participants indicated the activities they had engaged in the past hour using a “select all that apply” multiple choice question. The question stem was “During the PAST HOUR, I spent time doing the following activities (check all that apply)”. The response options consisted of 19 different behaviors (summarized in Table S41) of which one was “Using social media”. We created a new categorical dummy variable that indexed all instances of social media use (vs non-use). All instances of social media use were labelled as “1”. All instances of non-social media use were labelled as “0”. All missing values were preserved. We also assessed participants’ engagement in multitasking as the *number of activities* performed in the past hour, specifically calculated as the number of activities they indicated performing during the past hour.

Duration of Use. If participants selected “using social media” as an activity, branch logic displayed a follow-up question asking participants to rate the duration of their social media use in the past hour on a 4-point scale: 1 = 1-15 minutes, 2 = 16-30 minutes, 3 = 31-45 minutes, 4 = 46-60 minutes.

Context. At each ESM survey, participants indicated, via “select all that apply” multiple choice response, who they were with during the last hour (social context) and what places they had been in during the last hour (physical context). The social context question stem was: “During the PAST HOUR, I spent time with the following people in-person (check all that apply)”. Participants could indicate having spent time with 8 different categories of people (see Table S41). Based on past research, we created a set of 4 dummy variables from the 8 response options: alone, with family ties, with close ties, and with distant ties (see Table S41). Dummy variables were created such that target social context categories were encoded with a 1, and non-target categories were encoded with a 0 (e.g., Alone = 1, With Other People = 0). All missing values were preserved.

Similarly, the physical context question stem was: “During the PAST HOUR, I spent time in the following places (check all that apply)”. People could indicate having spent time in 13 different types of places. Motivated by theoretical frameworks about psychologically salient physical and social context (Kushlev & Leitao, 2020; Shankardass et al., 2019; Valkenburg & Peter, 2013), we created a set of 8 dummy variables from these responses: home, social places, natural places, work places, transit, study places, religious places (see Table S41). Dummy variables were created such that target places were encoded with a 1, while non-target places were encoded with a 0 (e.g., Home = 1, Other Places = 0). All missing values were preserved.

Individual Differences and Dispositional Measures

Demographics. Participants' *age* and *sex* was measured in the demographics survey administered prior to the experience sampling component of the study.

Personality Traits. Participants' Big Five Personality Traits were measured before the start of the experience sampling component of the study. We used the BFI-2 instrument, which consists of 60-items answered using a 5-point Likert Scale (John & Srivastava, 1999; Soto & John, 2017). The Big Five Traits measure uses the average of 12 items to measure interindividual differences in extraversion, agreeableness, neuroticism, conscientiousness, and openness. Extraversion captures differences in individuals' tendency to be gregarious, assertive, energetic, and talkative. Agreeableness captures differences in individuals' tendency to be trustful, altruistic, modest, and warm. Neuroticism capture one's tendency to be anxious, angry/hostile, depressed, self-conscious, and impulsive. Conscientiousness captures one's tendency to be competent, orderly, dutiful achievement striving, self-discipline and deliberative. Finally, Openness captures one's tendency to be imaginative, have an aesthetic proclivity, preference for variety and curiosity.

Dispositional Wellbeing. The following wellbeing tendencies were measured before the start of the experience sampling component of the study: depressive symptoms, satisfaction with life, loneliness, and affect balance.

Depressive symptoms were measured using the Center for Epidemiological Studies-Depression scale that asks participants to indicate a variety of depressive symptoms in the preceding week, including loneliness, poor appetite, and restless sleep (Radloff, 1977). Higher values corresponded with greater depression symptomatology.

Satisfaction with life was measured using the Diener Satisfaction with Life Scale, as the average of responses provided on a 1 (strongly disagree) to 7 (strongly agree) scale to 5 statements that operationalizes a holistic perspective towards their lived and ideal lives (Diener et al., 1985). People's satisfaction with life scores are calculated by taking an arithmetic mean of the 5 items of the scale. Higher values corresponded with greater satisfaction with life.

Loneliness was measured using the UCLA loneliness scale, that measures participants' agreement with 9 statements that ask about the frequency with which participants experience moments of social connection or social disconnection (Luhmann et al., 2016). Participants responded using a 1(*I never feel this way)* to 4 (*I always feel this way)* scale. Upon reverse scoring a subset of the statements, the final score is calculated by computing an arithmetic mean of all response items. Higher values corresponded to greater loneliness.

Dispositional affect balance was measured using a modified form of the SOEP scales (e.g., Angry, Worried, Happy, Sad, Enthusiastic, Relaxed: (Schimmack, 2009)). People indicated the extent to which they felt angry, worried, happy, sad, enthusiastic, and relaxed using a 1 (*Very rarely)* – 5 (*Very often)* scale. People's dispositional affect balance was computed by subtracting the mean of their negative emotion scores (e.g., angry, worried, sad, relaxed) from their positive emotion scores (e.g., happy, sad, enthusiastic and relaxed). Hence, positive values corresponded to greater positive affect whereas negative values corresponded to greater negative affect.

Modelling Strategy

Data analyses for each of the three research questions was done using multilevel models that accommodated the nested nature of the data (repeated measures nested within persons). Following usual practice within and between-person effects are disentangled through person-mean centering of all time-varying (Level 1) predictor variables and sample-mean centering of all person-level (Level 2) predictor variables (Yaremych et al., 2021). Much of the past research has disproportionately focused on examining between-person associations between social media and wellbeing. Hence, to build upon past research, we were especially interested in cross-level interactions (e.g., the extent to which between-person differences in psychological dispositions explain within-person relationships between social media and wellbeing) and within-person moderation effects (e.g. comparing people's feelings of wellbeing after using social media as compared to when they did not use social media).

What is the relationship between social media use and wellbeing in young adults' daily lives?

We used frequentist linear regression models in lme4 (Bates et al., 2015) with random intercepts and random slopes allowed to vary across participants to determine the extent to which social media use and wellbeing are related at the within and between-person levels:

$$\begin{aligned} Wellbeing_{\,ti} = {} & \beta_{0i} + \beta_{1i}\, SocialMedia_{\,ti} + \beta_{2i}\, Wellbeing_{\,(t-1)i} + \beta_{3i}\, DurationSinceLastResponse_{\,ti} \\ & + \beta_{4i}\, Wellbeing_{\,(t-1)i}\, DurationSinceLastResponse_{\,ti} + \beta_{5i}\, NumberofActivities_{\,ti} \\ & + \beta_{6i}\, Weekend_{\,ti} + \beta_{7i}\, StudyDay_{\,ti} + e_{ti} \end{aligned}$$

where wellbeing at occasion *t* for person *i* is modeled as a function of a person-specific intercept coefficient β_{0i} that indicates the individual's prototypical level of wellbeing, a set of person-specific coefficients β_{1i} to β_{7i} that indicate the within-person associations between the predictor variables and wellbeing, and residual e_{ti}that are assumed normally distributed with standard deviation σ_e. The person-specific coefficients are then modeled as a function of between-person differences. Specifically,

$$\beta_{0i} = \gamma_{00} + \gamma_{01}\, SocialMedia_{\,i} + \gamma_{02}\, Age_{\,i} + \gamma_{03}\, Sex_{\,i} + \gamma_{04}\, NumberOfResponses_{\,i} + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + u_{1i}$$

$$\beta_{2i} = \gamma_{20}$$

$$\beta_{3i} = \gamma_{30}$$

$$\beta_{4i} = \gamma_{40}$$

$$\beta_{5i} = \gamma_{50}$$

$$\beta_{6i} = \gamma_{60}$$

$$\beta_{7i} = \gamma_{70}$$

where the gammas are sample-level parameters that indicate the intercept and effects for the prototypical individuals, and the residuals u_{0i} and u_{1i} are residual individual differences in intercept and the within-person association between social media use and wellbeing that are assumed multivariate normal with standard deviations σ_{u0} and σ_{u1} and correlation $r_{\sigma_{u0}\sigma_{u1}}$. Of specific interest are the γ_{10} and σ_{u1} parameters. We define social media sensitivity as referring to the γ_{10} parameter whereas σ_{u1} captures the person-level heterogeneity of social media sensitivity.

What is the relationship between dispositional traits and social media sensitivity?

Dispositional moderators were fit using the lme4 package (Bates et al., 2015) in R with restricted maximum likelihood and missing data (< 0.1%) was treated as missing at random. Statistical significance was evaluated at alpha = .05. Dispositional moderators were modelling using the following model:

$$Wellbeing_{ti} = \beta_{0i} + \beta_{1i} SocialMedia_{ti} + e_{ti}$$

$$\beta_{0i} = \gamma_{00} + \gamma_{01} SocialMedia_i + \gamma_{02} Personality_i + \gamma_{03} SocialMedia_i Personality_i + u_{0i}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11} Personality_i + u_{1i}$$

Where γ_{03} is the between-person interaction and γ_{11} is the cross-level interaction.

What is the relationship between context of use and social media sensitivity?

Random intercepts and slopes were specified for social media, context, and their resulting interactions, resulting in complex models that did not converge in a frequentist framework. Hence, we used a Bayesian paradigm for model estimation to facilitate model convergence. The move to Bayesian estimation allowed us to examine the extent to which multiple momentary contexts moderate the relationship between momentary social media use and wellbeing. The expanded model is specified by the following equation:

$$\begin{aligned} Wellbeing_{ti} = \beta_{0i} + \beta_1 SocialMedia_{ti} + \beta_2 SocialMedia_i \\ + \beta_2 AffectiveWellbeing_{(t-1)i} + DurationSinceLastResponse_{ti} \\ + \beta_2 AffectiveWellbeing_{(t-1)i} DurationSinceLastResponse_{ti} \\ + \beta_3 NumberofActivities_{ti} + \beta_4 Weekend_{ti} + \beta_8 StudyDay_{ti} \\ + \beta_9 SocialMedia_{ti} Context_{ti} + e_{ti} \end{aligned}$$

$$\begin{aligned} \beta_{0i} = \gamma_{00} + \gamma_{01} SocialMedia_i + \gamma_{02} Context_i + \gamma_{03} SocialMedia_i Context_i + \beta_5 Age_i \\ + \beta_6 Sex_i + \beta_7 NumberOfResponses_i + u_{0i} \end{aligned}$$

$$\beta_{1i} = \gamma_{10} + \gamma_{11} Context_i + u_{1i}$$

Where β_9 is the within person interaction, γ_{03} is the between-person interaction and γ_{11} is the cross-level interaction between average social media use and context. Contextual moderators were fit using the brms package (Bürkner, 2017) with 12,000 iterations (half warm-up) since convergence was not possible with lme4.

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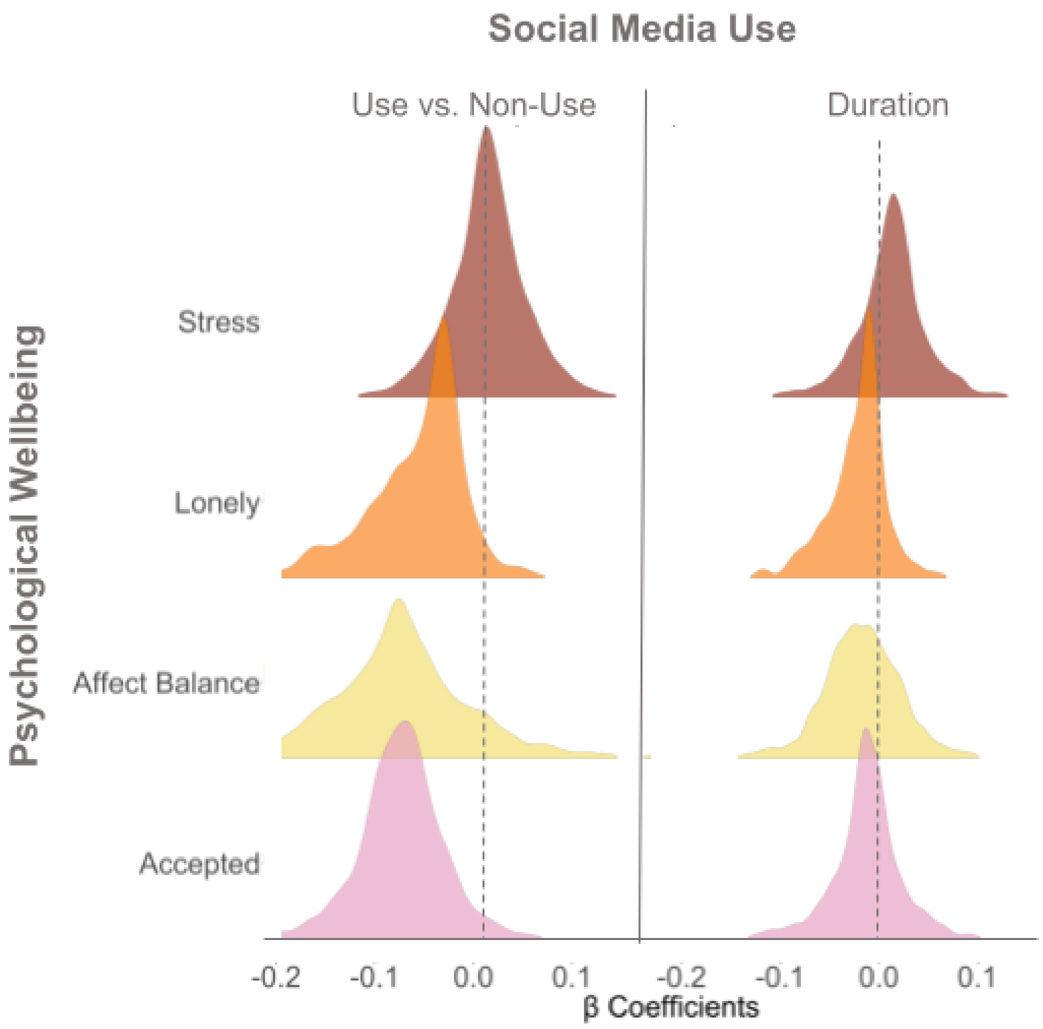
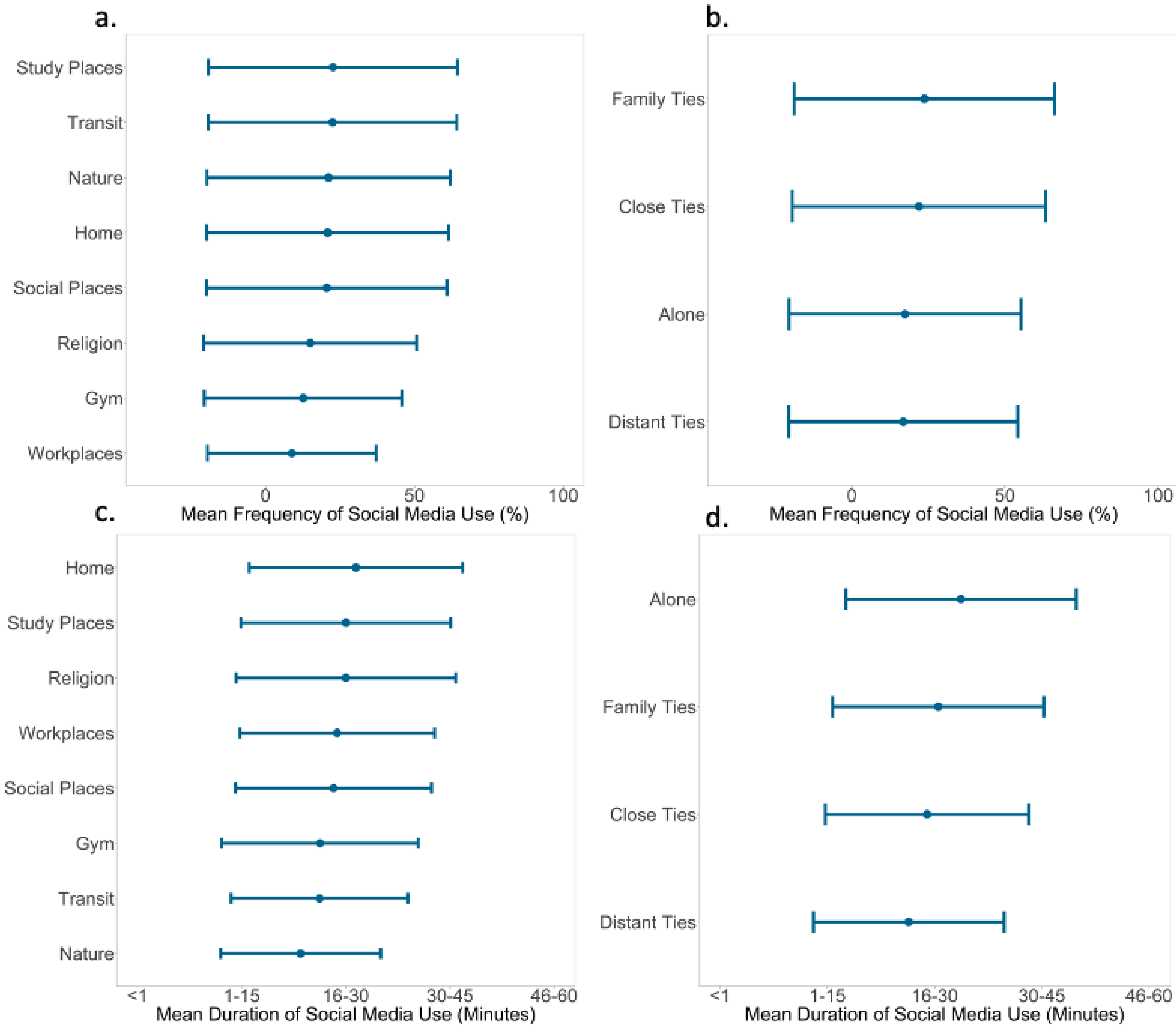
Figure 1: Social Media Sensitivity Across Affective and Social Wellbeing



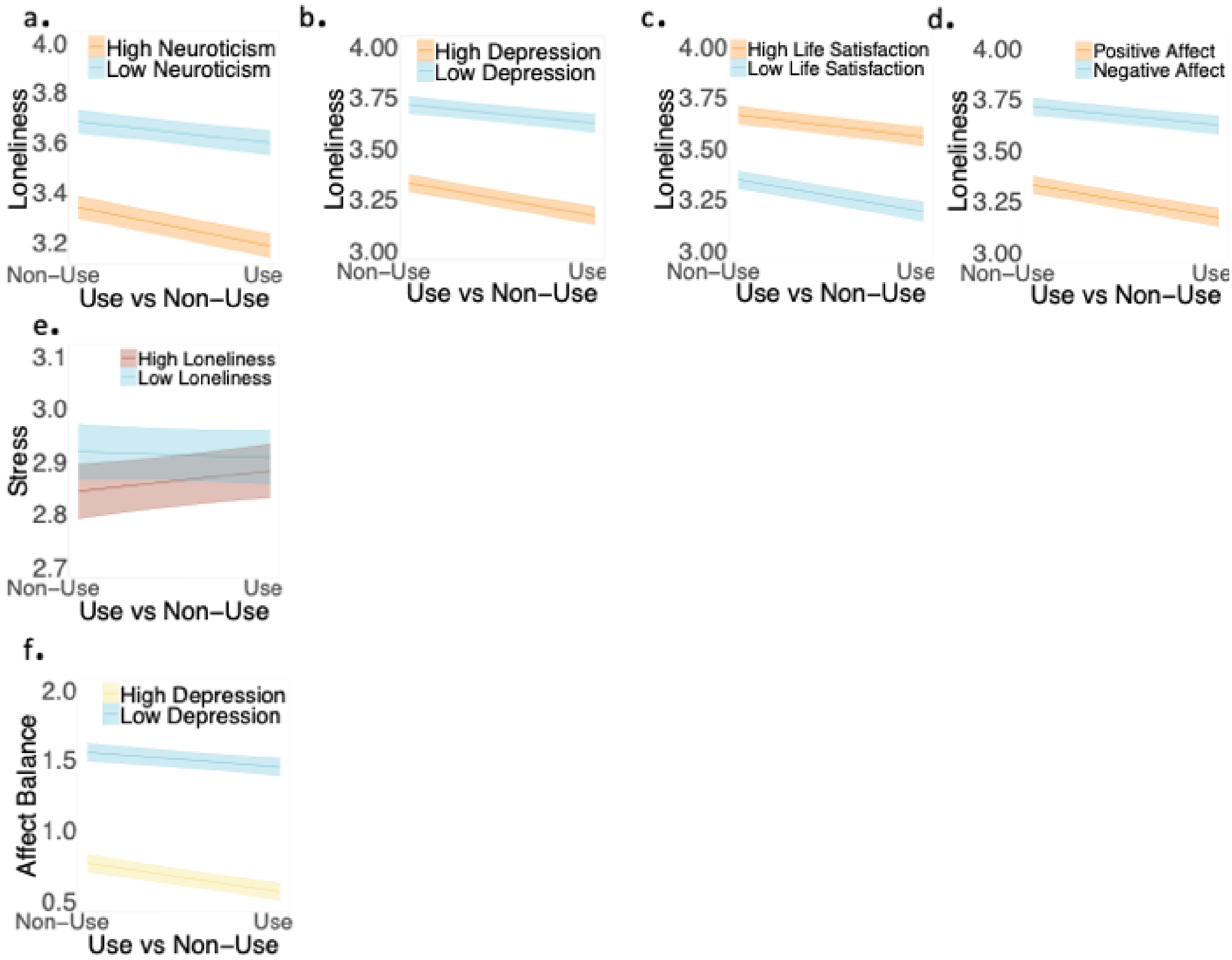
Note: Stress and loneliness were reverse coded such that higher values (>0) indicate lower levels of stress and loneliness.

Figure 2: Social Media Usage Across Physical and Social Contexts



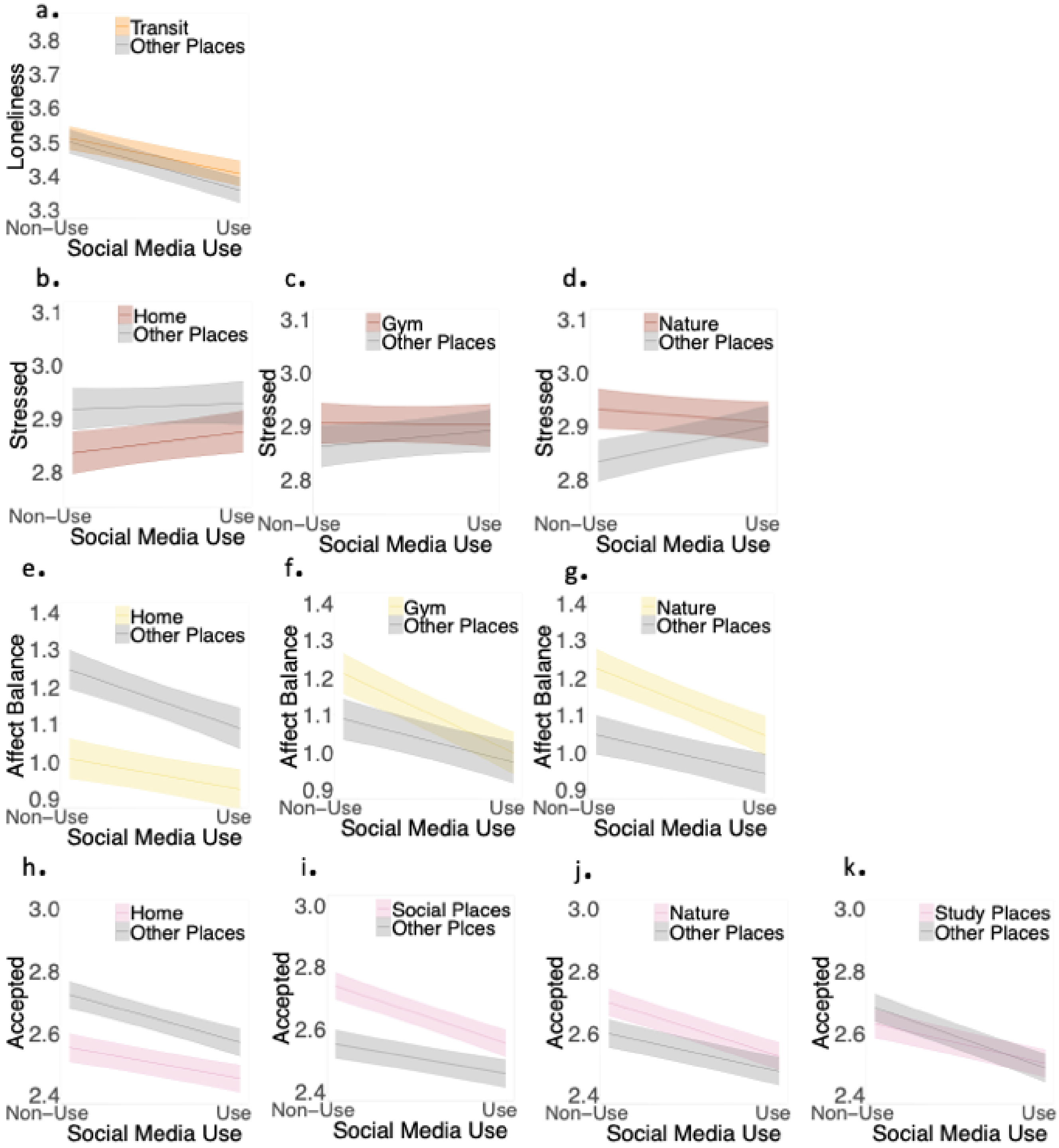
Note: Social media use frequency represents the % of observations in which people reported using social media. Duration represents the average time spent in the past hour using social media platforms. Points depict the mean level of social media use in different contexts. Error bars depict one standard deviation above and below the mean for social media use in different contexts.

Figure 3: Dispositional Moderators of Social Media Sensitivity (Use vs. Non-Use)



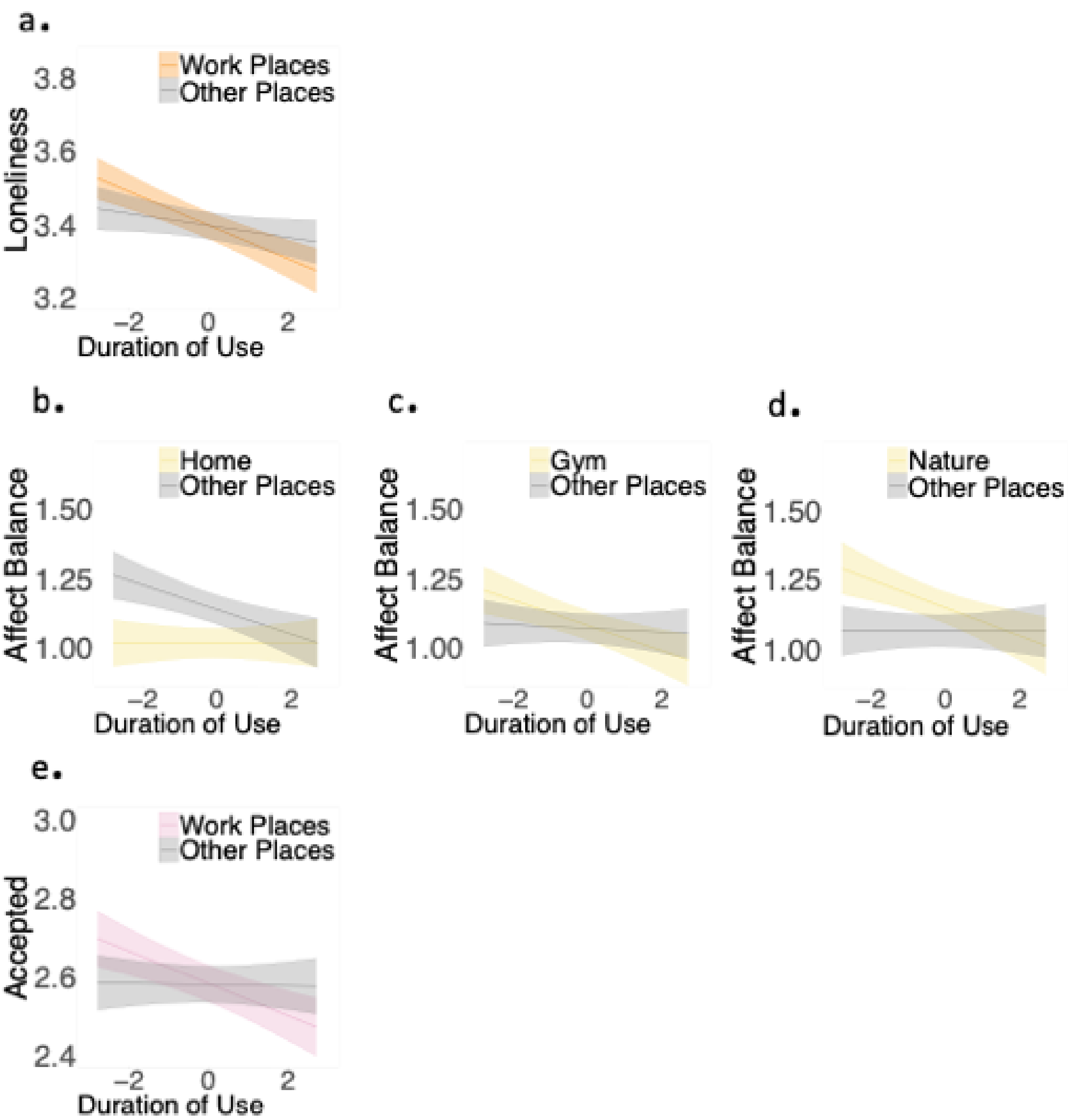
Note: Stress and loneliness were reverse coded such that higher values indicate lower levels of stress and loneliness. Bands depict standard deviation of simple slope estimates.

Figure 4: Physical Context Moderators of Social Media Sensitivity (Use vs Non-Use)



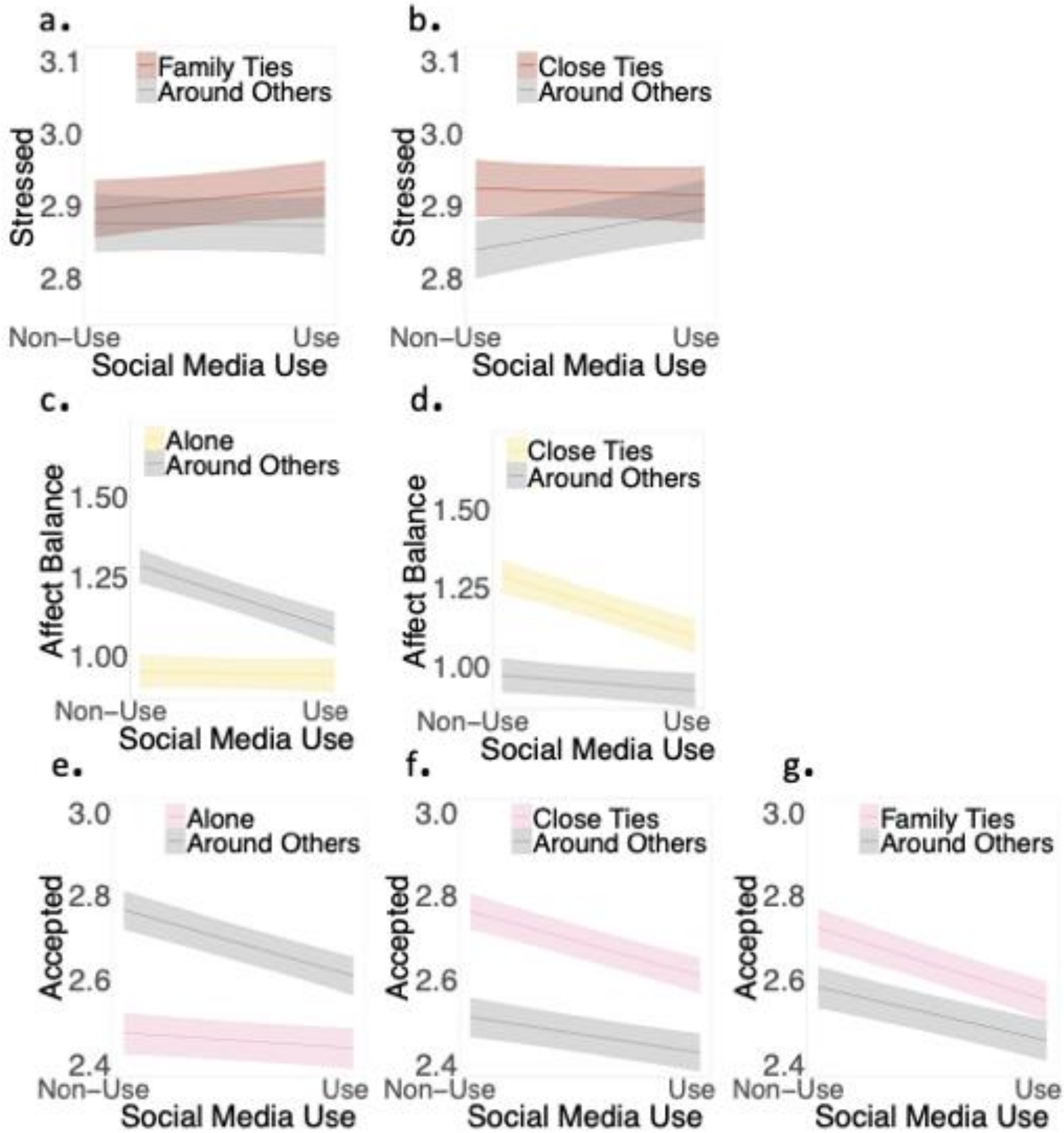
Note: Stress and loneliness were reverse coded such that higher values indicate lower levels of stress and loneliness. Bands depict standard deviation of simple slope estimates.

Figure 5: Physical Context Moderators of Social Media Sensitivity (Duration of Use)



Note: Stress and loneliness were reverse coded such that higher values indicate lower levels of stress and loneliness. Bands depict standard deviation of simple slope estimates. Values less than 0 denote below person-specific average duration of social media use. Values greater than 0 denote above person-specific average duration of social media use.

Figure 6: Social Context Moderators of Social Media Sensitivity (Use vs Non-Use)



Note: Stress and loneliness were reverse coded such that higher values indicate lower levels of stress and loneliness. Bands depict standard deviation of simple slope estimates