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Daily Perceived Stress Predicts Less Next Day Social Interaction: Evidence From a Naturalistic Mobile Sensing Study

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Although mammals have a strong motivation to engage in social interaction, stress can significantly interfere with this desire. Indeed, research in nonhuman animals has shown that stress reduces social interaction, a phenomenon referred to as "stress-induced social avoidance." While stress and social disconnection are also intertwined in humans, to date, evidence that stress predicts reductions in social interaction is mixed, in part, because existing paradigms fail to capture social interaction naturalistically. To help overcome this barrier, we combined experience sampling and passive mobile sensing methods with time-lagged analyses (i.e., vector autoregressive modeling) to investigate the temporal impact of stress on real-world indices of social interaction. We found that, across a 2-month period, greater perceived stress on a given day predicted significantly decreased social interaction–measured by the amount of face to face conversation–the following day. Critically, the reverse pattern was not observed (i.e., social interaction did not temporally predict stress), and the effect of stress on social interaction was present while accounting for other related variables such as sleep, movement, and time spent at home. These findings are consistent with animal research on stress-induced social avoidance and lay the groundwork for creating naturalistic, mobile-sensing based human models to further elucidate the cycle between stress and real-world social interaction.

Keywords: stress, social interaction, mobile sensing, naturalistic experiment

Supplemental materials: https://doi.org/10.1037/emo0000994.supp

Few factors diminish wellbeing as much as social disconnection and stress. For decades, scientists interested in affect and emotion have shown that restricted social contact and perceived stress are each risk-factors, consequences, and maintenance factors in poor mental and physical health (Holt-Lunstad et al., 2017; Kendler et al., 1999). Moreover, social disconnection and stress may operate in conjunction to compromise wellbeing. Feeling socially isolated is a common source of stress (Cacioppo & Hawkley, 2003; Kendler et al., 2003; Slavich & Irwin, 2014) and social withdrawal is a symptom of multiple stress-related disorders (Beidel et al., 1999; Berton et al., 2006; Plana et al., 2014).

Although it is clear from human research that stress and social disconnection are highly intertwined, an important question remains unanswered: how does the affective experience of stress impact naturalistic social interaction in humans? Answering this question is critical to affect and emotion research, as it would help generate a more complete understanding of the real-world consequences of stress, a pervasive affective state. Insight into the question of how stress impacts naturalistic social interaction may come from research in nonhuman animals, which consistently finds that inducing stress reduces the overall amount of social interaction in rodents (Beery & Kaufer, 2015; DeVries et al., 1996; Donahue et al., 2014; Kirby et al., 2009; Lukas et al., 2011; Meerlo et al., 1996). For example, rodents randomly assigned to experience stress on one day engage in significantly less social interaction the next day (Haller & Bakos, 2002; Mikics et al., 2008). This is true regardless of whether the source of stress is social in nature (i.e., "social defeat stress") or nonsocial (i.e., electric shocks; Haller & Bakos, 2002). In fact, a typical rodent spends the vast majority of its time (90%) exploring a new

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environment in close proximity to a peer. However, if a rodent has experienced the stressors used in electric shock and social defeat paradigms, this tendency is reduced dramatically (<50%; Haller & Bakos, 2002). Moreover, these findings are often used to understand human psychology; for example, the reversal of stress-induced social avoidance in rodents has been used to test the effectiveness of anxiolytic pharmaceuticals prescribed to humans (Leveleki et al., 2006).

However, whether stress predicts subsequent reductions in social interaction in humans is less clear cut. On the one hand, studies suggest that greater daily stress (both in terms of perceived stress and responses to objective stressors) corresponds with less interest in social interaction and more avoidant behavior *during* social interaction (e.g., reduced eye-contact; Repetti & Wood, 1997; Repetti, 1989). Likewise, anxiety, a construct highly related to perceived stress, predicts fewer friendships (Scharfstein et al., 2011) and perceived social support (Jacobson & Newman, 2016), both of which likely have implications for one's amount of social interaction. Social anxiety in particular is associated with social withdrawal (Beidel et al., 1999; Kashdan et al., 2014) and, based on self-report evidence, less frequent socializing with peers (Faytout & Swendsen, 2009). These findings are consistent with the idea that stress may compromise social connection broadly speaking. However, unlike the research in rodents, this past work does not show the critical temporal link between stress and subsequent reductions in social interaction.

On the other hand, experimental research designed to measure the impact of stress on subsequent social behavior finds mixed support for stress-induced social avoidance in humans (Roelofs et al., 2005, 2007). For example, in one study, after experiencing a stressor, participants' social avoidance motivation was assessed based on how quickly they pulled a lever away from themselves in response to photographs of angry faces (Roelofs et al., 2005). Although stress responses (here, based on physiological stress responding) were not clearly associated with increased social avoidance motivation post-stressor, pulling a lever in response to static photographs does not closely mirror human social interaction in real life. Thus, it is possible that there may be evidence in humans consistent with the animal literature's findings of reduced social interaction in response to stress when social interaction is assessed more naturally.

To further complicate the possibility of stress predicting subsequent decreases in social interaction in humans, another area of research suggests people commonly cope with stress by seeking social support (Taylor et al., 2004); particularly through conversation during social interaction (Lakey & Orehek, 2011; Pistrang et al., 1997). The "tend-and-befriend" hypothesis (Taylor, 2006) suggests that individuals, particularly females (Armstrong & Kammrath, 2015; Astor-Dubin & Hammen, 1984; Felsten, 1998; Frydenberg & Lewis, 1993; O'Hare & Beutell, 1987), commonly seek out social contact in response to stress to ensure their affiliative needs are met and to help cope with their stress. At first blush, support-seeking in response to stress may seem to indicate that stress would increase, rather than decrease, social interaction in humans, particularly among females. However, this literature finds that in response to stress, people report seeking only a moderate amount of support and seeking it from only a few of their closest social ties (Armstrong & Kammrath, 2015; Markiewicz et al., 2006; Marroquín et al., 2017). These latter findings suggest that while people may seek support in response to stress, this coping strategy does not necessarily imply an overall increase in social interaction. Moreover, to our knowledge, empirical evidence in humans for support-seeking relies on either retrospective or simulated assessments of social behavior (Ishii et al., 2017; Jiang et al., 2018; Kim et al., 2006; Taylor et al., 2007) rather than measuring the actual amount of social interaction in response to stress, and there is evidence that individuals overestimate their amount of socializing with close contacts (Mastrandrea et al., 2015). Collectively, these various threads of research make it challenging to assess whether stress reduces the overall amount of real-world, social interaction in humans.

To help begin to fill this gap, we tested the temporal relationship between daily perceived stress and social interaction in humans naturalistically. To do so, we used a dataset that assessed participants' ($N = 88$) daily behavior for roughly 2 months ($M = 67$ days; Wang et al., 2018). Ecological momentary assessments (EMA) and passive mobile sensing were collected through a single smartphone app (the StudentLife app; Wang et al., 2014). EMA sampling allowed participants to report on their daily stress-levels. The mobile sensing passively monitored several aspects of participants' behaviors, including their social interaction through face to face conversation.

Critically, in everyday life, social interaction and stress do not exist in isolation, but rather occur in the context of multiple, interrelated variables. To help assess the relative specificity of our findings to stress and social interaction, we capitalized on the fact that the mobile-sensing app monitored multiple variables related to stress and social interaction, including participants' sleep, movement, and time spent at home. Given that these variables have also been related to stress (Beiter et al., 2015; Lee & Jang, 2015), including them in our models as covariates allowed us to examine the predictive relationship between stress and subsequent social interaction, above and beyond movement, sleep, and time spent at home. Specifically, just as inducing stress on Day 1 reduces social interaction on Day 2 in rodents (Haller & Bakos, 2002), we were able to test whether self-reported stress on a prior day uniquely predicted less social interaction the next day in humans. Additionally, given suggestions that females may be more inclined to seek social contact in response to stress (i.e., the "tend and befriend" hypothesis; Taylor, 2006), we also explored whether gender moderated the temporal relationship between stress and social interaction.

Method

Participants

Data were collected from 99 participants who were Dartmouth College undergraduates and agreed to provide mobile sensing data across the winter and/or spring academic terms. After removing participants with poor data quality (see online supplemental materials for more information, including the power analysis demonstrating the adequacy of the final sample size), 88 participants were left for analysis with 66.83 days of data on average (SD = 20.46). The mean age of the 88 participants was 20.95 (SD = 2.35) years. With respect to gender, 59 (55.68%) were females and 39 (44.32%) were males. This study was approved by the Dartmouth Committee for the Protection of Human Subjects. Participants received course credit for their participation.

Smartphone Measures

The StudentLife app (Wang et al., 2014) was used to collect sensing data and to administer EMAs. A version of the app exists for both Android and iOS operating systems and participants downloaded the app at the onset of their enrollment in the study. The EMA and Passive Mobile Sensing features are described in detail below. For the interested reader, further information on the app can be found in the following publications: (Chen et al., 2013; Lane et al., 2011; Rabbi et al., 2011; Wang et al., 2014).

EMA of Stress

The Mobile Photographic Stress Meter (MPSM) was used to assess daily stress (DaSilva et al., 2019; Haim et al., 2015) and administered randomly once per day between the hours of 9 a.m. and 8 p.m. Random administration of when participants report on their daily stress helps ensure that results are not confounded with the time of day in which the assessment is made. The MPSM is a series of 16 images depicting varying levels of stress, providing a Likert scale of stress reflecting 1 (*no stress*) to 16 (*extreme stress*). A participant taps on the image that best describes their stress level. Past work has shown that responses to the MPSM significantly correlate with responses on the Perceived Stress Scale, which is a standard measure of perceived stress (Cohen, 1988; Cohen et al., 1983). Critically, however, the MPSM is more conducive to frequent, longitudinal sampling because users report that the MPSM is enjoyable to interact with and easy to use (Chan et al., 2018; Haim et al., 2015).

Passive Mobile Sensing

Passive mobile sensing data was collected via the StudentLife app running in the background of participants' smartphones. Thus, participants did not actively interact with the app in order for it to collect the passively sensed data. Given that we wanted to test whether stress predicts decreases in social interaction, the passive mobile sensing variable we were most interested in was the social interaction variable. We also included other passively assessed variables in our models that past work has shown to relate to stress (sleep, movement, and time spent at home; Beiter et al., 2015; Darling et al., 2007; Lee & Jang, 2015), which further allowed us to assess the relative specificity of the stress-socializing relationship. All passive sensing features were aggregated at the daily level, providing a single value for a given variable per day.

Social Interaction. Social interaction was detected via a smartphones' microphone sensor and a conversation classifier that detects the number of independent conversations a participant was around, along with the respective duration of the conversation. Specifically, StudentLife inferred face to face conversation from a two state Hidden Markov Model: a classifier to infer human voice and a classifier to detect conversation (Lane et al., 2014). A participants' microphone was sampled every fourth minute (1 min on 3 min off) and sampling continued until a conversation was finished. The duration of time spent around conversation for a given day was used as a measure of social interaction. This method has been shown to accurately (84% to 94% accuracy) segment inputs from microphones into meaningful audio derived features (voices, noise, and silence; Lane et al., 2011; Rabbi et al., 2011). In addition, to protect participant privacy, the content of the conversation was never recorded; the audio was processed on the fly to extract and record features.

Sleep. Sleep duration was computed from four phone sensors: screen on/off, activity, audio amplitude, and ambient light. It is noteworthy that relying on only one of these measures on their own does not predict sleep well, given the wide variety of phone usage patterns among individuals. However, using a linear combination of these features to predict sleep duration has been shown to be accurate ±40 min, when the ground truth was obtained from a Zeo headband, which uses a combination of inertial sensors and electroencephalogram (EEG) to quantify sleep (Chen et al., 2013). For this reason, our measure of sleep used the linear combination of these features to assess sleep duration.

Location and Movement. Location (Global Positioning System [GPS]) data was sampled every 10 min. Density-based spatial clustering of applications with noise (DBSCAN) was used to pinpoint location data (Ester et al., 1996). DBSCAN is a clustering algorithm commonly used with spatial data that can uncover complex clusters, which provides an accurate estimate of where on campus a given participant spent time. Each student's home location was determined by where they dwell the majority of time between 2 a.m. and 6 a.m. The GPS data was also used to calculate the total distance traveled (movement) on a given day.

Data Preprocessing

Before any analyses were conducted, the data were cleaned to include only participants and days with sufficient data quality (for more details about all aspects of data cleaning/preprocessing see online supplemental materials). In general, mixed effect models are robust to missing data in predictors and irregularly spaced measurement periods (Gibbons et al., 2010). However, shifting the data to calculate lagged estimates resulted in a near doubling of the percentage of rows containing missing data. Thus, missing data were imputed using Amelia (Honaker et al., 2011). Amelia uses a multiple imputation algorithm to impute missing data, imputing m values for each missing data point and creating m imputed data sets. Moreover, Amelia was specifically designed to accommodate longitudinal data and includes features such as the ability to include lags/leads, polynomial terms, and the ability to impute with trends specific to each cross-section unit (here, a person). We set m to 45, following guidelines that m should be similar to the percentage of cases that are incomplete (Bodner, 2008; White et al., 2011). Following data imputation, point estimates, pooled standard errors, and degrees of freedom were calculated following guidelines set forth by (Rubin, 2004). For the interested reader, as a sensitivity check, we also analyzed our data without imputation and the primary results remain unchanged across all three networks (see online supplemental materials).

Data Analysis

To capitalize on the longitudinal nature of the data, we used a two-step multilevel vector autoregressive model (two-step mlVAR), which isolates within and between-subjects relationships between multiple variables (Epskamp et al., 2016, 2018). Specifically, this approach extends Gaussian graphical models (GGM; a network model comprising a set of variables denoted by circles [nodes] with lines [edges] that visualize the relationship between variables) to multilevel data. This approach generates three "networks," defined as the simultaneous relationships between variables of interest. Specifically, each variable of interest (here, social interaction, stress, sleep, movement, or time spent at home) is a node in a graph and nodes are connected together by edges, where an edge between each node reflects the partial β coefficients or partial correlations, reflecting the unique associations between a pair of variables. The three networks generated in the mlVAR framework are: (1) a directed *temporal* network that reveals within-subjects, time-lagged relationships between variables; (2) an undirected *between-subjects* network, which identifies variables that fluctuate together at the subject level; and (3) an undirected *contemporaneous* network, which identifies within-subjects relationships on a given time point (here, a day).

The "two-step" in "two-step mlVAR" refers to the two-step process by which these models are estimated. In the first step, two out of the three networks are generated: the temporal network and the between-subjects network. To estimate these two networks, five multilevel models (one for predicting each variable of interest) are sequentially estimated. In this step, each daily variable (i.e., stress, social, sleep, movement, or time at home) at time t is predicted by the five within-subjects lagged variables (t-1: lag of 1 day) and four trait-level predictors (the mean of the response variable is not included as a covariate). Trait-level predictors are the mean of a measure over the course of the study (e.g., a participant's average amount of socializing over the course of the study). With respect to the random terms, random subject intercepts were included while random slopes were omitted after observing problems with model singularity (i.e., imposing a random effects structure too complex for the data). From the resulting models, the lagged β coefficients go on to make up the edges. Temporal relationships between variables (e.g., how stress on a previous day relates to social interaction the following day), as well as temporal relationships for the same variable (i.e., how social interaction on a prior day relates to social interaction the next day [i.e., autoregressive relationships]) are edges in the temporal network. For the between-subjects network, the β coefficients representing the trait-level relationships between variable pairs are standardized and averaged (see online supplemental materials and Epskamp et al., 2018]) to partial correlations and comprise the edges in the between-subjects network.

In the second step, the third network, referred to as the "contemporaneous network," is estimated. The contemporaneous network assesses within-subjects relationships measured at the same time point (here, a day). This network is estimated by leveraging the residuals from the five models run in Step 1. Specifically, a series of five multilevel models are sequentially fit where the residuals of one variable are predicted by the residuals of the other four variables. Orthogonal random slopes for each variable were incorporated when appropriate (see online supplemental materials). Like the trait-level coefficients in Step 1, the coefficients representing these contemporaneous relationships between variable pairs are standardized and averaged to partial correlations and comprise the edges in the contemporaneous network.

Results

To provide a high-level look at the data, several summary statistics are presented in Table 1 including, for each variable, the: mean, median, standard deviation, and two different intraclass correlation coefficients, ICC1 (the proportion of between group variance to total variance), and ICC3k (the consistency of the behaviors over time). The summary statistics for our social interaction variable are similar to those found in other work using the same mobile sensing application to investigate social processes (Harari et al., 2020).

Temporal Network

Consistent with the animal literature which finds that inducing stress on one day decreases social interaction the next day, the results from the temporal network depicted a negative temporal relationship between stress and social interaction; that is, higher stress at time t-1 (i.e., a prior day) predicted a decrease in social interaction at time t (the next day; $b = -.040$, $t = -3.037$, $p = .002$). In addition to being negatively related to social interaction, increased stress also predicted lower subsequent levels of movement the next day ($b = -.036$, $t = -2.570$, $p = .010$) and less sleep ($b = -.033$, $t = -2.420$, $p = .016$). Further, we also found that greater social interaction positively predicted spending more time at home the next day ($b = .047$, $t = 3.000$, $p = .003$). Moreover, spending more time at home was related to decreased next-day levels of movement ($b = -.144$, $t = -8.880$, $p < .001$) and social interaction ($b = -.068$, $t = -4.422$, $p = <.001$), as well as increased next-day stress ($b = .052$, $t = 2.723$, $p = .007$). All variables with the exception of sleep exhibited positive autoregressive relationships with their previous time point (ts > 4.62, $p < .001$). This indicates, for example, that greater stress on a given day also predicts greater stress the next day. In terms of sleep, along with a nonsignificant autoregressive slope (i.e., amount of sleep on one day did not predict amount of sleep the next day), sleep was not related to any of the other four measures in a temporal fashion. Results from the temporal network are depicted in Figure 1. In each of the models, to account for temporal effects, we also conducted an analysis with time (day in the term) and a quadratic term for time as fixed effects. The statistical significance of the results persisted and the β coefficients were largely unchanged (see Online Supplemental Materials Table 1 for more details).

Between-Subjects Network

Only one significant connection was observed in the between-subjects network. Participants who, on average, tended to spend more time at home also moved less ($r_p = -.362$). Stress was unrelated to the mobile sensing variables in this network. Thus, it is not the case that participants who tend to be more stressed at the trait level necessarily engage in less social interaction, at least in the way perceived stress and social interaction was measured here. Results from the between-subjects network are depicted in Figure 2, with more details provided in Online Supplemental Materials Table 3.

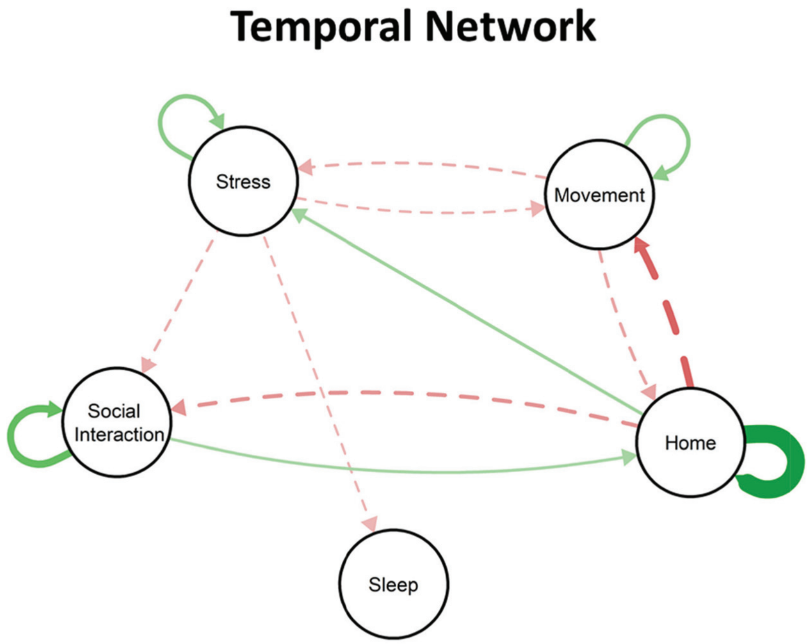
Table 1

Descriptive Statistics for Passive Mobile-Sensing and Ecological Momentary Assessment (EMA) Measures

Variable	*M*	*Mdn*	*SD*	ICC1	ICC3k
Social (min)	175.78	148.13	135.31	.36	.98
Stress (1−16 scale)	8.67	9.00	4.19	.13	.96
Move (km)	234.82	4.36	2,627.79	.42	.99
Home (hr)	13.10	13.40	5.33	.33	.99
Sleep (hr)	7.03	7.25	2.29	.31	.99

Note. ICC = intraclass correlation coefficient; ICC3k = the consistency of the behaviors over times.

Figure 1
Temporal Network



Note. Solid green edges represent positive partial β-coefficients while red dashed lines represent negative partial β-coefficients. Arrows represent the direction of the effect (i.e., a variable at time t-1 predicting a variable at time t). The thickness and shade of the edge represents the strength of the association. All shown edges are statistically significant.

Contemporaneous Network

We found the following significant relationships for a given measurement period (a day): stress was negatively associated with social interaction ($r_p = -.061$), movement ($r_p = -.040$), and sleep ($r_p = -.038$). Greater social interaction was related to increased movement ($r_p = .310$) and decreased time spent at home ($r_p = -.071$). Along with decreased social interaction, spending more time at home was associated with increased sleep ($r_p = .037$), and decreased movement ($r_p = -.303$). Results from the contemporaneous network are depicted in Figure 2, with more details provided in Online Supplemental Materials Table 4.

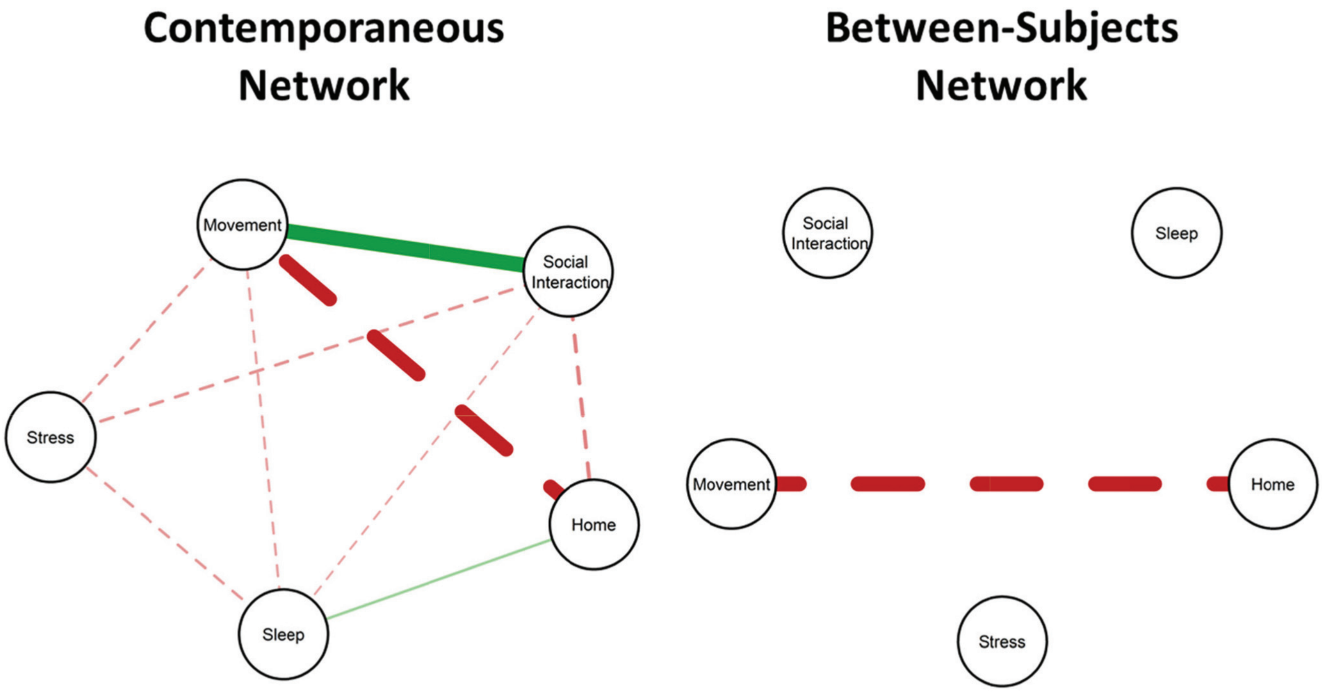
Gender Differences

Although our results so far suggest greater perceived stress on a given day temporally predicts less social interaction in humans the next day, it is possible that this effect varies between men and women. For example, the social support literature suggests females engage in more support-seeking in response to stress than males (Armstrong & Kammrath, 2015; Astor-Dubin & Hammen, 1984; Felsten, 1998; Frydenberg & Lewis, 1993; O'Hare & Beutell, 1987), which may attenuate the negative temporal relationship between perceived stress and social interaction. Thus, we next ran an exploratory test of whether gender moderated the relationships between stress and social interaction. The tendency for stress on a prior day to predict less subsequent social interaction the next day was not moderated by gender ($b = .007$, $t = .276$, $p = .783$), nor was the relationship between social interaction and trait level stress moderated by gender ($b = .444$, $t = 1.260$, $p = .201$; though we may have been underpowered to detect a significant interaction). In addition, on a given day, the relationship between social interaction and stress was not moderated by gender ($b = .012$, $t = .500$, $p = .618$). These findings suggest that gender may not impact the relationship between stress and the overall amount of real-world social interaction, at least in the way perceived stress and social interaction was measured here.

Length of Temporal Effects

Given that stress on a given day corresponds with less social interaction the next day, a natural question is how long this temporal relationship persists. Thus, we next assessed the temporal network, with a time lag of 2 days (rather than 1 day). That is, how does stress at time t-2 relate to behaviors at time t? Stress did not significantly predict social interaction ($b = -.018$, $t = -1.326$, $p = .185$), movement ($b = -.008$, $t = -.609$, $p = .543$), or sleep ($b = -.019$, $t = -1.449$, $p = .148$) at a lag of 2 days. Stress's autoregressive relationship was significant with the 2 day lag ($b = .0426$, $t = 2.691$, $p = .007$). However, at a lag of 3 days, stress was not predictive of any behaviors and its autoregressive relationship was no longer significant ($b = .020$, $t = 1.235$, $p = .218$). Collectively, these findings suggest that while the effect of perceived daily stress on behavior may be shorter term (e.g., by roughly 1 day), a stressful state can be slightly longer lasting, bleeding into the next few days.

Figure 2
Contemporaneous and Between-Subject Networks



Note. Solid green edges represent positive partial correlations while negative dashed lines represent negative partial correlations. The thickness and shade of the edge represents the strength of the association. All shown edges are statistically significant.

Discussion

Stress and social disconnection frequently go hand-in-hand (Eisenberger & Cole, 2012). Yet, whether stress temporally predicts decreased social interaction in humans has been inconclusive, in part, due to the challenge of measuring real-world socializing. Here, we capitalized on recent advances in passive mobile sensing and experience sampling approaches to reveal the interplay between stress and social interaction naturalistically, in a real world setting. Consistent with animal models of stress and social behavior (Beery & Kaufer, 2015; Haller & Bakos, 2002), we found that, in humans, greater perceived stress on a given day predicted less social interaction through conversation the next day. Critically, this relationship was not bidirectional and was observed when controlling for overall movement, sleep, and time spent at home. Our results align nicely with those found in rodent studies assessing the role of stress on subsequent social interaction. In typical stress-induced social avoidance paradigms, rodents randomly assigned to experience stress on a given day will show reduced social interaction the next day (Beery & Kaufer, 2015; Haller & Bakos, 2002; Leveleki et al., 2006). Likewise, we found that greater perceived stress on a given day in humans predicted less social interaction the next day. The stress-induced social avoidance paradigm in rodents has been used to understand the neural basis of anxiety disorders in humans. However, to our knowledge, this line of research has persisted without concrete evidence that stress prospectively reduces future social interaction in humans. Thus, our findings add important support for this approach.

Our findings also offer novel insight into the potentially specific role of stress in predicting decreased social interaction, above and beyond other confounding variables. In extant animal paradigms, social interaction is measured by assessing the degree to which a rodent will traverse a room and interact with another rodent placed at the back of the room. As a result, the desire to move around is conflated with motivation for social interaction. Given that stress is known to induce freezing in animals (Blanchard et al., 2003; Edmunds, 1974; Roelofs, 2017; Schöner et al., 2017; Yamamoto et al., 2009), it is not entirely clear whether stress reduces social interaction, restricts movement, or both. While there are certainly differences between animal paradigms and measuring human behavior through mobile sensing, it is worth noting that our approach can tease apart social interaction from movement. That is, separate classifiers are used to detect social interaction through conversation and ambulatory movement (Wang et al., 2014). We found that stress on a given day has independent effects on social interaction and movement (as well as sleep) the next day, uniquely predicting decreases in each of these variables. These findings suggest that stress may impact social interaction above and beyond its effect on movement, extending what we could discern from the existing animal literature.

Of course, there are many ways to measure stress and distinctions are often made between responses to objective "stressors," like those used in stress-induced social avoidance paradigms in rodents, and "perceived stress" as measured in our study (Epel et al., 2018). On the one hand, this would suggest there are likely important distinctions between the underlying mechanisms linking stress to decreases in social interaction in our results and those found in rodents. On the other hand, it is compelling that the findings are similar, despite potential differences in the types of stress experienced. Future research may be able to disentangle the potential role of objective stressors versus perceived stress in moderating social interaction in humans.

The two-step mlVAR approach was key to disentangling how stress and social interaction prospectively relate to one another. Indeed, the contemporaneous network, which identifies within-subject relationships independent of temporal effects, also showed that on a given day greater stress was related to less social interaction. However, because this network does not include temporal information, the direction of this pattern is unclear if only the contemporaneous relationships are considered. Thus, the temporal network reveals precise insight into the prospective relationship between stress and social interaction, identifying that feeling more stressed on a given day corresponds with less social interaction the next day, relative to one's baseline level of social interaction. This finding underscores the value of assessing personality and emotion dynamics within-subjects over time. Moreover, because stress and social interaction do not interact in a vacuum, the mlVAR approach was key to observing the prospective relationship between these two variables, while still accounting for other interacting variables such as sleep, movement, and time spent at home.

How do our results fit within the context of social support seeking in response to stress? A large body of work suggests that social support may provide a buffer against stress (Beiter et al., 2015; Lee & Jang, 2015) and that people, particularly females, may seek support in response to stress. In our data, we observed that the directional, prospective relationship between stress and social interaction was not reciprocal; that is, increased social interaction did not predict a subsequent decrease (or increase) in stress. Moreover, our results were not moderated by gender. However, our results do not necessarily imply that social support does not ameliorate stress, nor that stress does not trigger support-seeking. Past work has shown that in response to stress, people report seeking support from only a few key individuals (Armstrong & Kammrath, 2015). As such, it could very well be the case that participants in our study sought support from a few friends, but that this targeted strategy corresponds with their overall decrease in global levels of social interaction. In other words, support-seeking and stress-induced social avoidance are not mutually exclusive. Indeed, theoretical accounts of coping responses to stress suggest that these are not incompatible strategies (Skinner & Zimmer-Gembeck, 2007). An interesting direction for future research will be to naturalistically capture both global amounts of social interaction, who participants are interacting with (e.g., one of their support providers vs. a less close friend) and the extent to which they sought support from the interaction. This approach would help determine whether stress-induced decreases in overall social interaction and support-seeking may operate in conjunction in everyday life.

Another possibility is that social support's impact on stress varies from population to population. Many populations used to test the buffering hypothesis represent a highly distressed group of adults (e.g., breast cancer survivors [Kroenke et al., 2006; Lutgendorf et al., 2005; Muscatell et al., 2016] or recently laid off workers [Cohen & Wills, 1985; Mallinckrodt & Bennett, 1992]). It is possible that college students' social behavior following stress may be different from the aforementioned groups, particularly in a competitive campus environment, where other students may be reminders of stressors. Additionally, stressors commonly faced by students (e.g., course work and exams) may systematically demand time spent alone (e.g., studying in the library), which could contribute to the effects observed here. Likewise, stress may impact support seeking differently across the adult life span; indeed, there is some evidence that older adults are less likely to rely on avoidance coping strategies than younger adults (Amirkhan & Auyeung, 2007; Uchino, 2009). Testing whether support-seeking may be less stress-buffering and/or a less commonly used coping strategy in college samples will be critical for future work, given that mental health problems related to stress, including anxiety and depression, are highly prevalent among college students (Auerbach et al., 2018; Eisenberg et al., 2013).

Another interesting direction for future research will be to determine the physiological pathways by which stress predicts reductions in real-world social interaction in humans. Daily stressors trigger a cascade of physiological reactions, including endocrine and immune system responses (Herman et al., 1995; Matteri et al., 2000; Segerstrom & Miller, 2004). For example, stress initiates a negative feedback loop, whereby the activation of the hypothalamic pituitary adrenal axis that activates stress responses simultaneously activates systems that down-regulate the stress response to help it end (Bohringer et al., 2008; Tsigos & Chrousos, 2002). Here, we found that perceived stress prospectively decreased social interaction the next day, but that individuals' amount of social interaction was unrelated to stress by the second day (i.e., extending the temporal lag of our analyses to 2 days showed that stress no longer significantly predicted less social interaction 2 days later). Moreover, the autoregressive relationship between greater stress on a given day predicting greater stress the next day lasted only a little bit longer, up to roughly 2 days. Recent work has combined surveys, EMAs, and cortisol sampling to better understand the link between behavior and physiology (Charles et al., 2020; Smyth et al., 2017). Continuing in that vein, future research that combines mobile sensing approaches with physiological measures may also reveal whether, how, and the temporal nature by which objectively measured social interaction relates to biological stress responses.

Limitations

The naturalistic approach we used to measuring social interaction is an advance from past work, which tends to rely on the retrospective and simulated assessments of interaction (Ishii et al., 2017; Jiang et al., 2018; Kim et al., 2006; Taylor et al., 2007) that are susceptible to biased reporting (Mastrandrea et al., 2015). That said, a limitation to our approach is that we can only infer the overall *amount* of social interaction and only through face to face *conversation*. Other aspects of social interaction, such as nonverbal behavior and social media use, as well as the types of relationship partners interacted with (e.g., close friends vs. acquaintances) were not measured but may also be impacted by perceived daily stress. Moreover, many of these kinds of social behaviors could be obtained from smartphones (text messages, phone calls); however, this information was not able to be collected in the vast majority of our participants due to their operating system (iOS). Nonetheless, in our view, focusing on the amount of social interactions through face to face conversation is a key first step in assessing whether, as suggested by rodent models, stress predicts a general decrease in social interaction. Face to face conversation is a pervasive form of social interaction and conversation is theorized to be one of the primary ways in which humans maintain their social networks (Dunbar, 2018), both of which justify its use as a dependent variable for social interaction. Nonetheless, future research that combines conversation detection with additional measures of social behavior will help develop a complete understanding of how stress impacts naturally occurring social interaction in humans. Finally, while our measure of perceived stress has been validated, it does not rule out the possibility that other forms of negative affect similarly correspond with reduced social interaction. As a consequence, we cannot determine the extent to which the present findings are preferential to stress, versus negative affect more generally. It is worth pointing out that the same issue pertains to the animal literature examining stress-induced social avoidance, as to our knowledge the impact of stress on social interaction has not been compared and contrasted with other emotional states within the same study. That said, an interesting direction for future research will be to elucidate the consequences of various negative affective states on naturalistic, real-world social interaction.

Conclusion

In summary, we helped begin to bridge the gap between animal and human research regarding the role of stress on everyday social interaction. Animal models suggest a robust tendency to reduce social interaction following a stressor. With a naturalistic mobile sensing paradigm, we were able to put that model to test in humans and found that higher levels of reported stress on a given day predicted less social interaction the next day. More broadly, our results lay the groundwork for creating naturalistic, mobile-sensing based human models to further elucidate the cycle between stress and real-world social interaction.

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