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Stress restricts social interaction in humans: Evidence from a naturalistic mobile sensing study

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Abstract

Although mammals have a strong motivation to engage in social interaction, stress can significantly interfere with this desire. Indeed, research in non-human animals has shown that stress restricts social interaction, a phenomenon referred to as 'stress-induced social avoidance.' While stress and social disconnection are also intertwined in humans, to date, evidence for stress-induced social avoidance in humans is mixed, in part, because existing paradigms fail to capture social interaction naturalistically. To 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 two-month period, greater perceived stress on a given day predicted significantly decreased social interaction 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 socializing was present while accounting for other related variables such as sleep, movement, and time spent at home. These findings help to substantiate the translational value of 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, sociality, and mental health.

Significance Statement

Humans are fundamentally a social species and social contact is critical to mental and physical health. Yet, stress may dampen our desire to socialize with others, hampering this basic need for human connection. Somewhat surprisingly, extant evidence that greater stress leads to less social interaction relies heavily on studies conducted on rodents. Here, we tested this possibility in humans, using continuously collected data from smartphones. By obtaining daily ratings of stress through a smartphone application and measuring time spent around others through mobile phone microphones, we found that experiencing higher levels of stress on a given day reduced the amount of time people spent in live social interactions the following day. These findings are consistent with animal research suggesting stress reduces social interaction. More broadly, they underscore the social cost of stress: we may sabotage our need to connect with others during the times we need them the most.

Few factors diminish wellbeing as much as social disconnection and stress. For decades, scientists have shown that restricted social contact and perceived stress are each risk-factors, consequences, and maintenance factors in poor mental and physical health (1, 2). Moreover, social disconnection and stress may operate in conjunction to compromise wellbeing. Feeling socially isolated is a common source of stress (3–5) and social withdrawal is a symptom of multiple stress-related disorders (6–8)

Although it is clear from human research that stress and social disconnection are highly intertwined, evidence that stress can reduce actual social interaction comes almost exclusively from animal research (9–12). For example, rodents randomly assigned to experience stress on one day engage in significantly less social interaction the next day (13). This is true regardless of whether the source of stress is social in nature (i.e. 'social defeat stress') or non-social (i.e. electric shocks; (13)). In fact, a typical rodent spends the vast majority of its time (90%) exploring a new 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%; (13)). 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 (14).

Yet, whether stress reduces social interaction in humans is less clear cut.   On the one hand, some studies suggest that greater daily stress corresponds with less interest in interaction and more avoidant behavior *during* social interaction (e.g., reduced eye-contact;(15, 16)). Likewise, anxiety, a construct highly related to perceived stress, predicts fewer friendships (17) and perceived social support (18). Social anxiety in particular is associated with social withdrawal (8, 19) and, based on self-report evidence, less frequent socializing with peers (20). These findings are consistent with the idea that stress may reduce social connection, though notably do not show a temporal link between stress and actual, subsequent social interaction.

On the other hand, experimental research designed to measure the impact of stress on subsequent social behaviour finds mixed support for stress-induced social avoidance in humans (21, 22). For example, in one study, after experiencing a stressor, participants' social avoidance was assessed based on how quickly they pulled a lever away from themselves in response to photographs of angry faces (21). Although stress responses were not associated with increased social avoidance post-stressor, pulling a lever in response to static photographs does not closely mirror how humans engage in or disengage from social interaction in real life. To further complicate things, other research suggests that people commonly cope with stress by seeking social support (23), which may increase, rather than decrease, social interaction. However, evidence in support of this possibility relies on either retrospective or simulated assessments of coping strategies (24–27), rather than measuring actual social interaction in response to stress. Collectively, these various threads of research make it challenging to determine whether stress reduces real-world, subsequent social interaction in humans.

To help overcome these barriers, we tested for stress-induced social avoidance in humans naturalistically. To do so, we used a dataset that assessed participants' (N=74) daily behavior for roughly two months (mean = 64 days; (28). Ecological momentary assessments (EMA) and passive mobile sensing were collected through a single smartphone app (the StudentLife app; (29)). 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. In addition to our variables of interest (daily perceived stress and social interaction), mobile sensing was also used to extract covariates of interest, including students' movement, sleep, and time spent at home. Given that movement, sleep, and time spent at home have also been related to stress (30, 31), including them in our models allowed us to examine the predictive relationship between stress and subsequent social interaction, above and beyond these related variables. Specifically, just as inducing stress on Day 1 restricts social interaction on Day 2 in rodents (13), we were able to test whether self-reported stress on a given day uniquely predicted less social interaction the next day in humans.

Results

Animal paradigms that test for stress-induced social avoidance typically randomly assign rodents to experience stress (or no stress) on Day 1 and assess social interaction on Day 2 (13, 14). To parallel this temporal unfolding, we used a two-step multilevel vector autoregressive model (two-step mlVAR), which can isolate both within-subjects and between-subjects longitudinal relationships between multiple variables (32). Specifically, this approach extends gaussian graphical models (GGM) to multilevel data generating three "networks" (i.e., relationships between variables), with network edges reflecting the unique associations between variables. The primary network of interest here is the temporal network, which reveals within-subjects, time-lagged relationships between variables. This network allowed us to assess whether stress on a given day (time t) predicts less social interaction the next day (time t + 1). The approach further generates a between-subjects network, which identifies variables that fluctuate together at the subject level (e.g., whether participants who tend to be more stressed also engage in the least social interaction), and a contemporaneous network, which identifies within-subjects relationships on a given day. Critically, network edges--which reflect relationships between each variable pair--identify partial correlations (contemporaneous and between-subjects network)/beta-coefficients (temporal networks). Thus, any significant association between variable pairs/nodes, such as stress and social interaction, exists after controlling for all other variables in the model. For the contemporaneous and between-subjects networks, edges were included if the respective betas from one of the two univariate multilevel models were significant (i.e., OR rule (33)). As described in detail in the methods section, stress was assessed by daily EMA responses and social interaction, movement, sleep, and time spent at home was assessed with passive mobile sensing.

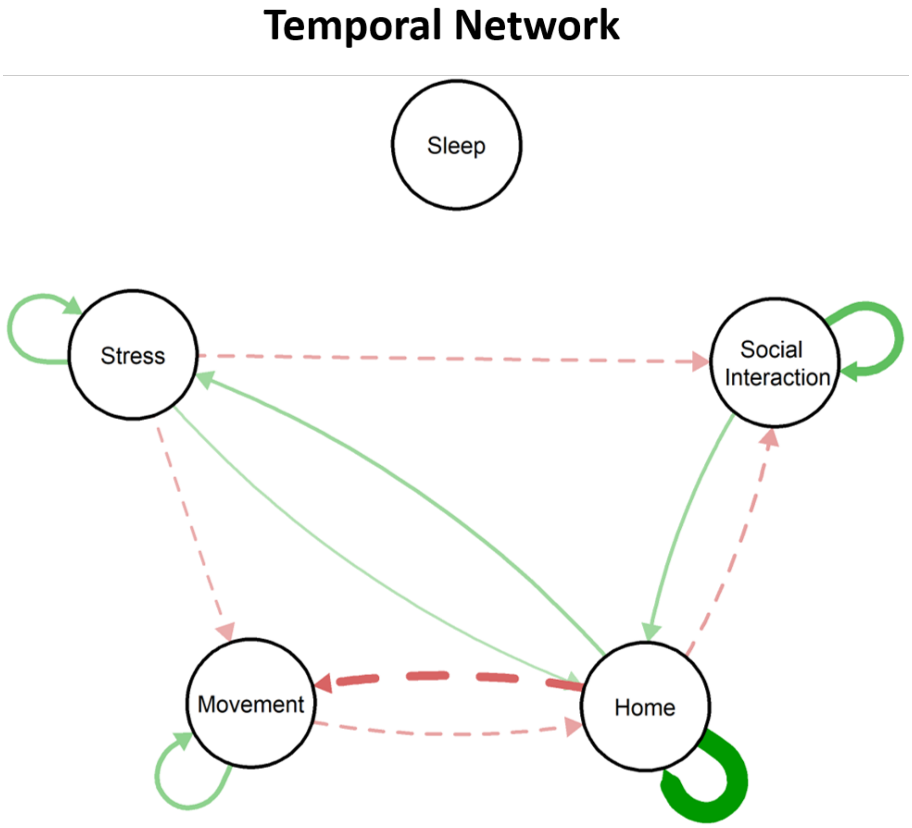

Fig 1. Temporal Network. Solid green edges represent positive partial beta-coefficients while red dashed lines represent negative partial beta-coefficients. Arrows represent the direction of the effect (i.e., a variable at time t predicting a variable at time t+1). The thickness of the edge represents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

Temporal Network. Consistent with the animal literature, the results from the temporal network depicted a negative relationship between stress and social interaction; that is, higher stress at time t (i.e., a given day) predicted a decrease in social interaction at time t + 1 (the next day; b = -.045, t = -3.035, p = .003). In addition to its relation with sociality, increased stress at time t also predicted lower subsequent levels of movement the next day (b = -.041, t = -2.703, p = .007) and spending more time at home (b =.033, t =2.342, p = .019. Further, we also found that greater social interaction at time t positively predicted spending more time at home the next day (b = .055, t = 3.133, p = .002). Moreover, spending more time at home at time t was related to decreased future levels of movement (b = -.141, t = -7.540, p < .001), social interaction (b = - .054, t = - 3.170, p = .002), and increased stress (b = .055, t = 2.714, p = .007). All variables with the exception of sleep exhibited positive autoregressive relationships with their previous time point (t's > 4.0, 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 non-significant 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 Fig. 1. In each of the models, to account for temporal effects, we also conducted an analysis with time (day in the term) and quadratic term for time as fixed effects. The statistical significance of the results persisted and the beta coefficients were largely unchanged See Supplementary Tables 1-2 for more details.

Contemporaneous Network. We found the following significant relationships for a given measurement period (a day): stress was negatively associated with social interaction (r_p = - .054), movement (r_p = - .042), and sleep (r_p = - .037). Greater social interaction was related to increased movement (r_p =.317) and decreased time spent at home (r_p = -.093). Along with decreased social interaction, spending more time at home was associated with increased sleep (r_p = .053) and decreased movement (r_p = -.310). Results from the contemporaneous network are depicted in Fig. 2, with more details provided in Supplementary Table 3.

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 moved less (r_p = -.318). Interestingly, 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 socialize more or less. Results from the between-subjects network are depicted in Fig. 2, with more details provided in Supplementary Table 4.

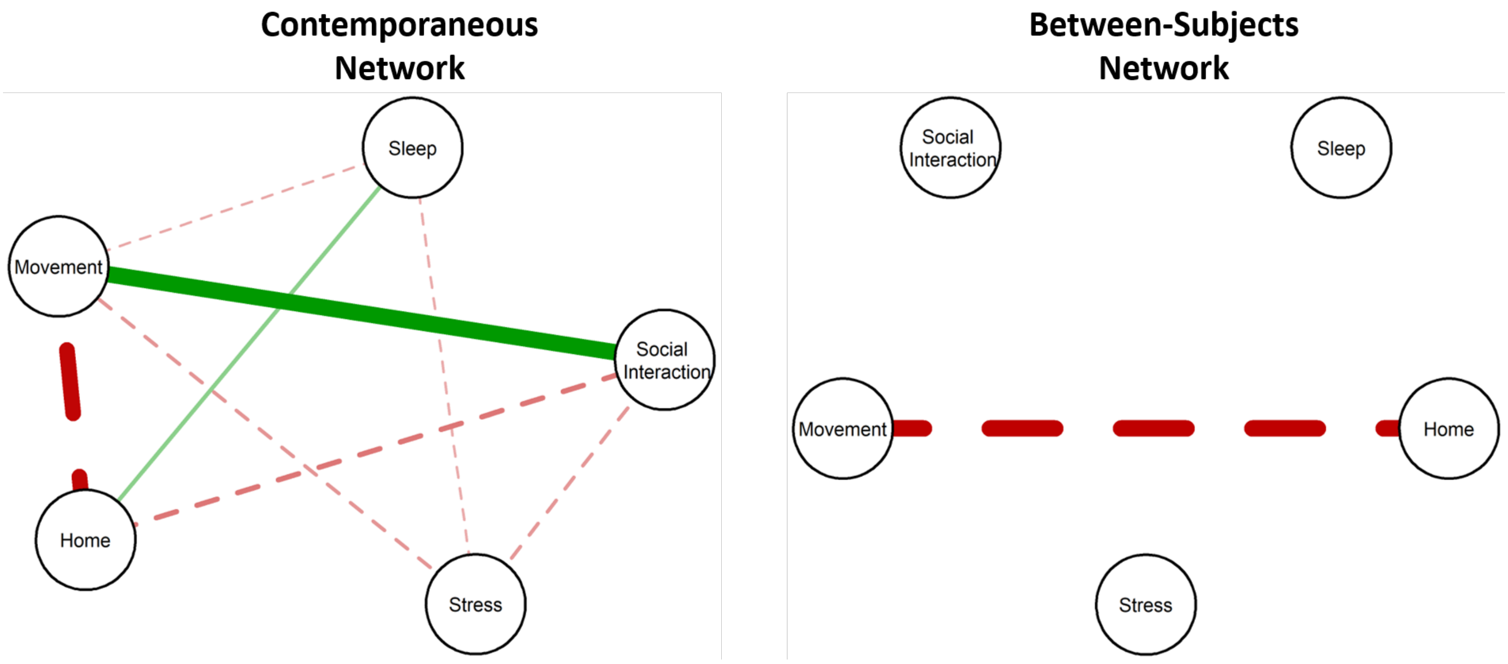

Fig 2. Contemporaneous and Between-Subject Networks. Solid green edges represent positive partial correlations while negative dashed lines represent negative partial correlations. The thickness of the edge represents the strength of the association. All shown edges are statistically significant.

Discussion

Stress and social disconnection frequently go hand-in-hand (34). Yet, whether stress directly decreases social interaction in humans has been largely overlooked, likely due, in part, to the difficulty 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-word setting. Consistent with animal models of stress and social behavior (9, 13), 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 bi-directional and was observed when controlling for overall movement, sleep, and time spent at home. Collectively, our results suggest that perceived stress specifically restricts social interaction in humans.

Our results align nicely with those found in rodent studies. In typical stress-induced social avoidance paradigms, rodents randomly assigned to experience stress on a given day will show restricted social interaction the next day (9, 13, 14). Likewise, we found that greater perceived stress on a given day in humans predicted less socializing 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 restricts future social interaction in humans. Thus, our findings add important support for this approach.

Our findings also offer some insight into the potentially specific role of stress on social avoidance, 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. Thus, the desire to move around is conflated with motivation for social interaction. Given that stress is known to induce freezing in animals (35), it is not entirely clear whether stress reduces social approach, 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 (29). Importantly, we found that stress on a given day has independent effects on socializing and movement the next day, uniquely decreasing both. These findings suggest that stress may impact socializing above and beyond its effect on movement, thus 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 (36). On the one hand, this would suggest there are likely important distinctions between the underlying mechanisms linking stress to social avoidance 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 vs. 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 socializing. However, because this network does not include temporal information, the direction of this pattern is unclear if only the contemporaneous relationships are considered. Moreover, no significant associations between stress and any of the other passive mobile sensing variables were observed in the between-subjects network. In other words, participants who tend to be more stressed do not necessarily socialize less. Thus, the temporal network reveals precise insight into the prospective relationship between stress and socializing, identifying that feeling more stressed on a given day corresponds with less socializing the next day, relative to one’s baseline level of socializing. This finding underscores the value of assessing personality and emotion dynamics within-subjects over time.

It is noteworthy 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. A large body of work suggests that social support may provide a buffer against stress (i.e., the “buffering hypothesis”; (37, 38)). At first glance, it looks like our results may be at odds with that account. If social support buffers stress, spending more time interacting with people on a given day should predict less stress the next day. However, it is important to consider how social support is traditionally operationalized when testing the buffering hypothesis. Most research testing the buffering hypothesis measures *perceived* social support (39). In contrast, we are measuring actual social interaction through conversation. Given past work suggesting that perceived and objective social connection may impact mental and physical health through distinct routes (1), it is possible that perceived social support is more important for buffering stress than objective social support garnered through interaction. 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 (40–42) or recently laid off workers (39, 43). It is possible that college students’ social behavior following stress may be different from the aforementioned groups, particularly in a highly competitive campus environment, where other students may be reminders of stressors. Testing these competing possibilities regarding the role of social support on stress-buffering 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 (44, 45).

Conclusion

In summary, we helped bridge the gap between animal and human research regarding the role of stress on social behavior. Animal models suggest a robust tendency to avoid 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. These findings help validate a rich animal literature on the neurobiology of stress and social withdrawal and lay the groundwork for creating naturalistic, mobile-sensing based human models to elucidate the cycle between stress, sociality, and mental health.

Methods

Participants

Data were collected from 102 participants who agreed to provide mobile sensing data across the winter and/or spring academic terms. After removing participants with poor data quality (See Supplementary Materials for more information), 74 participants were left for analysis with 63.26 days of data on average (SD = 19.55). Of the 74 participants with sufficient data quality, 2 had incomplete demographic information. For the 72 participants with complete demographic information, 57% percent were female (41/72). The mean age of participants was 20.98 (SD = 2.48) years. This study was approved by the Dartmouth Committee for the Protection of Human Subjects.

Smartphone Measures

The StudentLife app (29) 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.

Ecological Momentary Assessments (EMA) of Stress

The Mobile Photographic Stress Meter (MPSM) was used to assess daily stress (46, 47). The MPSM is a series of 16 images depicting varying levels of stress. A participant simply taps on the image that best describes their stress level. Users report that the MPSM is enjoyable to interact with and easy to use (46) which is critical, as usability is a crucial aspect of any mobile app, particularly when used longitudinally (46).

Passive Mobile Sensing

Because we wanted to test whether stress decreases social interaction, the passive mobile sensing variable we were most interested in was the sociality 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; (30, 31, 48), which further allowed us to determine the specificity of the stress-socializing relationship.

Social Interaction. StudentLife infers face to face conversation from a two state Hidden Markov Model: a classifier to infer human voice and a classifier to detect conversation (49). The conversation classifier infers the number of independent conversations a participant is around and their duration. The frequency and duration of time spent around conversation for a given day is used as a measure of sociality. Importantly, to protect participant privacy, the conversation is never recorded; the audio is processed on the fly to extract and record features.

Sleep. Sleep duration is computed by measures from four phone sensors: screen on/off, activity, audio amplitude, and ambient light. This process of estimating sleep duration has been shown to be accurate +/- 30 minutes (50).

Location/Movement. Density-based spatial clustering of applications with noise (DBSCAN) is used to pinpoint location data. DBSCAN is an algorithm that uses GPS coordinates to uncover where on campus students are spending time. Each student's home location is where they dwell between 2-6 am. Total distance traveled on a given day is also calculated.

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 Supplement). In general, mixed effect models are robust to missing data in predictors and irregularly spaced measurement periods (51). 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 (52). Amelia uses a bootstrap-EM algorithm to impute missing data, imputing m values for each missing data point and creating m imputed datasets. 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 40 following guidelines that m should be similar to the percentage of cases that are incomplete (53, 54). Following data imputation, point estimates, pooled standard errors, and degrees of freedom were calculated following guidelines set forth by (55).

Data Analysis

Before model fitting, steps were taken to ensure data quality and that the assumptions of multilevel modeling were met (see Supplementary Materials). Next, two-step multi-level vector autoregressive models were fit with the mlVAR package in the R environment (56, 57). This multilevel modeling procedure is a multi-step process that computes fixed and random effects for temporal and contemporaneous networks as well as fixed effects for between-subjects networks. In the first step, a series of *n* (*n* = the number of variables in the network model, here 5) univariate multilevel models are fit. In this step, each model (for each variable), consists of lagged within-subject centered predictor variables and between-subject predictors, a value equal to the mean of a measure over the course of the study. For each univariate multilevel model, along with the fixed effects, random subject intercepts were included. Random slopes were omitted after observing problems with model singularity (i.e., imposing a random effects structure too complex for the data). Estimates obtained from these models were used to create temporal and between-subjects networks. In the second step, residuals from the first set of models were incorporated into a second set of multilevel models to estimate the contemporaneous network. In these models, residuals from one variable were predicted by the residuals from the rest of the variables at the same time point. Orthogonal random slopes for each variable were incorporated when appropriate (see Supplementary Material). Following the “OR-rule” (33), edges for the between-subjects and contemporaneous networks were included in the network models if at least one of the beta values from the multilevel models were significant (32, 58).

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Supplementary Materials

Data Preprocessing

Before any analyses were conducted, the data were cleaned to remove participants who: experienced technological difficulties with their phone, failed to respond to over 50% of the EMA prompts, or failed to have at least 50% percent of their total days in the study containing at least 16 hours of quality conversation and location data, a quality mark similar to those used in other mobile sensing studies using the StudentLife application (1, 2).

Next, the extent to which a participant had missing data, or 'missingness' was assessed. A day's given conversation, sleep, or location data was counted as missing if the total data quality for that day was less than 16 hours. The rates of missingness were as follows for our five variables of interest: conversation - 19.12%, sleep duration - 4.46%, stress - 24.05%, location home - 19.14%, distance traveled - 19.53%. In total, 17.26 % of the data were missing and 35.04% of cases (rows) contained at least one missing value. As noted in the manuscript, mixed effect models are robust to missing data and irregularly spaced measurement periods (3). However, shifting the data to calculate lagged estimates resulted in a near doubling of the percentage of rows containing missing data, an issue also noted in (4). For example, stress and sociality may be complete cases at time *t* while stress contains a missing value at t - 1. For this reason, missing data were imputed. Before imputation, we checked to see if stress, at the trait level (mean over the study), was associated with missing conversation, location, sleep, or stress data to ensure that our factor related to mental health was not related to the amount of participants' missing data. Trait level stress was not associated with percentage of missing stress ($r = .055$, $p = .645$), location ($r = .-.071$, $p = .546$), conversation ($r = -.021$, $p = .656$), or sleep data ($r = -.151$, $p = .198$). As it was heavily skewed, the movement variable was log transformed in the imputation model and log transformed for the two-step mlVAR analysis. Finally, variables were standardized to help with model convergence.

Multiple Imputation: Pooling

Following data imputation using Amelia, estimates were combined following guidelines set forth by (5). The multiple imputation point estimate is the average of the 40 complete estimates for each dataset. Here, each point estimate is a beta from one of the resulting univariate multilevel models. Pooled standard errors were calculated incorporating information from within-imputation (average of the point estimate variances) and between-imputation (variance in the point estimates) variation. A resulting test-statistic was calculated from the average of point estimates and the pooled standard error. A lambda parameter was derived from the variance components and combined with *m* to calculate the degrees of freedom for the t-distribution.

In the final step before model fitting, as in (4), stationarity in the data was checked via a Kwiatkowski-Phillips-Schmidt-Shin (KPSS) test from the tseries package (6). An assumption of the data analysis approach used here, (2 step mlVAR), is that the data are stationary; that is, the mean and variance of a given time series of data should remain unaltered over time. Thus, a KPSS test was run for every subject and variable on every one of the 40 imputed datasets. Across subjects and datasets, the data were largely stationary (85%), and as expected, there was very little variability across imputed dataset (SD = .010).

In addition to the series of KPSS tests, we also re-ran the first step of the 2 part mlVAR model with time and time^2 as fixed effects (for each of the 5 univariate multilevel models) to account for linear and nonlinear effects of time. The coefficients remained largely unchanged.

	Stress	Social Interaction	Home	Movement	Sleep
Stress	0.07	-0.03	0.04	-0.03	-0.01
	4.08	-1.25	2.02	-1.20	-0.30
	0.000	0.210	0.044	0.232	0.766
Social Interaction	-0.04	0.15	-0.05	-0.00	0.01
	-2.94	8.60	-2.98	-0.02	0.96
	0.003	0.000	0.003	0.987	0.339
Home	0.03	0.05	0.36	-0.04	-0.02
	1.88	2.78	20.57	-2.29	-1.03
	0.061	0.005	0.000	0.023	0.303
Movement	-0.04	0.01	-0.13	0.07	-0.01
	-2.47	0.71	-6.51	3.76	-0.30
	0.014	0.476	0.000	0.000	0.764
Sleep	-0.02	0.01	-0.01	0.01	-0.02
	-1.26	0.54	-0.41	0.48	-1.40
	0.209	0.590	0.683	0.629	0.163

Table 1. Temporal model parameters with time and time^2 as fixed effects. For each cell, from top - middle - bottom, the numbers represent: parameter estimates, test-statistics, and p-values.

Results expanded

The results in their entirety from the network models are depicted below. In each of the tables, for each cell, the numbers represent: parameter estimates, test-statistics, and p-values from top to middle to bottom. For the temporal network, the relationships on the diagonal depict each variable's autoregressive relationship with itself. Dashes are present on the diagonal of the between-subjects and contemporaneous tables as these relationships are not assessed. For the between-subjects and contemporaneous networks, following the 'OR' rule (7), one of the associations between variables needs to be significant for it to be included in the model. Specifically, these two networks are a function of two parameters from two multiple regression models for each node. Thus, there are two sets of summary statistics and two *p*-values, and from here we use the 'OR' rule to retain an edge if one of the *p*-values is significant. The edges in these models (partial correlations) are calculated by standardizing and averaging parameters from each one of the aforementioned 2 models.

	Stress	**Social Interaction**	**Home**	**Movement**	**Sleep**
Stress	0.08 4.44 0.000	-0.03 -1.19 0.235	0.05 2.71 0.007	-0.03 -1.33 0.185	-0.01 -0.48 0.628
Social Interaction	-0.04 -3.03 0.003	0.15 8.58 0.000	-0.05 -3.17 0.002	0.00 0.02 0.983	0.02 0.99 0.321
Home	0.03 2.34 0.019	0.05 3.13 0.002	0.38 22.64 0.000	-0.05 -2.70 0.007	-0.02 -1.22 0.223
Movement	-0.04 -2.70 0.007	0.01 0.45 0.650	-0.14 -7.54 0.000	0.08 4.05 0.000	-0.00 -0.21 0.832
Sleep	-0.02 -1.44 0.151	0.01 0.53 0.598	-0.01 -0.66 0.507	0.01 0.52 0.603	-0.02 -1.31 0.191

Table 2. Temporal Network. These relationships reflect how a variable on a given day relates to the other variable the next day.

	Stress	Social Interaction	Home	Movement	Sleep
Stress	---	-0.07	0.01	-0.05	-0.04
	---	-3.00	0.33	-2.34	-1.85
	---	0.003	0.740	0.020	0.064
Social Interaction	-0.04	---	-0.09	0.32	-0.01
	-2.95	---	-4.29	11.09	-0.87
	0.004	---	0.000	0.000	0.385
Home	0.00	-0.09	---	-0.31	0.05
	0.24	-4.46	---	-14.10	3.09
	0.812	0.000	---	0.000	0.002
Movement	-0.03	0.32	-0.30	---	-0.03
	-2.35	11.24	-14.27	---	-1.71
	0.019	0.000	0.000	---	0.087
Sleep	-0.03	-0.02	0.06	-0.05	---
	-2.05	-1.10	3.16	-2.44	---
	0.041	0.270	0.002	0.015	---

Table 3: Contemporaneous network. These relationships depict associations between variables on a given day.

	Stress	Social Interaction	Home	Movement	Sleep
Stress	---	0.04	0.01	0.01	-0.06
	---	0.48	0.15	0.15	-0.73
	---	0.632	0.880	0.882	0.465
Social Interaction	0.08	---	-0.08	0.20	-0.09
	0.46	---	-0.64	1.50	-0.72
	0.643	---	0.523	0.133	0.471
Home	0.02	-0.07	---	-0.33	-0.05
	0.14	-0.64	---	-2.82	-0.44
	0.889	0.520	---	0.005	0.662
Movement	0.02	0.15	-0.31	---	0.07
	0.10	1.50	-2.88	---	0.71
	0.918	0.133	0.004	---	0.479
Sleep	-0.12	-0.09	-0.05	0.10	---
	-0.68	-0.77	-0.43	0.75	---
	0.497	0.441	0.670	0.455	---

Table 4. Between-subjects network. These relationships represent trait level associations between variables.

Random effects structures

For the first step of the two-part mlVAR model, models were initially estimated with a maximal random effect structure (correlated random intercepts and slopes). Upon observing issues related to convergence, we simplified the random effect structure. Problems with convergence remained when specifying uncorrelated random effects; thus, we opted to use random intercept only models. A similar pattern of convergence issues emerged when estimating the contemporaneous networks. In order to keep the multilevel structure for these models, we took a closer look at the random effect variance/covariance matrices for each of the 5 univariate models across the 40 imputed data sets. Random slopes for variables were retained if the variance for that particular random effect never dipped below .0001 for any of the models in any of the imputed data sets. That left the following random effect structure for each of the respective univariate models:

DV	RF Structure
Stress	Sleep
Sociality	Home, Movement
Home	Sociality, Movement
Movement	Sociality, Home, Sleep
Sleep	Movement, Stress

Table 5. Random effect structure for the contemporaneous models.

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