Social microclimates and well-being

Andrea L. Courtney^{1*}, Dean Baltiansky¹, Wicia M. Fang¹, Mahnaz Roshanaei¹, Yunus C. Aybas², Natalie A. Samuels³, Everett Wetchler³, Zhengxuan Wu⁴, Matthew O. Jackson^{2,5}, Jamil Zaki^{1*}

¹Department of Psychology, Stanford University; Stanford, CA USA 94305.

²Department of Economics, Stanford University; Stanford, CA USA 94305.

³Department of Psychology, University of California at Berkeley; Berkeley, CA USA 94720.

⁴Symbolic Systems Program, Stanford University; Stanford, CA USA 94305.

⁵Santa Fe Institute; Santa Fe, NM USA 87501.

*Corresponding authors. Email: acourtne@stanford.edu; jzaki@stanford.edu

Abstract

Direct social ties bolster mental health; do ambient features of local communities also play a role? This work takes advantage of university students' assignment to different local networks—or “social microclimates”—to probe this question. We quantify the collective impact of individual, social network, and microclimate factors in the well-being of a cohort of first-year college students. Students who belonged to emotionally stable and tight-knit microclimates reported reduced psychological distress, even when controlling for factors such as personality and personal social ties. Although rarely discussed or acknowledged in the policies that create them, social microclimates are consequential to mental health, especially during life transitions.

Introduction

Social ties are critical to mental health, especially during difficult times. Do characteristics of one's local community—or “social microclimates”—also play a role?

Here we explore this idea in a cohort of students during their transition to college. In their first months on campus, students experience dips in life satisfaction and spikes in stress, anxiety, depression, and loneliness, relative to pre-college levels ¹. Subjective well-being during this transition is strongly linked to personality traits, like emotional stability and extraversion ^{2–5}; social connections are also a bulwark against psychological upheaval ^{6–8}, fostering resilience to stress and mitigating mental health issues ^{9–15}.

Young adult social life is also anchored in larger communities, which could also affect well-being. Some researchers have suggested that mood states and well-being spread across social networks ^{16–19}, wherein having mentally healthy friends can stave off the threat of mental health disorders ^{20,21}. However, when individuals choose their social networks, it can be difficult to disentangle so-called “contagion” of psychological states such as depression from “homophily,” or social attraction between similar individuals ²². By contrast, some aspects of students' social community—such as the hall within a dormitory in which they live, and their direct hall neighbors—are randomly assigned.

Previous work has leveraged this random assignment to demonstrate that one's college neighbors affect academic performance and employment ^{23–25}, but no previous research has used this approach to examine the influence of local social community on mental health. Students are disproportionately likely to connect with people who live near them in their dormitory ^{26,27}; but even absent direct friendship connections, they can still be affected by ambient features of the social environment, or “social microclimate.”

Social microclimates are rarely acknowledged by educators or policymakers, but we hypothesize that they could nonetheless affect well-being. For instance, having friends and neighbors who are empathic and emotionally stable, or residing in a tightly-knit and supportive community, might bolster an individuals' well-being and protect their mental health, above and beyond the personal ties they form^{18,19}. Because microclimates are not chosen by students, we can draw inferences about the impact of the local community on mental health that are uncontaminated by homophily.

In this work, we measured the personality traits of a large sample ($N = 798$) of incoming first-year college students before they arrived on campus. Then, midway through their first term, we assessed their mental health (i.e., psychological distress) and social connections to peers on campus. We obtained data at both pre-college and first term time points from 41% of the first-year class ($N = 702$; $N = 670$ included in analysis). See Table S1 for summary statistics and Table S2 for comparisons with population demographics.

Results

We use a 10-fold cross-validated LASSO regression to identify individual, social network, and microclimate factors most associated with psychological distress in students' first term in college (Fig. 1). The model explains 29% of the variance in psychological distress during cross-validation (averaged across folds) on the training sample (Root mean square error [RMSE] = 0.84, $R^2 = 0.29$), and 30% when tested on a hold-out sample (30% of original data; RMSE = 0.84, $R^2 = 0.30$, lambda tuning parameter = 0.04). LASSO regression, zero-order correlation, and multiple regression coefficients are presented in Table S3 and Fig. 2 (see Fig. S1 for matrix of correlations among all predictors). All methods and additional results from a model of life

satisfaction, a positive index of well-being, are included in the supplementary materials (see Table S4, Fig. S2, Fig. S3).

Fig. 1. Schematic representing the layers of social factors in well-being. Well-being is affected by (i) individual factors, related to the person's demographics (e.g., family income) and personality traits, (ii) social network factors, such as the number of supportive ties and connections among one's friends, and (iii) microclimate factors, including the emotional stability of direct ties and the density of connections among hall mates. Exemplar factors for each layer are depicted here (see Methods for full list).

Fig. 2. Model coefficients for the predictors associated with psychological distress. (A)

Individual, social network, and microclimate factors most predictive of psychological distress.

Dashed line reflects the mean optimized lambda value across 10 folds. (B) Zero-order correlation coefficients for the reduced set of predictors associated with psychological distress. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = non-significant.

Consistent with past work, much of the variance in students' psychological distress is explained by individual factors, including personality (e.g., emotional stability and extraversion) and demographic characteristics (e.g., family income). In addition, participants with a greater number of direct social connections (i.e., outdegree) reported reduced distress.

Interestingly, psychological distress also negatively tracks two features of social microclimates: the density of within-hall connections and the emotional stability of one's direct connections. Hall network density represents the percentage of all connections reported on a hall that went to other members of the hall, or its social connectedness. For instance, on a hall with 20% density, two of every ten nominations made go to hall mates; by contrast, on a hall with 60% density, six of every ten nominations remain within the hall (Fig. 3). Our halls range from 6% to 68% density; and importantly, this measure is exogenous to students' direct ties. Students cannot determine whether they land in a densely connected hall, and yet this microclimate factor

tracked their mental health. Students who live on a hall where no one is close (i.e., 0% density) experience a 16% increase in psychological distress, relative to those on a hall where 60% of all close relationships are between hall mates.

Fig. 3. Psychological distress is associated with the density of social connections within one's hall. (A) An exemplary network of social connections in a low density hall and high density hall. (B) Histogram of the density of within-hall social connections across all sampled halls. Hall networks presented in (A) were drawn from the highlighted bins. (C) Model predicted psychological distress for a student living in halls of 0%, 20%, 40%, and 60% density with 95% confidence intervals.

Discussion

Here, we introduce a novel framework of the “social microclimate”, demonstrating that the qualities of local communities track well-being. Students who reported more supportive connections, befriended emotionally stable peers, and resided in a tight-knit dorm environment reported less psychological distress. Our results connect with prior work linking psychological distress to life circumstances and community characteristics, like safety and trust ^{28,29}. The social environment, like one’s dorm, contains sources of stress and support, which can toggle psychological distress up or down ³⁰.

Unsurprisingly, demographic profiles and personality traits explain relatively large proportions of variance in well-being among first-year college students. For example, low-income students reported increased psychological distress during their first term of college. Moreover, we replicate prior research linking well-being to the individual’s emotional stability and extraversion ²⁻⁵. That said, it is noteworthy that microclimate factors such as hall density track mental health even when controlling for these better-known factors.

The effects observed here are small: a one standard deviation increase in hall density is associated with a 3% decrease in psychological distress. Nonetheless, considering the size of the college student population and the growing number of students facing a mental health crisis, even small effects can have a meaningful impact on mental health. The university residence hall is a unique, but constrained environment; and our sample is notably well-educated and socioeconomically advantaged relative to the broader population. Thus, the scale of impact should be validated among other communities, like neighborhoods, workplaces, and families.

Students have little control over their social microclimates. They cannot select for local communities that include tight-knit social bonds, or peers who effectively cope with stress. And yet these features affect students’ own mental health burden. University administrators might

consider ways to increase the supportive nature of dorm environments so that this “microclimate” can serve as a source of mental health support, rather than stress, for vulnerable student populations. These results also validate ongoing initiatives at universities, and other organizations, that prioritizes community building.

Methods

Participants

We invited all first-year students at a private university in the Western United States to complete two online Qualtrics surveys. The first assessed their personality traits in the weeks just prior to starting college, and the second assessed their social connections and well-being midway through their first term on campus (Fall 2019). Seven hundred ninety-eight participants completed the pre-college survey and 862 participants completed the fall survey, yielding a total of 702 participants with responses to both measures. Our sample is representative of the target population, the first-year cohort (class of 2023), on most demographic measures (Table S1 and S2). Study procedures were conducted in accordance with the guidelines set by Stanford University’s Institutional Review Board, and participants received monetary compensation for completing the surveys.

Well-being Measures

Our primary dependent variables are psychological distress (presented in the main text) and life satisfaction (presented in Supplementary Materials). These composite measures are defined from the Fall trait survey items that loaded mostly strongly (positive and negative) onto a well-being factor derived from an independent factor analysis (see Supplementary Text for details). The psychological distress composite includes items from the Center for Epidemiological Studies

Depression scale (CES-D) ³¹, the State–Trait Anxiety Inventory (STAI) ³², the Rosenberg Self-Esteem Scale ³³, and Emotion Regulation of Other and Self ³⁴ scale. All well-being items were measured on a scale from 1 (“Strongly disagree”) to 7 (“Strongly agree”). Participants missing responses to this measure are excluded from analyses (N = 2).

Individual Demographic and Personality Factors

Participants also provided information about their demographic background (measured during the fall term) and personality traits (measured prior to the beginning of the fall term), and these items are included as covariates in models of well-being.

Demographic variables include participants’ gender, under-represented minority status, international student status, family income, and perceived socioeconomic status. Our sample is representative of the first-year student population on most of these measures (see Table S2).

Gender was measured by having participants select from: *Man*, *Woman*, or *Other*. Race and ethnicity were measured by having participants select all that apply from: *American Indian*, *East Asian*, *Pacific Islander*, *Black or African American*, *White or Caucasian*, *Hispanic or Latino/a*, *South Asian*, *Middle Eastern*, *Other*. Using responses to this question, we created a binary factor reflecting participants’ under-represented minority (URM) status, which adhered to the university’s definition ³⁵. International student status was derived from responses to the question “Are you an international student?” (Yes = 1, No = 0). Family income was reported as: (1) *\$0-20K*, (2) *\$20-40K*, (3) *\$40-60K*, (4) *\$60-80K*, (5) *\$80-100K*, (6) *\$100-120K*, (7) *\$120-140K*, (8) *\$140-160K*, (9) *\$160-180K*, (10) *\$180-200K*, (11) *Over \$200K*. Responses were coded into 11 levels.

Big-five personality variables were derived by averaging the two items associated with each factor in the Ten-Item Personality Inventory ³⁶. The empathy composite was derived from

the factor analysis on Fall 2019 survey items (see Supplementary Text for details). The empathy variable averaged responses to items from the Adults Prosocialness scale ³⁷, Interpersonal Reactivity Index ³⁸, and Single Item Trait Empathy Scale ³⁹. Due to a correlation with trait agreeableness, participants' empathy is not included as a covariate in the LASSO model; but direct ties' and dorm mates' empathy are included, as described below.

Social Network Factors

To identify their peer connections on campus, participants nominated up to six undergraduate students in response to each of the following prompts: “Who are your closest friends?”, “Who do you turn to when something bad happens?”, and “Who makes you feel supported and cared for?”⁴⁰. They entered their peer's name into a text field, which was auto-completed with names from the undergraduate student roster ($N \sim 7,000$). We combine all unique network nominations from these three prompts into a single union graph that represented students' “support network” within their community.

From the network graph, we calculate the number of connections associated with each participant. *Outdegree* reflects the number of unique nominations made by a participant, whereas *indegree* reflects the number of nominations received by a participant from their peers. Notably, outdegree has a minimum value of 0 (for participants who made no nominations) and a maximum value of 18 (for participants who nominated 6 unique individuals in each of the three network prompts). By contrast, indegree has a minimum value of 0 and a theoretical maximum equal to the sample size minus one (e.g., theoretical maximum for fall indegree = 861, implying that all other participants nominated that student as a support connection).

In addition to the complete network graph, we construct an ego-network for each participant, which includes the friends they nominated (i.e., direct ties) and links among those

friends. We then estimate the density of these ego-networks (i.e., clustering), as a measure of the interconnectedness of one's friend group. Ego-network density reflects the number of nominations between one's friends (or alters) relative to the total number of between-friend nominations that are possible, or the number of pairs in the network (i.e., $\text{density} = N \text{ ties} / [N \text{ alters} * N-1 \text{ alters}]$). These values range from 0 (no friends are connected) to 1 (all friends are connected). To reduce the effects of sampling bias on our calculation of density (i.e., underestimating ego-network density for participants whose friends did not participate), we only include alters that were also participants in the study, and assume a link between alters if either alter in a pair nominated the other. This measure indicates how tight-knit one's friend group is, and might have implications for their well-being ⁴¹.

Microclimate Factors

Finally, to assess the contributions of community characteristics to students' well-being, we derive personality variables for both direct social ties and those living in the same hall as the participant, as well as the density of within-hall connections. Tie-average emotional stability and tie-average empathy are derived for each participant by averaging the trait values, reported prior to students' arrival on campus, of their nominated support ties. These measures are calculated for alters who participated and completed the trait surveys.

To capture these characteristics in the randomly assigned dorm environment, part of the "social microclimate", we average the emotional stability and empathy for all members of one's dorm hall for which we have data (*median* = 8 other participants / hall, where halls have 9 - 36 students). To ensure these ambient trait variables are statistically independent of the tie-average measures, we exclude traits from the participant and any direct ties living in the same hall in this calculation.

As such, hall ambient traits reflect the characteristics of hall mates that participants are not friends with. In our sample, there is no correlation between ambient traits and participants' traits ($-0.06 < r < -0.03$, $ps > 0.11$); and correlations between ambient traits and traits of direct ties are absent for empathy ($r = -0.013$, $p = 0.75$) but low for emotional stability ($r = 0.11$, $p = 0.005$)—confirming that the traits of direct ties and other hallmates were not redundantly measured in these models. Finally, to assess the overall interconnectedness of peers living in one's hall, we calculated a ratio of the number of nominations between hallmates relative to the total number of nominations made by individuals in the participant's hall (i.e., hall-based network density).

Identifying Predictors of Well-being During the Transition to College

To identify the best predictors of fall well-being, we apply cross-validated Least Absolute Shrinkage and Selection Operator (LASSO) regression predicting (i) life satisfaction and (ii) psychological distress in Fall 2019 from the individual, social network, and microclimate factors outlined above. LASSO (L1-norm) regression shrinks less predictive variable coefficients toward zero, helping to identify the most important predictors while dropping others from the model.

Data from participants who failed to report their gender ($N = 1$) or reported their gender as “Other” ($N = 5$) are excluded from LASSO regressions, as there are too few cases to accurately impute or model data for these factor levels. Participants who made no network nominations ($N = 24$), and those missing well-being ($N = 2$) are also excluded from analyses, yielding a final sample size of 670 in these analyses. With this sample size, we have 74% power to detect a small effect of $r = 0.10$, and 97% power to detect a slightly larger effect of $r = 0.15$. We split the data into a training (70%) and hold-out sample (30%) in order to test model performance on unseen data. Missing data are imputed separately for each sample using the *mice*

package in R ⁴². All numeric variables are standardized prior to modeling and imputed using predictive mean matching. Binary categorical variables are imputed using logistic regression, and ordered categorical variables with more than two levels are imputed using polytomous regression.

On the training data, we conduct a 10-fold cross-validated LASSO regression with an L1-norm penalty parameter, using the *caret* ⁴³ and *glmnet* ⁴⁴ packages in R. Within each fold, the model tuning parameter (lambda) is optimized, for the least mean square error, in a nested 10-fold cross-validation. Model fit is validated on each fold using the optimized lambda value optimized. Next, a LASSO model is trained on the entire training set, using the average optimized lambda value, and tested on the hold-out sample. Mean cross-validated performance, model coefficients derived from the full training set, and hold-out performance are reported.

On the full, non-imputed data set, we conduct pairwise correlation and multiple regression analyses on the reduced set of predictors selected by the LASSO regression. We rely on the cross-validated LASSO regression for variable selection, and the ordinary least squares approach for a more interpretable coefficient. To address non-independence in hall-derived microclimate variables, we run an additional multiple regression analysis in which standard errors are clustered by hall. These model coefficients are reported along with the LASSO coefficients in Tables S3 and S4.

Supplementary information

Well-being Composite Measures

The well-being composite measures, used as dependent variables in the presented analyses, are derived from an independent factor analysis conducted on all items in the Fall 2019 network survey. Using a minimum residual algorithm, we uncover six distinct factors: well-being, empathy, social emotionality, political ideology, need to belong, and narcissism. The psychological distress composite is defined by averaging the top 7 items that negatively load onto the well-being factor, whereas the life satisfaction composite is defined by averaging the top 8 items that positively load onto this factor. These composites are negatively correlated with each other $r(698) = -0.62, p < 0.001$. The psychological distress composite includes the items outlined above. The life satisfaction composite combines items from the Satisfaction with Life Scale ⁴⁵, the Subjective Happiness Scale ⁴⁶, and a single item about feelings of belongingness in the college community. An empathy composite score is derived by averaging the values of the top-loading items on this factor. Tie-mean and ambient empathy variables, included as predictors in the LASSO regressions, are derived from this measure. All items included in the final composites have factor loadings of at least 0.40 and precede a meaningful drop in factor loading.

LASSO Regression Predicting Life Satisfaction

We run a second LASSO regression model, parallel to the one described in the main text, which predicted life satisfaction—a positive measure of well-being. This model explains 24% of the variance in life satisfaction during 10-fold cross-validation (averaged across folds) on the training sample (Root mean square error [RMSE] = 0.87, $R^2 = 0.24$), and 29% when tested on a hold-out sample (30% of original data; RMSE = 0.84, $R^2 = 0.29$, lambda tuning parameter = 0.02). Model coefficients are presented in Fig. S2 and Table S3. As with psychological distress,

most of the variance in students' life satisfaction is explained by individual factors, like their personality (e.g., emotional stability and extraversion) and demographic characteristics (e.g., family income). In addition, life satisfaction increases with greater outdegree, or the number of supportive connections identified by the participant. Participants with more supportive connections experience higher levels of life satisfaction (Fig. S3). Moreover, as in the model of psychological distress, the emotional stability of direct ties and hall network density are associated with greater life satisfaction.

Exploring the Evidence for Sampling Bias

Our data set is unique in that 41% of the first-year class responded at both time points, providing a clear snapshot of students' well-being and social lives. However, when partially sampling from a population of interest, one runs the risk of introducing sampling bias if key characteristics of the individual determine whether they participate or not. Particularly when predictors of interest (e.g., social factors) are highly correlated with participant characteristics, it can lead researchers to falsely conclude that these factors are related to the outcome measure (i.e., well-being), when the effect should instead be attributed to the biased sample. Our data show little evidence of sampling bias. Our sample matches the first-year student population on almost every demographic characteristic (Table S2). In addition, the predictors included in our models are largely uncorrelated (Fig. S1), and multicollinearity in the multiple regression models is low (variance inflation factor < 1.2).

Fig. S2. Model coefficients for the predictors associated with life satisfaction. (A) Estimated model coefficients, across a range of lambda values, for the reduced set of individual, social network, and microclimate factors most predictive of life satisfaction. Dashed line reflects the mean optimized lambda value across 10 folds. (B) Zero-order correlation coefficients for the reduced set of predictors associated with life satisfaction. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = non-significant.

Fig. S3. Social network of first-year students in a single residence hall. Edges reflect outgoing nominations; node size is proportional to outdegree; color is scaled by life satisfaction (blue = low, red = high, white = no data).

Table S1. Summary statistics on the sample.

Variable	N	Mean	SD	Min	Max
Age	702	18.18	0.47	18	23
Gender	701				
... Man	289	41%			
... Other	5	1%			
... Woman	407	58%			
Race / Ethnicity	684				
... Under-represented	241	35%			
... Not under-represented	443	65%			
International student	698				
... Yes	92	13%			
... No	606	87%			
Family Income	681				
... \$0-\$20,000	50	7%			
... \$20,001-\$40,000	67	10%			
... \$40,001-\$60,000	37	5%			
... \$60,001-\$80,000	51	7%			
... \$80,001-\$100,000	59	9%			
... \$100,001-\$120,000	66	10%			
... \$120,001-\$140,000	33	5%			
... \$140,001-\$160,000	30	4%			
... \$160,001-\$180,000	38	6%			
... \$180,001-\$200,000	35	5%			
... Over \$200,000	215	32%			
Life Satisfaction	701	4.93	1.22	1.17	7
Psychological Distress	701	3.2	1.38	1	7
Empathy	702	5.71	0.69	2.62	7
Extraversion	702	4.35	1.49	1	7
Agreeableness	702	4.95	1.11	1.5	7
Conscientiousness	702	5.48	1.16	1	7
Emotional Stability	702	4.78	1.34	1	7
Openness	702	5.39	0.98	2	7
Ego-network density	692	0.19	0.17	0	1
Hall density	702	0.31	0.12	0.06	0.68
Outdegree	678	6.62	2.45	1	13
Indegree	687	3.01	2.23	0	12
Tie-mean empathy	627	5.78	0.44	3.38	6.88
Ambient empathy	702	5.72	0.23	4.75	6.69
Tie-mean emotional stability	627	4.75	0.89	1.5	7
Ambient emotional stability	702	4.79	0.44	2	6.33

We report the number of participants (N) with usable data, mean, standard deviation (SD), minimum (Min), and maximum (Max) values for each variable included in the presented analyses.

Table S2. Comparison of sample demographics to those of the first-year student population.

Demographic	Sample %	Population %	Comparison	Sig
Gender (Woman)	58.06	52	10.31	0.001
Race / Ethnicity				
American Indian or Alaska Native	0.81	1	0.31	0.58
Asian	23.79	21	3.29	0.07
Black or African American	7.41	8	0.33	0.56
Hispanic / Latino	16.81	17	0.02	0.89
International	13.11	12	0.81	0.37
Native Hawaiian or Pacific	0.71	<1	2.95	0.09
Two or more races	10.83	9	2.86	0.09
White	23.93	27	3.35	0.07
Unknown	3.42	6	8.29	0.004
Family income				
Below \$150K	53.30	51	1.45	0.23

Chi-squared one-proportion tests are used to compare sample proportions to the population proportions reported for each demographic predictor. Our sample does not differ from the first-year student population (class of 2023) on most demographic characteristics. Our sample includes more females, but primarily matched the population on race / ethnicity and family income.

Table S3. Model coefficients for the reduced set of predictors related to psychological distress.

Predictor	LASSO coefficient	Correlation coefficient	Multiple regression	Clustered error regression
Emotional stability	-0.44	-0.5 [-0.56, -0.44] ***	-0.45 [-0.52, -0.37] ***	-0.45 [-0.52, -0.37] ***
Extraversion	-0.07	-0.13 [-0.2, -0.05] ***	-0.1 [-0.17, -0.03] **	-0.1 [-0.17, -0.03] **
Conscientiousness	-0.07	-0.24 [-0.31, -0.17] ***	-0.12 [-0.19, -0.05] ***	-0.12 [-0.19, -0.06] ***
Family income	-0.03	-0.11 [-0.19, -0.04] **	-0.04 [-0.11, 0.03] ns	-0.04 [-0.12, 0.04] ns
Agreeableness	-0.01	-0.15 [-0.22, -0.08] ***	-0.03 [-0.1, 0.04] ns	-0.03 [-0.1, 0.05] ns
Ego-network density	0.04	0.07 [-0.01, 0.14] ns	0.05 [-0.03, 0.12] ns	0.05 [-0.02, 0.12] ns
Outdegree	-0.01	-0.12 [-0.2, -0.05] **	-0.07 [-0.14, 0.01] ns	-0.07 [-0.15, 0.02] ns
Hall network density	-0.03	-0.13 [-0.2, -0.05] ***	-0.07 [-0.14, 0] *	-0.07 [-0.14, 0] *
Tie mean emotional stability	-0.01	-0.13 [-0.21, -0.05] **	-0.09 [-0.16, -0.02] *	-0.09 [-0.16, -0.02] *

We report the non-zero LASSO coefficients for the model predicting psychological distress. Of

the reduced set of predictors, we report Pearson correlation coefficients for numeric variables

and point biserial correlation coefficients for binary factors, along with 95% confidence intervals

and significance. In addition, multiple regression coefficients are reported from a model fitted to

the reduced set of predictors, and an identical model which clustered standard errors according to

the participant's dorm hall. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = non-significant.

Table S4. Model coefficients for the reduced set of predictors related to life satisfaction.

Predictor	LASSO coefficient	Correlation coefficient	Multiple regression	Clustered error regression
Emotional stability	0.26	0.37 [0.3, 0.43] ***	0.35 [0.27, 0.43] ***	0.35 [0.25, 0.46] ***
Family income	0.18	0.25 [0.18, 0.32] ***	0.18 [0.1, 0.25] ***	0.18 [0.09, 0.26] ***
Extraversion	0.13	0.24 [0.16, 0.31] ***	0.17 [0.1, 0.24] ***	0.17 [0.09, 0.25] ***
Gender (Woman)	0.10	0.03 [-0.05, 0.1] ns	0.18 [0.02, 0.33] *	0.18 [0, 0.35] *
Conscientiousness	0.08	0.21 [0.13, 0.28] ***	0.1 [0.03, 0.18] **	0.1 [0.02, 0.18] *
URM status	-0.06	-0.11 [-0.18, -0.03] **	-0.06 [-0.14, 0.01] ns	-0.06 [-0.14, 0.01] ns
International student	0.04	-0.01 [-0.08, 0.07] ns	0.02 [-0.06, 0.09] ns	0.02 [-0.05, 0.09] ns
Agreeableness	0.02	0.14 [0.07, 0.22] ***	0.04 [-0.03, 0.12] ns	0.04 [-0.05, 0.14] ns
Outdegree	0.11	0.18 [0.1, 0.25] ***	0.11 [0.03, 0.18] **	0.11 [0.03, 0.18] **
Ambient empathy	0.05	0.03 [-0.05, 0.1] ns	0.04 [-0.03, 0.11] ns	0.04 [-0.04, 0.12] ns
Hall network density	0.03	0.08 [0.01, 0.16] *	0.05 [-0.02, 0.12] ns	0.05 [-0.03, 0.13] ns
Tie mean emotional stability	0.02	0.08 [0, 0.16] *	0.03 [-0.04, 0.1] ns	0.03 [-0.05, 0.12] ns

We report the non-zero LASSO coefficients for the model predicting psychological distress. Of

the reduced set of predictors, we report Pearson correlation coefficients for numeric variables

and point biserial correlation coefficients for binary factors, along with 95% confidence intervals

and significance. In addition, multiple regression coefficients are reported from a model fitted to

the reduced set of predictors, and an identical model which clustered standard errors according to

the participant's dorm hall. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, ns = non-significant.

References

1. Conley, C. S., Kirsch, A. C., Dickson, D. A. & Bryant, F. B. Negotiating the Transition to College. *Emerging Adulthood* vol. 2 195–210 (2014).
2. DeNeve, K. M. & Cooper, H. The happy personality: a meta-analysis of 137 personality traits and subjective well-being. *Psychol. Bull.* **124**, 197–229 (1998).
3. Diener, E., Oishi, S. & Lucas, R. E. Subjective Well-Being: The Science of Happiness and Life Satisfaction. *The Oxford Handbook of Positive Psychology* 186–194 (2009)
doi:10.1093/oxfordhb/9780195187243.013.0017.
4. Rich, A. R. & Scovel, M. Causes of Depression in College Students: A Cross-Lagged Panel Correlational Analysis. *Psychological Reports* vol. 60 27–30 (1987).
5. Hills, P. & Argyle, M. Emotional stability as a major dimension of happiness. *Personality and Individual Differences* vol. 31 1357–1364 (2001).
6. Helliwell, J. F. & Putnam, R. D. The social context of well-being. *Philos. Trans. R. Soc. Lond. B Biol. Sci.* **359**, 1435–1446 (2004).
7. Conner, K. A., Powers, E. A. & Bultena, G. L. Social interaction and life satisfaction: an empirical assessment of late-life patterns. *J. Gerontol.* **34**, 116–121 (1979).
8. Berg, A. I., Hassing, L. B., McClearn, G. E. & Johansson, B. What matters for life satisfaction in the oldest-old? *Aging Ment. Health* **10**, 257–264 (2006).
9. Fiori, K. L. & Consedine, N. S. Positive and negative social exchanges and mental health across the transition to college. *Journal of Social and Personal Relationships* vol. 30 920–941 (2013).
10. Williams, W. C., Morelli, S. A., Ong, D. C. & Zaki, J. Interpersonal emotion regulation: Implications for affiliation, perceived support, relationships, and well-being. *J. Pers. Soc. Psychol.* **115**, 224–254 (2018).

11. Santini, Z. I., Koyanagi, A., Tyrovolas, S., Mason, C. & Haro, J. M. The association between social relationships and depression: A systematic review. *Journal of Affective Disorders* vol. 175 53–65 (2015).
12. Hagerty, B. M. & Williams, R. A. The Effects of Sense of Belonging, Social Support, Conflict, and Loneliness on Depression. *Nursing Research* vol. 48 215–219 (1999).
13. Teo, A. R., Choi, H. & Valenstein, M. Social Relationships and Depression: Ten-Year Follow-Up from a Nationally Representative Study. *PLoS ONE* vol. 8 e62396 (2013).
14. Uchino, B. N. Understanding the Links Between Social Support and Physical Health: A Life-Span Perspective With Emphasis on the Separability of Perceived and Received Support. *Perspectives on Psychological Science* vol. 4 236–255 (2009).
15. Uchino, B. N. & Garvey, T. S. The availability of social support reduces cardiovascular reactivity to acute psychological stress. *J. Behav. Med.* **20**, 15–27 (1997).
16. Cacioppo, J. T., Fowler, J. H. & Christakis, N. A. Alone in the crowd: the structure and spread of loneliness in a large social network. *J. Pers. Soc. Psychol.* **97**, 977–991 (2009).
17. Fowler, J. H. & Christakis, N. A. Dynamic spread of happiness in a large social network: longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ* **337**, a2338 (2008).
18. Rosenquist, J. N., Fowler, J. H. & Christakis, N. A. Social network determinants of depression. *Mol. Psychiatry* **16**, 273–281 (2011).
19. Hill, A. L., Rand, D. G., Nowak, M. A. & Christakis, N. A. Infectious disease modeling of social contagion in networks. *PLoS Comput. Biol.* **6**, e1000968 (2010).
20. Bryant, R. A. *et al.* Mental Health and Social Networks After Disaster. *Am. J. Psychiatry* **174**, 277–285 (2017).

21. Hill, E. M., Griffiths, F. E. & House, T. Spreading of healthy mood in adolescent social networks. *Proc. Biol. Sci.* **282**, 20151180 (2015).
22. Shalizi, C. R. & Thomas, A. C. Homophily and Contagion Are Generically Confounded in Observational Social Network Studies. *Sociol. Methods Res.* **40**, 211–239 (2011).
23. Sacerdote, B. Peer effects with random assignment: Results for Dartmouth roommates. *Q. J. Econ.* **116**, 681–704 (2001).
24. Hasan, S. & Bagde, S. The mechanics of social capital and academic performance in an Indian college. *Am. Sociol. Rev.* **78**, 1009–1032 (2013).
25. Carrell, S. E., Fullerton, R. L. & West, J. E. Does your cohort matter? Measuring peer effects in college achievement. *J. Labor Econ.* **27**, 439–464 (2009).
26. Oloritun, R. O., Madan, A., Pentland, A. & Khayal, I. Identifying Close Friendships in a Sensed Social Network. *Procedia - Social and Behavioral Sciences* vol. 79 18–26 (2013).
27. Marmaros, D. & Sacerdote, B. How do Friendships Form?*. *Quarterly Journal of Economics* vol. 121 79–119 (2006).
28. Phongsavan, P., Chey, T., Bauman, A., Brooks, R. & Silove, D. Social capital, socio-economic status and psychological distress among Australian adults. *Soc. Sci. Med.* **63**, 2546–2561 (2006).
29. Lin, J., Thompson, M. P. & Kaslow, N. J. The mediating role of social support in the community environment-psychological distress link among low-income African American women. *J. Community Psychol.* **37**, 459–470 (2009).
30. Ensel, W. M. & Lin, N. The life stress paradigm and psychological distress. *J. Health Soc. Behav.* **32**, 321–341 (1991).
31. Radloff, L. S. The CES-D Scale. *Applied Psychological Measurement* vol. 1 385–401 (1977).

32. Spielberger, C. D. *State-Trait Anxiety Inventory for Adults: Manual and Sample : Manual, Instrument and Scoring Guide*. (1983).
33. Rosenberg, M. Society and the Adolescent Self-Image. (1965)
doi:10.1515/9781400876136.
34. Niven, K., Totterdell, P., Stride, C. B. & Holman, D. Emotion Regulation of Others and Self (EROS): The Development and Validation of a New Individual Difference Measure. *Current Psychology* vol. 30 53–73 (2011).
35. Dashboard Definitions. <https://ideal.stanford.edu/resources/ideal-dashboard/dashboard-definitions>.
36. Gosling, S. D., Rentfrow, P. J. & Swann, W. B. Ten-Item Personality Inventory. *PsycTESTS Dataset* (2012) doi:10.1037/t07016-000.
37. Caprara, G. V., Steca, P., Zelli, A. & Capanna, C. A New Scale for Measuring Adults' Prosocialness. *European Journal of Psychological Assessment* vol. 21 77–89 (2005).
38. Davis, M. H. *A Multidimensional Approach to Individual Differences in Empathy*. (1980*).
39. Konrath, S., Meier, B. P. & Bushman, B. J. Development and validation of the Single Item Trait Empathy Scale (SITES). *J. Res. Pers.* **73**, 111–122 (2018).
40. Morelli, S. A., Ong, D. C., Makati, R., Jackson, M. O. & Zaki, J. Empathy and well-being correlate with centrality in different social networks. *Proc. Natl. Acad. Sci. U. S. A.* **114**, 9843–9847 (2017).
41. Zou, X., Ingram, P. & Higgins, E. T. Social networks and life satisfaction: The interplay of network density and regulatory focus. *Motiv. Emot.* **39**, 693–713 (2015).
42. van Buuren, S. & Groothuis-Oudshoorn, K. mice: Multivariate Imputation by Chained Equations in R. *Journal of Statistical Software* vol. 45 (2011).
43. Kuhn, M. Classification and Regression Training [R package caret version 6.0-86]. (2020).

44. Friedman, J., Hastie, T. & Tibshirani, R. Regularization Paths for Generalized Linear Models via Coordinate Descent. *Journal of Statistical Software* vol. 33 (2010).
45. Diener, E., Emmons, R. A., Larsen, R. J. & Griffin, S. The Satisfaction With Life Scale. *Journal of Personality Assessment* vol. 49 71–75 (1985).
46. Lyubomirsky, S. & Lepper, H. S. Subjective Happiness Scale. *PsycTESTS Dataset* (2012) doi:10.1037/t01588-000.

Acknowledgments

This work was supported by the U.S. Army Research Office award number 71134 to JZ and by the National Science Foundation award number SES-2018554 to MOJ.

Author contributions

Conceptualization: ALC, JZ, MOJ, NAS, DB, WMF, MR

Data Curation: ALC, NAS, DB, WMF, MR

Formal Analysis: ALC

Funding acquisition: JZ, MOJ

Investigation: ALC, NAS, DB, WMF, MR

Methodology: ALC, EW, ZW

Project administration: ALC, NAS, DB, WMF, MR

Supervision: JZ, MOJ

Visualization: ALC

Writing – original draft: ALC

Writing – review & editing: ALC, DB, MWF, MR, YCA, NAS, EW, ZW, MOJ, JZ

Competing interests

The authors declare no competing interests.

Data Availability

The data and code for the analyses presented here are available at <https://osf.io/gyzjk/>. Because raw network nomination data are potentially identifiable, reduced and pre-processed participant-level data are provided.

Materials & Correspondence

Correspondence and materials requests should be address to Andrea Courtney (acourtne@stanford.edu) and Jamil Zaki (jzaki@stanford.edu).