Emotion

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Social Microclimates and Well-Being

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Emotional well-being has a known relationship with a person's direct social ties, including friendships; but do ambient social and emotional features of the local community also play a role? This work takes advantage of university students' assignment to different local networks—or "social microclimates"—to probe this question. Using Least Absolute Shrinkage and Selection Operator (LASSO) regression, we quantify the collective impact of individual, social network, and microclimate factors on the emotional well-being of a cohort of first-year college students. Results indicate that well-being tracks individual factors but also myriad social and microclimate factors, reflecting one's peers and social surroundings. Students who belonged to emotionally stable and tight-knit microclimates (i.e., had emotionally stable friends or resided in densely connected residence halls) reported lower levels of psychological distress and higher levels of life satisfaction, even when controlling for factors such as personality and social network size. Although rarely discussed or acknowledged in the policies that create them, social microclimates are consequential to well-being, especially during life transitions. The effects of microclimate factors are small relative to some individual factors; however, they explain unique variance in well-being that is not directly captured by emotional stability or other individual factors. These findings are novel, but preliminary, and should be replicated in new samples and contexts.

Keywords: social networks, well-being, emotional stability, psychological distress

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Social ties are critical to emotional well-being and mental health, especially during difficult times. People who maintain larger social networks and who turn to friends for emotional support are able to cope with stress more effectively (Cohen & Wills, 1985; Teo et al., 2013; Thoits, 1986; Uchino, 2009). But our communities extend beyond personal ties; and yet we know little about the role of the local community in well-being. Moreover, each person resides in a unique "social microclimate," characterized by the dispositions and emotions of friends and community members, and social connections among neighbors. Although aspects of one's microclimate are incidental (i.e., unselected), these structural and ambient dispositional features of the local community could affect well-being.

We explore this idea by examining a cohort of students during their transition to college. In their first months on campus, students commonly experience dips in life satisfaction and spikes in stress, anxiety, depression, and loneliness, relative to precollege levels (Conley et al.,

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2014). Emotional well-being during this transition is strongly linked to personality traits, like emotional stability and extraversion (DeNeve & Cooper, 1998; Diener et al., 2009; Hills & Argyle, 2001; Rich & Scovel, 1987). Social connections are also a bulwark against psychological upheaval (Helliwell & Putnam, 2004; Holt-Lunstad et al., 2015; Kawachi & Berkman, 2001). Students who turn to supportive peers in times of need suffer fewer mental health issues and are more resilient to stress (Fiori & Consedine, 2013; Hagerty & Williams, 1999; Santini et al., 2015; Teo et al., 2013; Uchino, 2009; Uchino & Garvey, 1997; Williams et al., 2018).

Another key feature of young adults' social lives is that they are anchored in larger communities on campus and within the residence hall. Young adults are motivated to grow their social networks in pursuit of developmental friendship, romantic, and identity goals (Barry et al., 2016; Roisman et al., 2004). As a result, their social networks are larger and contain a greater proportion of weak, peripheral ties relative to later in life (English & Carstensen, 2014). Although often overlooked, these peripheral network ties can have positive or negative influences on well-being. Interacting with acquaintances, like neighbors or classmates, increases feelings of happiness and belonging (Sandstrom & Dunn, 2014). Moreover, some researchers have suggested that mood states and well-being spread across social networks: that the happiness or depression of friends and friends-of-friends can rub off on us (Cacioppo et al., 2009; Fowler & Christakis, 2008; Rosenquist et al., 2011). By contrast, having mentally healthy friends can stave off the threat of mental health disorders (Bryant et al., 2017; E. M. Hill et al., 2015).

However, when individuals choose their social networks—as they do when making friends—it can be difficult to disentangle the "contagion" of psychological states such as depression from "homophily," or social attraction between similar individuals (Shalizi & Thomas, 2011). Much of the existing research connecting a person's well-being to (indirect) network ties is limited by this alternative explanation. By investigating communities that did not evolve from friendship selection, one can better disentangle climate effects from homophily. In addition, to circumvent third variable explanations, one can consider tie characteristics that are unlikely to share a common source with individuals' well-being. Whereas a common stressor could increase distress for all hallmates (and mimic contagion), it would be unlikely to influence their personality traits. One way to explore these community-based predictors of well-being is through an analysis of the social microclimate—which is distinct but complementary to a contagion analysis. Here, we relate stable, trait-level features from an assigned dorm community to an individual's well-being. We expect these ambient traits to contribute to the emotional tone of the environment; but importantly, they are not expected to be endogenous to well-being or "contagious."

Psychologists have long acknowledged the importance of the broader social community for human development and well-being. For instance, ecological systems theory describes concentric layers of relational, community, and societal influence on development (Bronfenbrenner, 1977). Similar to these models, we estimate the association between an individual's well-being and concentric layers of influence, by modeling characteristics of the individual, their social network (i.e., peer relationships), and the social microclimate, including hallmate characteristics and relationships among others in their dorm.

"Social microclimates" describe the social and emotional milieu of the environment in which a person arrives. They are distinct from characteristics of selected communities, like friendship networks, as microclimates reflect a person's social circumstance. When moving to a new city, attending a new school, or starting a new job, one joins a community. People may choose a community based on aspects of the social climate; but they often land incidentally in microclimates within these communities. There is random variation in the social climate characterizing their new neighborhood or workplace, and yet this social circumstance impacts their stress, mental health, and ability to cope with adversity (Bronkhorst et al., 2015; Longhi et al., 2021; Putnam, 1995).

For instance, little is known about how landing in a more or less connected community affects well-being; but research suggests social cohesion offers unique benefits. Densely connected communities foster a greater sense of belonging, social trust, and civic engagement—sources of increased social capital (Putnam, 1995). Relationships between coworkers reliably contribute to organizational climate, and reduce burnout, depression, and anxiety among healthcare workers (Bronkhorst et al., 2015). Likewise, socially cohesive neighborhood communities provide a source of resilience, buffering adolescent mental health against the threat of negative childhood experiences (Aneshensel & Sucoff, 1996; Longhi et al., 2021). The current study combines social network and psychological data to gain a deeper understanding of community contributors to well-being.

The college campus provides a unique opportunity to study the influence of social microclimates on well-being. Some aspects of students' social community—such as the hall within a dormitory in which they live, and their direct hall neighbors—are not explicitly selected, but are quasi-randomly assigned when students are placed in university housing. Students are disproportionately likely to connect with people who live near them in their dormitory (Marmaros & Sacerdote, 2006; Oloritun et al., 2013); but even absent direct friendship connections, they can still be affected by ambient features of the social environment, or "social microclimate." For instance, having friends and neighbors who are empathic and emotionally stable, or residing in a tightly knit and supportive community, could bolster an individual's well-being and protect their mental health, above and beyond the personal ties they form (A. L. Hill et al., 2010a; Rosenquist et al., 2011).

Because these aspects of microclimates are not chosen by students, we can draw inferences about the impact of the local community on well-being that is uncontaminated by homophily. Previous research has leveraged random assignment to demonstrate that one's college neighbors affect academic performance and employment (Carrell et al., 2009; Hasan & Bagde, 2013; Sacerdote, 2001), but this approach has not been used to examine the influence of the local social community on mental health. By contrast, it is challenging to dissociate friend networks from students' selection without having rich data on exposure (Chetty et al., 2022), and thus those associations are interpreted with greater caution.

The Present Investigation

The present investigation capitalizes on college students' assignment to housing communities to examine the influence of local social and emotional environments on well-being. 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 emotional well-being (i.e., psychological distress and life satisfaction) 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 in the online supplemental materials for summary statistics and Table S2 in the online supplemental materials for comparisons with population demographics.

We apply LASSO regression to a collection of individual, social network, and microclimate factors which we hypothesized could impact a person's well-being. This model performs variable selection to surface the most predictive variables among the set. We subsequently estimate effect sizes with correlation and multiple regression and present the results of these complementary analyses. We observe some deviation in significance across models, but the overall pattern of results is fairly robust to operationalization and modeling decisions.

With this approach, we identify the impact of microclimates on psychological distress and life satisfaction by controlling for individual factors and social network factors that are reliably related to well-being. Based on prior research, we hypothesize that individual factors (e.g., emotional stability, extraversion, family income) and social network factors (e.g., network outdegree) are positively related to well-being, and other individual factors (e.g., underrepresented minority status) are negatively associated. We include additional individual factors (e.g., openness to experience, conscientiousness) and social network factors (e.g., ego network density) as covariates, but have no strong predictions about their relationship to well-being.

Social microclimates are rarely acknowledged by educators or policymakers, but we hypothesize that they could nonetheless affect students' well-being. Key to our estimation of the microclimate are the personality traits (empathy and emotional stability) of friends and hallmates and the density of social connections among hallmates—central social actors in college students' lives. We hypothesize that being surrounded by empathic and emotionally stable peers and residing in a connected community could bolster students' well-being; whereas an environment with fewer of these characteristics could feel stressful, isolated, and/or antagonistic. This is an exploratory analysis, but our findings add to research on community-based resilience (Longhi et al., 2021) and emotion contagion in social networks (English & Carstensen, 2014; A. L. Hill et al., 2010b), and highlight new routes through which the social community and emotional environment could influence well-being.

Method

Participants

We invited all first-year students at Stanford University ($N = 1{,}701$) 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 academic term). Seven hundred ninety-eight participants completed the precollege survey and 862 participants completed the fall survey, yielding a total of 702 participants with responses to both measures (i.e., 41%). Our sample is predominantly from high socioeconomic backgrounds, but representative of the target population, the first-year cohort (class of 2023), on most demographic measures (Tables S1 and S2 in the online supplemental materials). 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 and life satisfaction. These composite measures are defined from trait survey items that load mostly strongly (positive and negative) onto a latent well-being factor derived from an independent factor analysis. Using a minimum residual algorithm, we uncover six distinct latent factors: well-being, empathy, social emotionality, political ideology, need to belong, and narcissism. The psychological distress composite is defined by averaging the top seven items ($\alpha = .90$) that negatively load onto the well-being factor, whereas the life satisfaction composite is defined by averaging the top six items ($\alpha = .87$) that positively load onto this factor. All items included in the final composites have factor loadings of at least .40 and precede a meaningful drop in factor loading. These composites are negatively correlated with each other $r(698) = -.62$, $p < .001$.

The psychological distress composite includes items from the Center for Epidemiological Studies Depression Scale (Radloff, 1977), the State–Trait Anxiety Inventory (Spielberger, 1983), the Rosenberg Self-Esteem Scale (Rosenberg, 1965), and Emotion Regulation of Other and Self Scale (Niven et al., 2011; Table S3 in the online supplemental materials). The life satisfaction composite combines items from the Satisfaction with Life Scale (Diener et al., 1985), and the Subjective Happiness Scale (Lyubomirsky & Lepper, 2012; Table 4 in the online supplemental materials). All well-being items were measured on a scale from 1 (*strongly disagree*) to 7 (*strongly agree*) so that they could be included in composite measures. These items were not scaled or scored according to validated instruments; and composites combined items from multiple instruments. This precludes direct comparisons (e.g., of mean values and effect sizes) between our sample and existing research on these individual constructs. 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 academic term) and personality traits (measured prior to the beginning of the Fall academic 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. 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, and other*. Using responses to this question, we created a binary factor reflecting participants' underrepresented minority (URM) status. Following Stanford's definition of URM status (Dashboard Definitions), all individuals who self-identified as *American Indian*, *Black or African American*, *African* (specified in "other"), *Hispanic or Latino/a*, and/or *Pacific Islander* were considered underrepresented. International student status was derived from responses to the question "Are you an international student?" (*yes* = 1, *no* = 0). Participants self-reported or estimated their family income as: (a) $0–20K, (b) $20–40K, (c) $40–60K,

(d) \$60–80K, (e) \$80–100K, (f) \$100–120K, (g) \$120–140K, (h) \$140–160K, (i) \$160–180K, (j) \$180–200K, and (k) 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 10-Item Personality Inventory (Gosling et al., 2012). An empathy composite variable is derived by averaging the values of the top eight items ($\alpha = .80$) loading on a latent empathy factor (from a factor analysis on responses to the Fall survey) which were also included in the precollege survey. Precollege responses are used in order to derive a measure of empathy that is uncontaminated by peer responses or campus culture. The empathy variable averages responses to items from the Adults Prosocialness Scale (Caprara et al., 2005), Interpersonal Reactivity Index (Davis, 1980*), and Single Item Trait Empathy Scale (Konrath et al., 2018; Table S5 in the online supplemental materials). 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?" (Morelli et al., 2017). They entered their peer's name into a text field, which was autocompleted with names from the entire undergraduate student roster ($N \sim 7{,}000$). We combine all unique network nominations from these three prompts into a single union graph that represents 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 six 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 term indegree = 861, implying that all other participants nominated that student as a support connection). Participants could nominate any undergraduate student on campus, including those who did not participate in the survey. That is, some outgoing nominations were "lost" and not converted to incoming nominations by other participants. As a result, mean outdegree ($M = 6.62$, $SD = 2.45$) is greater than mean indegree ($M = 3.01$, $SD = 2.23$) in our sample.

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., density = N ties/[N alters $\times$ $N - 1$ 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 could have implications for their well-being (Zou et al., 2015).

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. Before arriving on campus, students submit preferences for dorm types (e.g., first-year students only vs. mixed class), but these are not used by administrators in making hall assignments. Whereas roommate and dorm assignments are partially susceptible to students' preferences, hall assignments are not. Although halls are nested within dorms, students cannot explicitly choose their hall—so variation among halls within a dorm is expected to vary randomly. For this reason, we estimated the quasi-causal connection between microclimates and individuals' well-being by relying on hall characteristics as a proxy for the social microclimate.

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 quasi-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 ($Mdn = 8$ other participants/hall, where halls have 9–36 students). To ensure these ambient trait variables (i.e., traits of unconnected hallmates) 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 hallmates that participants are not friends with. In our sample, there is no correlation between ambient traits and participants' traits ($-.06 < r < -.03$, $ps > .11$); and correlations between ambient traits and traits of direct ties are absent for empathy ($r = -.013$, $p = .75$) but low for emotional stability ($r = .11$, $p = .005$)—confirming that the traits of direct ties and other hallmates are not redundantly measured in these models.

Finally, to assess the overall interconnectedness of peers living in one's hall, we calculate 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). Within-hall connections are estimated for first-year students and upper-class students living in dorms with first-year students. There is variability across dorms and halls in class year representation: some are mixed-class while others contain only first-year students. Participation was lower among upper-class students. To avoid underestimating hall density measures for first-year students living in dorms with upper-class students, we operationalize the density of within-hall connections as the proportion of nominations made by survey participants (across all class years) that went to hallmates.

LASSO Regression to Identify Predictors of Well-Being

To identify the best predictors of well-being, we apply cross-validated LASSO regression predicting (a) life satisfaction and (b) psychological distress from the individual, social network, and microclimate factors outlined above. LASSO (L1-norm) regression performs variable selection by shrinking less predictive variable coefficients toward zero (i.e., dropping them from the model). This is a conservative test of the novel microclimate factors, as it identifies the most important subset of predictors from a set that includes individual and social network factors known to be associated with well-being. We further validate these relationships by testing our models on a hold-out sample. Nonetheless, these analyses are exploratory, and we hope the results will be replicated in independent data sets.

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 672 in these analyses. With this sample size, we have 74% power to detect a small effect of $r = .10$, and 97% power to detect a slightly larger effect of $r = .15$. 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 (van Buuren & Groothuis-Oudshoorn, 2011). 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* (Kuhn, 2020) and *glmnet* (Friedman et al., 2010) 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. 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, nonimputed data set, we conduct pairwise correlation and multiple regression analyses on the reduced set of predictors selected by the LASSO regression (i.e., those presented in Tables 1 and 2). We rely on the cross-validated LASSO regression for variable selection, and the ordinary least squares approach for a more interpretable coefficient. To address nonindependence in hall-derived microclimate variables, we run additional multiple regression analyses: including (a) one in which standard errors are clustered by hall and (b) one which includes a random intercept for the dorm. These model coefficients are reported along with the LASSO coefficients in Tables 1 and 2.

Transparency and Openness

This study was not preregistered. The data and code for the analyses presented here are available on the Open Science Framework at https://doi.org/.org/10.17605/OSF.IO/GYZJK (Courtney et al., 2021). Because raw network nomination data are potentially identifiable, reduced and preprocessed participant-level data are provided.

Results

We use a 10-fold cross-validated LASSO regression to identify the individual, social network, and microclimate factors (Figure 1)

Table 1

Model Coefficients for the Reduced Set of Predictors Related to Psychological Distress

Predictor	LASSO coefficient	Correlation coefficient	Multiple regression	Clustered error regression	Mixed effects model
Individual factors					
Emotional stability	−0.44	−.5, [−0.56,−0.44], $p < .001$	−.45, [−0.52,−0.37], $p < .001$	−.45, [−0.52,−0.37], $p < .001$	−0.45, [−0.52,−0.37], $p < .001$
Extraversion	−0.07	−.13, [−0.2,−0.05], $p < .001$	−.1, [−0.17,−0.03], $p = .006$	−.1, [−0.17,−0.03], $p = .006$	−0.1, [−0.17,−0.03], $p = .005$
Conscientiousness	−0.07	−.24, [−0.31,−0.17], $p < .001$	−.12, [−0.19,−0.05], $p < .001$	−.12, [−0.19,−0.06], $p < .001$	−0.12, [−0.19,−0.05], $p < .001$
Family income	−0.03	−.11, [−0.19,−0.04], $p = .004$	−.04, [−0.11, 0.03], $p = .238$	−.04, [−0.12, 0.04], $p = .284$	−0.04, [−0.11, 0.03], $p = .240$
Agreeableness	−0.01	−.15, [−0.22,−0.08], $p < .001$	−.03, [−0.1, 0.04], $p = .479$	−.03, [−0.1, 0.05], $p = .519$	−0.02, [−0.09, 0.05], $p = .486$
Social network factors					
Ego-network density	0.04	.07, [−0.01, 0.14], $p = .088$	.05, [−0.03, 0.12], $p = .209$	.05, [−0.02, 0.12], $p = .186$	0.05, [−0.03, 0.12], $p = .203$
Outdegree	−0.01	−.12, [−0.2,−0.05], $p = .002$	−.07, [−0.14, 0.01], $p = .094$	−.07, [−0.15, 0.02], $p = .140$	−0.07, [−0.14, 0.01], $p = .091$
Microclimate factors					
Hall density	−0.03	−.13, [−0.2,−0.05], $p < .001$	−.07, [−0.14, 0], $p = .049$	−.07, [−0.14, 0], $p = .050$	−0.07, [−0.14, 0], $p = .064$
Emotional stability (direct ties)	−0.01	−.13, [−0.21,−0.05], $p = .001$	−.09, [−0.16,−0.02], $p = .015$	−.09, [−0.16,−0.02], $p = .015$	−0.09, [−0.16,−0.02], $p = .015$

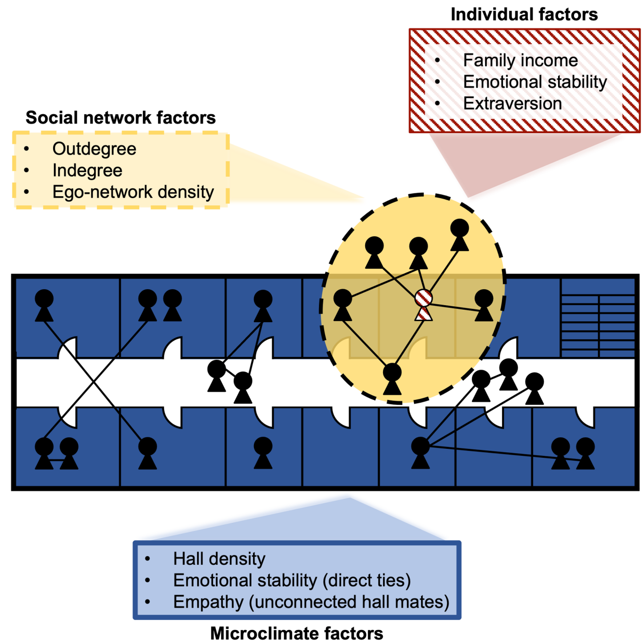
Note. We report (a) the non-zero LASSO coefficients for the model predicting psychological distress. In addition to the variables presented here, the full predictor set for the LASSO regression included gender, underrepresented minority status, international student status, openness to experience, indegree, empathy (direct ties), empathy (unconnected hallmates), and emotional stability (unconnected hallmates). Of the reduced set of predictors, we report (b) Pearson correlation coefficients for numeric variables and point biserial correlation coefficients for binary factors, along with 95% confidence intervals (CI) and significance. In addition, multiple regression coefficients are reported from (c) a model fitted to the reduced set of predictors, (d) an identical model which standard errors clustered according to the participant's dorm hall, and (e) a mixed effects model with a random intercept for dorm. LASSO = Least Absolute Shrinkage and Selection Operator.

Table 2
Model Coefficients for the Reduced Set of Predictors Related to Life Satisfaction

Predictor	LASSO coefficient	Correlation coefficient	Multiple regression	Clustered error regression	Mixed effects model
Individual factors					
Emotional stability	0.26	.37, [0.3, 0.43], $p < .001$	.35, [0.27, 0.43], $p < .001$	.35, [0.25, 0.46], $p < .001$	0.35, [0.27, 0.43], $p < .001$
Family income	0.18	.25, [0.18, 0.32], $p < .001$	.18, [0.1, 0.25], $p < .001$	.18, [0.09, 0.26], $p < .001$	0.18, [0.1, 0.25], $p < .001$
Extraversion	0.13	.24, [0.16, 0.31], $p < .001$	.17, [0.1, 0.24], $p < .001$	.17, [0.09, 0.25], $p < .001$	0.17, [0.1, 0.24], $p < .001$
Gender (woman)	0.08	.03, [−0.05, 0.1], $p = .471$	.18, [0.02, 0.33], $p = .023$	.18, [0, 0.35], $p = .046$	0.18, [0.02, 0.33], $p = .023$
Conscientiousness	0.08	.21, [0.13, 0.28], $p < .001$	.1, [0.03, 0.18], $p = .006$	.1, [0.02, 0.18], $p = .015$	0.1, [0.03, 0.18], $p = .006$
URM status	−0.05	−.11, [−0.18,−0.03], $p = .006$	−.06, [−0.14, 0.01], $p = .088$	−.06, [−0.14, 0.01], $p = .107$	−0.06, [−0.14, 0.01], $p = .088$
Agreeableness	0.02	.14, [0.07, 0.22], $p < .001$	.04, [−0.03, 0.12], $p = .236$	.04, [−0.05, 0.14], $p = .330$	0.04, [−0.03, 0.12], $p = .236$
International student	0.01	−.01, [−0.08, 0.07], $p = .884$	.02, [−0.06, 0.09], $p = .667$	.02, [−0.05, 0.09], $p = .655$	0.02, [−0.06, 0.09], $p = .667$
Social network factors					
Outdegree	0.11	.18, [0.1, 0.25], $p < .001$	.11, [0.03, 0.18], $p = .006$	.11, [0.03, 0.18], $p = .006$	0.11, [0.03, 0.18], $p = .006$
Microclimate factors					
Empathy (unconnected hall ties)	0.04	.03, [−0.05, 0.1], $p = .479$	.04, [−0.03, 0.11], $p = .270$	.04, [−0.04, 0.12], $p = .320$	0.04, [−0.03, 0.11], $p = .270$
Hall density	0.03	.08, [0.01, 0.16], $p = .033$	.05, [−0.02, 0.12], $p = .188$	.05, [−0.03, 0.13], $p = .213$	0.05, [−0.02, 0.12], $p = .188$
Emotional stability (direct ties)	0.02	.08, [0, 0.16], $p = .040$	.03, [−0.04, 0.1], $p = .384$	.03, [−0.05, 0.12], $p = .454$	0.03, [−0.04, 0.1], $p = .384$

Note. We report (a) the nonzero LASSO coefficients for the model predicting life satisfaction. In addition to the variables presented here, the full predictor set for the LASSO regression included openness to experience, ego-network density, indegree, empathy (direct ties), and emotional stability (unconnected hallmates). Of the reduced set of predictors, we report (b) Pearson correlation coefficients for numeric variables and point biserial correlation coefficients for binary factors, along with 95% CIs and significance. In addition, multiple regression coefficients are reported from (c) a model fitted to the reduced set of predictors, (d) an identical model that clustered standard errors by dorm hall, and (e) a mixed effects model with a random intercept for dorm. URM = underrepresented minority; LASSO = Least Absolute Shrinkage and Selection Operator.

Figure 1
Schematic Representing the Layers of Social Factors in Well-Being



Note. Well-being is affected by (a) individual factors (in red/diagonal fill), related to the person's demographics (e.g., family income) and personality traits, (b) social network factors (in yellow/dashed border), such as the number of supportive ties and connections among one's friends, and (c) microclimate factors (in blue/solid border), including the emotional stability of direct ties and the density of connections among hallmates. Exemplar factors for each layer are depicted here (see the Method section for full list). See the online article for the color version of this figure.

most associated with two sides of students' well-being during their first term in college: psychological distress and life satisfaction.

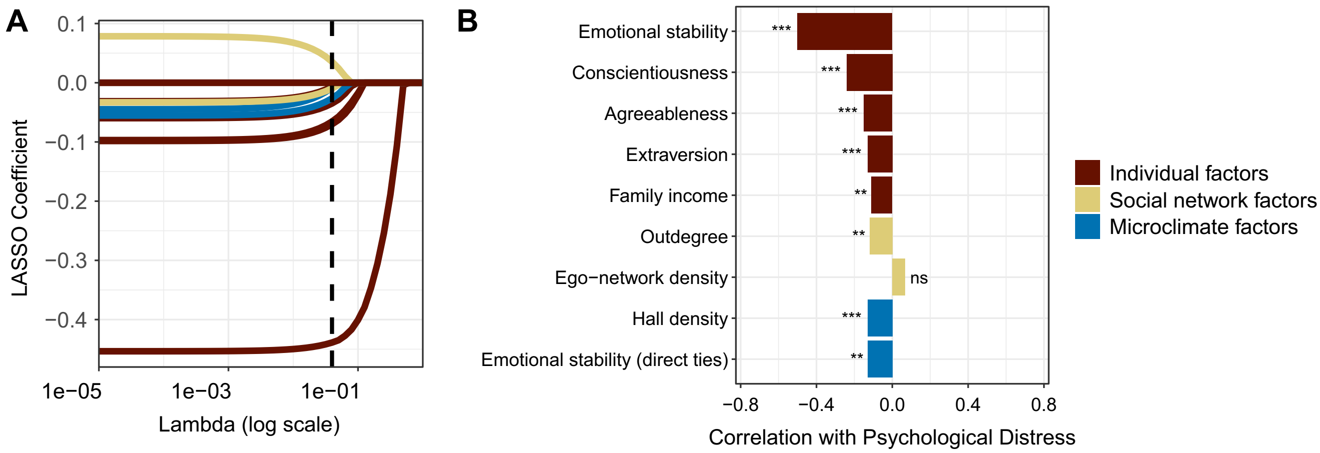
The model explains 29% of the variance in psychological distress during cross-validation (averaged across folds) on the training sample (root-mean-square error [RMSE] = 0.84, $R^2 = 0.29$), and 30% when tested on a hold-out sample (30% of original data; RMSE = 0.84, $R^2 = 0.30$, lambda tuning parameter = 0.04). LASSO regression, zero-order correlation, and multiple regression coefficients are presented in Figure 2 and Table 1 (see Figure S1 in the online supplemental materials for the matrix of correlations among all predictors).

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. Some factors correlated with well-being (e.g., family income, outdegree) are not significantly associated in multiple regression models, indicating they may explain variance in well-being that is redundantly explained by other covariates.

Interestingly, psychological distress is also negatively tracked by two features of social microclimates: the density of within-hall connections and the emotional stability of one's direct connections. Hall density represents the percentage of all connections reported by students in a hall that went to other members of the hall, or its social

Figure 2

Model Coefficients for the Predictors Associated With Psychological Distress



Note. (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. Individual factors indicated in red (black), social network factors in yellow (light gray), and microclimate factors in blue (dark gray). ns = nonsignificant. See the online article for the color version of this figure.

* $p < .05$. ** $p < .01$. *** $p < .001$.

connectedness. For instance, on a hall with 20% density, two of every 10 nominations made go to hallmates; by contrast, on a hall with 60% density, six of every 10 nominations remain within the hall (Figure 3). Our halls range from 6% to 68% density; and importantly, although students play a role in connecting their communities, they cannot choose which hall community they land in and yet this microclimate factor tracked their well-being. Students who live in a hall where no one is close (i.e., 0% density) experience a 16% increase in psychological distress, relative to those in a hall where 60% of all close relationships are between hallmates. The hall density effect falls below the level of significance in the mixed effects model, suggesting that a portion of the hall effect may be attributable to variation across dorms.

This measure of hall density is partly derived from a student's own connections within the community. When removing participant's connections on the hall from our measure of hall density results remain unchanged (see Tables S6 and S7 in the online supplemental materials). This indicates that the connectedness of one's community—regardless of personal ties to the community—is associated with psychological distress.

In addition, our model explains 24% of the variance in life satisfaction during 10-fold cross-validation (averaged across folds) on the training sample (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 = 0.03). Model coefficients are presented in Figure 4 and Table 2. 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 outdegree—the number of supportive connections identified by the participant. Participants with more supportive connections experience higher levels of life satisfaction (Figure S2 in the online supplemental materials). Moreover, as in the model of psychological distress, the emotional stability of direct ties and hall density are associated with greater life satisfaction; but these relationships are less reliably observed across different models. Although we hypothesized that the empathy of hallmates and friends are important predictors of well-being, we do not detect a reliable relationship in these models (Table 2).

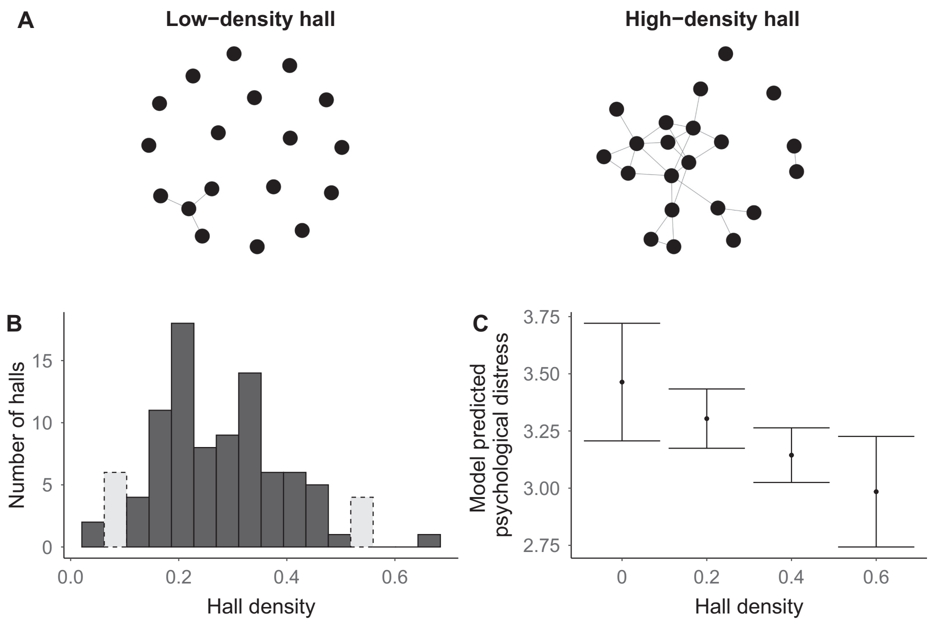
When we investigate the influence of ambient traits from alters 1, 2, 3, and 4+ degrees removed in the network, rather than based on colocation within a dorm hall, results are consistent with those presented here (Tables S8 and S9 in the online supplemental materials). The emotional stability of weak ties is associated with greater indices of well-being (i.e., lower psychological distress and higher life satisfaction). When modeling the individual constructs contributing to psychological distress and life satisfaction composites (i.e., depression, anxiety, self-esteem, emotion regulation of others and self, satisfaction with life, and subjective happiness), the pattern of results is consistent (Tables S10–S15 in the online supplemental materials). Emotional stability remains the strongest predictor in every model. Outdegree is a strong predictor in models of both life satisfaction components (i.e., satisfaction with life and subjective happiness); but only emerges in the depression model contributing to psychological distress. Critically, the primary microclimate factors, hall density and tie-average emotional stability (i.e., direct ties), emerge as significant predictors in each of the six construct-based well-being models.

Discussion

Here, we introduce a framework of the "social microclimate," demonstrating that the social and emotional qualities of a local community predict individuals' emotional well-being. Students who reported more supportive connections befriended more emotionally stable peers and resided in a tighter-knit dorm environment reported less psychological distress than peers in less connected and stable social circles. Our results connect with prior work linking psychological distress to life circumstances and community characteristics, like safety and trust (Lin et al., 2009; Phongsavan et al., 2006).

Figure 3

Psychological Distress Is Associated With the Density of Social Connections Within One's Hall



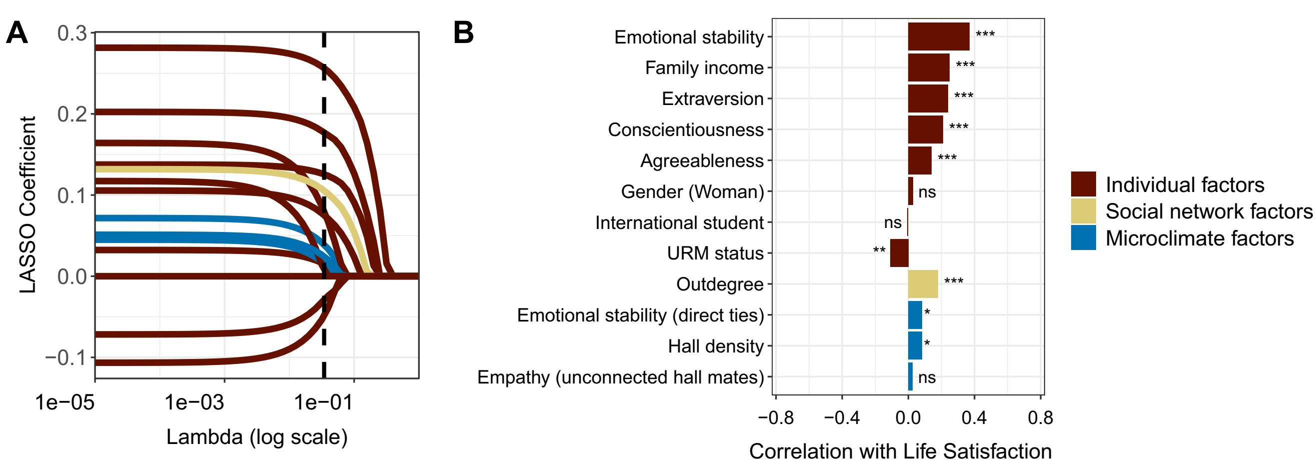
Note. (A) An exemplary network of social connections in a low-density hall and high-density hall. (B) Histogram of the density of within-hall social connections across all sampled halls. Hall networks presented in (A) were drawn from the highlighted bins. (C) Model predicted psychological distress for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

Social environments, like a university residence hall, contain sources of stress and support, which can toggle psychological distress up or down (Ensel & Lin, 1991).

We replicate prior research linking well-being to the individual's emotional stability and extraversion (DeNeve & Cooper, 1998; Diener et al., 2009; Hills & Argyle, 2001; Rich & Scovel, 1987). And 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 greater psychological distress during their first term of college than peers from higher-income families. Critically, we observe no evidence for biased sampling with respect to demographic

Figure 4

Model Coefficients for the Predictors Associated With Life Satisfaction



Note. (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. Individual factors indicated in red (black), social network factors in yellow (light gray), and microclimate factors in blue (dark gray). ns = nonsignificant. See the online article for the color version of this figure.

* $p < .05$. ** $p < .01$. *** $p < .001$.

characteristics (Note 1 in the online supplemental materials; Table S2 in the online supplemental materials); however, there could be sources of selective participation (e.g., friend groups participating together) that were not considered here.

Students have little control over their social microclimates. They cannot select local communities that include tight-knit social bonds, or peers who effectively cope with stress; and yet these features affect students' own well-being and mental health burden. The effects of our novel microclimate variables are small and hover around significance: a one standard deviation increase in hall density is associated with a 3% decrease in psychological distress. Nonetheless, it is noteworthy that microclimate factors, such as hall density, track well-being even when controlling for better-known individual difference factors. Moreover, 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. However, to have more confidence in the reliability of these effects, we hope the influence of similar microclimate factors will be replicated in new samples and contexts.

Our sample is notably better-educated and socioeconomically advantaged relative to the broader population. Thus, the scale of impact should be examined among other communities, like neighborhoods, workplaces, and families. Microclimate effects could, in fact, be strongest among young adults. Compared to older adults, the emotional tone of young adults' social networks is more negative, which influences their own downstream emotional experience (English & Carstensen, 2014). Moreover, microclimates are pervasive for college students: they live, study, and socialize with their peers.

The university residence hall is a unique, constrained environment. This enabled us to analyze the effects of quasi-randomly assigned hall features on students' well-being; but, importantly, this is not a controlled experiment. Hall features themselves are influenced by the people living in the hall. For instance, the number of within-hall connections could result from the personalities of hall members, the structure of the hall, or community-building efforts by a resident advisor—alternatives we cannot distinguish in our data.

We demonstrate that psychological distress is associated with the density of connections in one's residence hall—whether or not this measure includes participants' connections to hallmates (Tables S6 and S7 in the online supplemental materials). Nonetheless, we hope researchers continue to explore the relationship between individuals' well-being and their community's density to address the following potential explanations. Do individuals benefit simply from residing in a well-connected community, or does it help to be personally well-connected within the community? Or conversely, are those high in well-being likely to drive connections within their community? We also hope future research will explore the salutary effects of network density within other local communities, and work to identify the source of variation in network bonds.

Structural features of social networks, like size and density, may influence mental health directly or through a variety of psychosocial mechanisms: including access to social resources, perceived support, companionship, a sense of belonging, and stress buffering (Berkman et al., 2000; Thoits, 2011). We do not directly test mechanisms in the current work, but we expect that network (e.g., outdegree) and microclimate factors (e.g., hall density) influence well-being through an increase in perceived support and belongingness. Social bonds within a local network reflect one aspect of social capital and a source of resilience in the community (Longhi et al., 2021). These effects could be partially explained by stress buffering—whereby receiving emotional support mitigates the impacts of stress on mental health (Bolger & Eckenrode, 1991). Others' emotional stability could influence well-being through emotion or stress contagion or interpersonal conflict (Borghuis et al., 2020).

Emotional qualities of a network are often stronger predictors than structural qualities. For example, an individual's daily emotions track with the "emotional tone" of their social network, but not its size (English & Carstensen, 2014). But structural and emotional components are linked. Larger networks are more supportive, offering increased access to social resources and support; but they also have a greater proportion of support providers (Walker et al., 1993). Densely knit networks offer greater support and reduced stress (Thoits, 2011; Walker et al., 1993); but the effects may depend on the emotional nature of the network. In tight-knit networks, negative emotions could persevere and reverberate through the community.

Here we relate well-being to the size of an aggregate emotional support network, which combines friendship and emotional support ties. Historically, these networks overlap, but not perfectly (Kitts & Leal, 2021; Walker et al., 1993). These subnetworks are correlated in our sample (Table S16 in the online supplemental materials), so to reduce collinearity in our models, we aggregate across them. Still, different network types could represent distinct dimensions of social support. In previous research, a similar "Who do you turn to when something bad happens?" network loaded onto a latent support-seeking factor, whereas "Who makes you feel supported and cared for?" reflected perceived support (Williams et al., 2018). Furthermore, these subnetworks might influence well-being via different psychosocial mechanisms. For example, emotional support networks reflect the availability of emotional and instrumental aid, whereas friendship ties signal companionship (Walker et al., 1993). Characterizing the granular relationships between various social networks and well-being would be a valuable domain for future research.

Our work contributes to person-in-context theories, by demonstrating a relationship between an individual's well-being and characteristics of the broader social microclimate outside of their control. Both sets of variables (i.e., hall density and friends' personalities) contribute to the social microclimate—with direct ties reflecting the local climate in contexts of social support, and hallmates contributing to the background microclimate. We recognize that these are only two among many possible microclimate factors, and we highlight their effects here as a proof of concept. This initial demonstration is promising but warrants replication and further examination into potential mechanisms for this relationship. Moreover, future research might consider exploring the interactions between concentric—proximal and distal—influences on a person's well-being over time.

Our preliminary results, alongside prior research, point toward community connectedness as a protective factor for well-being (Longhi et al., 2021). Community leaders might consider ways to enhance the density of connections among their members. For instance, they could facilitate bonding through shared experiences or a combined focus on community-level goals, provide space for group-sharing, or encourage one-on-one connection through partner activities—especially if they bring together central and peripheral members of the group or rotate pairs (Gesell et al., 2013). The present findings validate ongoing initiatives at universities, and other organizations, that prioritize this type of community building.

These results also complement research on the "contagion" of emotion and well-being states in social networks (English &

Carstensen, 2014; A. L. Hill et al., 2010b), by demonstrating that the personalities of friends and friends-of-friends relate to an individual's well-being (see Tables S8–S9 in the online supplemental materials for analyses of first, second, third, and fourth-degree tie effects). They also build on existing research relating romantic partners' personality (including emotional stability) to well-being (Gray & Pinchot, 2018), by expanding the sphere of influence to one's incidental housing community. Characteristics of network members appear to color the ambient social environment in ways that influence their neighbors' well-being. Pending replication of these effects, university administrators might consider ways to increase the supportive nature of dorm environments so that the "microclimate" serves as a source of mental health support, rather than stress, for vulnerable student populations.

References

Aneshensel, C. S., & Sucoff, C. A. (1996). The neighborhood context of adolescent mental health. *Journal of Health and Social Behavior*, *37*(4), 293–310. https://doi.org/10.2307/2137258

Barry, C. M., Madsen, S. D., & Degrace, A. (2016). *Growing up with a little help from their friends in emerging adulthood* (J. J. Arnett, ed.; pp. 215–229). Oxford University Press.

Berkman, L. F., Glass, T., Brissette, I., & Seeman, T. E. (2000). From social integration to health: Durkheim in the new millennium. *Social Science and Medicine*, *51*(6), 843–857. https://doi.org/10.1016/s0277-9536(00)00065-4

Bolger, N., & Eckenrode, J. (1991). Social relationships, personality, and anxiety during a major stressful event. *Journal of Personality and Social Psychology*, *61*(3), 440–449. https://doi.org/10.1037/0022-3514.61.3.440

Borghuis, J., Bleidorn, W., Sijtsma, K., Branje, S., Meeus, W. H. J., & Denissen, J. J. A. (2020). Longitudinal associations between trait neuroticism and negative daily experiences in adolescence. *Journal of Personality and Social Psychology*, *118*(2), 348–363. https://doi.org/10.1037/pspp0000233

Bronfenbrenner, U. (1977). Toward an experimental ecology of human development. *American Psychologist*, *32*(7), 513–531. https://doi.org/10.1037/0003-066X.32.7.513

Bronkhorst, B., Tummers, L., Steijn, B., & Vijverberg, D. (2015). Organizational climate and employee mental health outcomes. *Health Care Management Review*, *40*(3), 254–271. https://doi.org/10.1097/HMR.0000000000000026

Bryant, R. A., Gallagher, H. C., Gibbs, L., Pattison, P., MacDougall, C., Harms, L., Block, K., Baker, E., Sinnott, V., Ireton, G., Richardson, J., Forbes, D., & Lusher, D. (2017). Mental health and social networks after disaster. *American Journal of Psychiatry*, *174*(3), 277–285. https://doi.org/10.1176/appi.ajp.2016.15111403

Cacioppo, J. T., Fowler, J. H., & Christakis, N. A. (2009). Alone in the crowd: The structure and spread of loneliness in a large social network. *Journal of Personality and Social Psychology*, *97*(6), 977–991. https://doi.org/10.1037/a0016076

Caprara, G. V., Steca, P., Zelli, A., & Capanna, C. (2005). A new scale for measuring adults' prosocialness. *European Journal of Psychological Assessment*, *21*(2), 77–89. https://doi.org/10.1027/1015-5759.21.2.77

Carrell, S. E., Fullerton, R. L., & West, J. E. (2009). Does your cohort matter? Measuring peer effects in college achievement. *Journal of Labor Economics*, *27*(3), 439–464. https://doi.org/10.1086/600143

Chetty, R., Jackson, M. O., Kuchler, T., Stroebel, J., Hendren, N., Fluegge, R. B., Gong, S., Gonzalez, F., Grondin, A., Jacob, M., Johnston, D., Koenen, M., Laguna-Muggenburg, E., Mudekereza, F., Rutter, T., Thor, N., Townsend, W., Zhang, R., Bailey, M., … Wernerfelt, N. (2022). Social capital II: Determinants of economic connectedness. *Nature*, *608*(7921), 122–134. https://doi.org/10.1038/s41586-022-04997-3

Cohen, S., & Wills, T. A. (1985). Stress, social support, and the buffering hypothesis. *Psychological Bulletin*, *98*(2), 310–357. https://doi.org/10.1037/0033-2909.98.2.310

Conley, C. S., Kirsch, A. C., Dickson, D. A., & Bryant, F. B. (2014). Negotiating the transition to college. *Emerging Adulthood*, *2*(3), 195–210. https://doi.org/10.1177/2167696814521808

Courtney, A. L., Baltiansky, D., Fang, W. M., Roshanaei, M., Aybas, Y. C., Samuels, N. A., Wetchler, E., Wu, Z., Jackson, M. O., & Zaki, J. (2021). *Social microclimates and well-being*. https://doi.org/10.17605/OSF.IO/GYZJK

Davis, M. H. (1980). *A multidimensional approach to individual differences in empathy*. https://books.google.com/books/about/A_Multidimensional_Approach_to_Individua.html?hl=&id=HUQHcgAACAAJ

DeNeve, K. M., & Cooper, H. (1998). The happy personality: A meta-analysis of 137 personality traits and subjective well-being. *Psychological Bulletin*, *124*(2), 197–229. https://doi.org/10.1037/0033-2909.124.2.197

Diener, E., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The Satisfaction With Life Scale. *Journal of Personality Assessment*, *49*(1), 71–75. https://doi.org/10.1207/s15327752jpa4901_13

Diener, E., Oishi, S., & Lucas, R. E. (2009). Subjective well-being: The science of happiness and life satisfaction. In S. J. Lopez & C. R. Snyder (Eds.), *The Oxford handbook of positive psychology* (2nd ed., pp. 187–194). Oxford University Press. https://doi.org/10.1093/oxfordhb/9780195187243.013.0017

English, T., & Carstensen, L. L. (2014). Selective narrowing of social networks across adulthood is associated with improved emotional experience in daily life. *International Journal of Behavioral Development*, *38*(2), 195–202. https://doi.org/10.1177/0165025413515404

Ensel, W. M., & Lin, N. (1991). The life stress paradigm and psychological distress. *Journal of Health and Social Behavior*, *32*(4), 321–341. https://doi.org/10.2307/2137101

Fiori, K. L., & Consedine, N. S. (2013). Positive and negative social exchanges and mental health across the transition to college. *Journal of Social and Personal Relationships*, *30*(7), 920–941. https://doi.org/10.1177/0265407512473863

Fowler, J. H., & Christakis, N. A. (2008). Dynamic spread of happiness in a large social network: Longitudinal analysis over 20 years in the Framingham Heart Study. *BMJ*, *337*(2), Article a2338. https://doi.org/10.1136/bmj.a2338

Friedman, J., Hastie, T., & Tibshirani, R. (2010). Regularization paths for generalized linear models via coordinate descent. *Journal of Statistical Software*, *33*(1), 1–22. https://doi.org/10.18637/jss.v033.i01

Gesell, S. B., Barkin, S. L., & Valente, T. W. (2013). Social network diagnostics: A tool for monitoring group interventions. *Implementation Science*, *8*(1), Article 116. https://doi.org/10.1186/1748-5908-8-116

Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2012). *Ten-Item Personality Inventory*. PsycTESTS Dataset. https://doi.org/10.1037/t07016-000

Gray, J. S., & Pinchot, J. J. (2018). Predicting health from self and partner personality. *Personality and Individual Differences*, *121*, 48–51. https://doi.org/10.1016/j.paid.2017.09.019

Hagerty, B. M., & Williams, R. A. (1999). The effects of sense of belonging, social support, conflict, and loneliness on depression. *Nursing Research*, *48*(4), 215–219. https://doi.org/10.1097/00006199-199907000-00004

Hasan, S., & Bagde, S. (2013). The mechanics of social capital and academic performance in an Indian college. *American Sociological Review*, *78*(6), 1009–1032. https://doi.org/10.1177/0003122413505198

Helliwell, J. F., & Putnam, R. D. (2004). The social context of well-being. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *359*(1449), 1435–1446. https://doi.org/10.1098/rstb.2004.1522

Hill, A. L., Rand, D. G., Nowak, M. A., & Christakis, N. A. (2010a). Emotions as infectious diseases in a large social network: The SISa model. *Proceedings of the Royal Society B: Biological Sciences*, *277*(1701), 3827–3835. https://doi.org/10.1098/rspb.2010.1217

Hill, A. L., Rand, D. G., Nowak, M. A., & Christakis, N. A. (2010b). Infectious disease modeling of social contagion in networks. *PLoS Computational Biology*, *6*(11), Article e1000968. https://doi.org/10.1371/journal.pcbi.1000968

Hill, E. M., Griffiths, F. E., & House, T. (2015). Spreading of healthy mood in adolescent social networks. *Proceedings of the Royal Society B: Biological Sciences*, *282*(1813), Article 20151180. https://doi.org/10.1098/rspb.2015.1180

Hills, P., & Argyle, M. (2001). Emotional stability as a major dimension of happiness. *Personality and Individual Differences*, *31*(8), 1357–1364. https://doi.org/10.1016/S0191-8869(00)00229-4

Holt-Lunstad, J., Smith, T. B., Baker, M., Harris, T., & Stephenson, D. (2015). Loneliness and social isolation as risk factors for mortality: A meta-analytic review. *Perspectives on Psychological Science: A Journal of the Association for Psychological Science*, *10*(2), 227–237. https://doi.org/10.1177/1745691614568352

Kawachi, I., & Berkman, L. F. (2001). Social ties and mental health. *Journal of Urban Health: Bulletin of the New York Academy of Medicine*, *78*(3), 458–467. https://doi.org/10.1093/jurban/78.3.458

Kitts, J. A., & Leal, D. F. (2021). What is (n't) a friend? Dimensions of the friendship concept among adolescents. *Social Networks*, *66*, 161–170. https://doi.org/10.1016/j.socnet.2021.01.004

Konrath, S., Meier, B. P., & Bushman, B. J. (2018). Development and validation of the Single Item Trait Empathy Scale (SITES). *Journal of Research in Personality*, *73*, 111–122. https://doi.org/10.1016/j.jrp.2017.11.009

Kuhn, M. (2020). *Classification and regression training* [R Package Caret Version 6.0-86]. https://CRAN.R-project.org/package=caret

Lin, J., Thompson, M. P., & Kaslow, N. J. (2009). The mediating role of social support in the community environment-psychological distress link among low-income African American women. *Journal of Community Psychology*, *37*(4), 459–470. https://doi.org/10.1002/jcop.20307

Longhi, D., Brown, M., & Fromm Reed, S. (2021). Community-wide resilience mitigates adverse childhood experiences on adult and youth health, school/work, and problem behaviors. *American Psychologist*, *76*(2), 216–229. https://doi.org/10.1037/amp0000773

Lyubomirsky, S., & Lepper, H. S. (2012). *Subjective Happiness Scale*. PsycTESTS Dataset. https://doi.org/10.1037/t01588-000

Marmaros, D., & Sacerdote, B. (2006). How do friendships form?*. *Quarterly Journal of Economics*, *121*(1), 79–119. https://doi.org/10.1162/qjec.2006.121.1.79

Morelli, S. A., Ong, D. C., Makati, R., Jackson, M. O., & Zaki, J. (2017). Empathy and well-being correlate with centrality in different social networks. *Proceedings of the National Academy of Sciences*, *114*(37), 9843–9847. https://doi.org/10.1073/pnas.1702155114

Niven, K., Totterdell, P., Stride, C. B., & Holman, D. (2011). Emotion regulation of others and self (EROS): The development and validation of a new individual difference measure. *Current Psychology*, *30*(1), 53–73. https://doi.org/10.1007/s12144-011-9099-9

Oloritun, R. O., Madan, A., Pentland, A., & Khayal, I. (2013). Identifying close friendships in a sensed social network. *Procedia—Social and Behavioral Sciences*, *79*, 18–26. https://doi.org/10.1016/j.sbspro.2013.05.054

Phongsavan, P., Chey, T., Bauman, A., Brooks, R., & Silove, D. (2006). Social capital, socio-economic status and psychological distress among Australian adults. *Social Science and Medicine*, *63*(10), 2546–2561. https://doi.org/10.1016/j.socscimed.2006.06.021

Putnam, R. D. (1995). Bowling alone: America's declining social capital. *Journal of Democracy*, *6*(1), 65–78. https://doi.org/10.1353/jod.1995.0002

Radloff, L. S. (1977). The CES-D Scale. *Applied Psychological Measurement*, *1*(3), 385–401. https://doi.org/10.1177/014662167700100306

Dashboard Definitions. Retrieved March 12, 2021, from https://ideal.stanford.edu/resources/ideal-dashboard/dashboard-definitions

Rich, A. R., & Scovel, M. (1987). Causes of depression in college students: A cross-lagged panel correlational analysis. *Psychological Reports*, *60*(1), 27–30. https://doi.org/10.2466/pr0.1987.60.1.27

Roisman, G. I., Masten, A. S., Coatsworth, J. D., & Tellegen, A. (2004). Salient and emerging developmental tasks in the transition to adulthood. *Child Development*, *75*(1), 123–133. https://doi.org/10.1111/j.1467-8624.2004.00658.x

Rosenberg, M. (1965). *Society and the adolescent self-image*. Princeton University Press. https://doi.org/10.1515/9781400876136

Rosenquist, J. N., Fowler, J. H., & Christakis, N. A. (2011). Social network determinants of depression. *Molecular Psychiatry*, *16*(3), 273–281. https://doi.org/10.1038/mp.2010.13

Sacerdote, B. (2001). Peer effects with random assignment: Results for Dartmouth roommates. *The Quarterly Journal of Economics*, *116*(2), 681–704. https://doi.org/10.1162/00335530151144131

Sandstrom, G. M., & Dunn, E. W. (2014). Social interactions and well-being: The surprising power of weak ties. *Personality and Social Psychology Bulletin*, *40*(7), 910–922. https://doi.org/10.1177/0146167214529799

Santini, Z. I., Koyanagi, A., Tyrovolas, S., Mason, C., & Haro, J. M. (2015). The association between social relationships and depression: A systematic review. *Journal of Affective Disorders*, *175*, 53–65. https://doi.org/10.1016/j.jad.2014.12.049

Shalizi, C. R., & Thomas, A. C. (2011). Homophily and contagion are generically confounded in observational social network studies. *Sociological Methods and Research*, *40*(2), 211–239. https://doi.org/10.1177/0049124111404820

Spielberger, C. D. (1983). *State-trait anxiety inventory for adults: Manual and sample: Manual, instrument and scoring guide*. https://books.google.com/books/about/State_Trait_Anxiety_Inventory_for_Adults.html?hl=&id=VXVuswEACAAJ

Teo, A. R., Choi, H., & Valenstein, M. (2013). Social relationships and depression: Ten-year follow-up from a nationally representative study. *PLoS ONE*, *8*(4), Article e62396. https://doi.org/10.1371/journal.pone.0062396

Thoits, P. A. (1986). Social support as coping assistance. *Journal of Consulting and Clinical Psychology*, *54*(4), 416–423. https://doi.org/10.1037/0022-006X.54.4.416

Thoits, P. A. (2011). Mechanisms linking social ties and support to physical and mental health. *Journal of Health and Social Behavior*, *52*(2), 145–161. https://doi.org/10.1177/0022146510395592

Uchino, B. N. (2009). 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*, *4*(3), 236–255. https://doi.org/10.1111/j.1745-6924.2009.01122.x

Uchino, B. N., & Garvey, T. S. (1997). The availability of social support reduces cardiovascular reactivity to acute psychological stress. *Journal of Behavioral Medicine*, *20*(1), 15–27. https://doi.org/10.1023/A:1025583012283

van Buuren, S., & Groothuis-Oudshoorn, K. (2011). Mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1–67. https://doi.org/10.18637/jss.v045.i03

Walker, M. E., Wasserman, S., & Wellman, B. (1993). Statistical models for social support networks. *Sociological Methods and Research*, *22*(1), 71–98. https://doi.org/10.1177/0049124193022001004

Williams, W. C., Morelli, S. A., Ong, D. C., & Zaki, J. (2018). Interpersonal emotion regulation: Implications for affiliation, perceived support, relationships, and well-being. *Journal of Personality and Social Psychology*, *115*(2), 224–254. https://doi.org/10.1037/pspi0000132

Zou, X., Ingram, P., & Higgins, E. T. (2015). Social networks and life satisfaction: The interplay of network density and regulatory focus. *Motivation and Emotion*, *39*(5), 693–713. https://doi.org/10.1007/s11031-015-9490-1

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