Nonlinear effect of social interaction quantity on psychological well-being

Ren, Dongning; Stavrova, Olga; Loh, Wen Wei

Published in:
Journal of Personality and Social Psychology

DOI:
10.1037/pspi0000373

Publication date:
2022

Document Version
Early version, also known as pre-print

Nonlinear effect of social interaction quantity on psychological well-being: Diminishing Returns or Inverted U?

In press at *Journal of Personality and Social Psychology*

Dongning Ren

Tilburg University, Tilburg, the Netherlands

Olga Stavrova

Tilburg University, Tilburg, the Netherlands

Wen Wei Loh

Ghent University, Ghent, Belgium

Contact details:

Dongning Ren

Department of Social Psychology, Tilburg University

Email: dren.psy@gmail.com

Abstract

Social contact is an important ingredient of a happy and satisfying life. But is more social contact necessarily better? While it is well-established that increasing the quantity of social interactions on the low end of its spectrum promotes psychological well-being, the effect of interaction quantity on the high end remains largely unexplored. We propose that the effect of interaction quantity is nonlinear; specifically, at high levels of interaction quantity, its positive effects may be reduced (Diminishing Returns Hypothesis) or even reversed (Inverted U Hypothesis). To test these two competing hypotheses, we conducted a series of six studies involving a total of 161,836 participants using experimental (Study 1), cross-sectional (Studies 2 & 3), daily diary (Study 4), experience sampling (Study 5), and longitudinal survey designs (Study 6). Consistent evidence emerged across the studies supporting the Diminishing Returns Hypothesis. On the low end of the interaction quantity spectrum, increasing interaction quantity enhanced well-being as expected; whereas on the high end of the spectrum, the effect of interaction quantity was reduced or became nearly negligible, but did not turn negative. Taken together, the present research provides compelling evidence that the well-being benefits of social interactions are nearly negligible after moderate quantities of interactions are achieved.

Key words: social interactions, well-being, happiness, life satisfaction, inverted-U

Nonlinear effect of social interaction quantity on psychological well-being: Diminishing Returns or Inverted U?

Social contact is essential for human beings (Baumeister & Leary, 1995; Ryan & Deci, 2000). The amount of social interactions—henceforth referred to as interaction quantity—has been shown to be one of the most consistent predictors of psychological well-being (Diener & Seligman, 2002; Lucas, & Dyrenforth, 2006; Lucas, Dyrenforth, & Diener, 2008; Myers, 2000; Rohrer et al., 2018; Srivastava et al., 2008; Sun et al., 2019).

Despite the essential role of interaction quantity in predicting psychological well-being, there is limited understanding of how well-being changes as a function of interaction quantity. Almost all existing studies have assumed and only tested linear relations between indicators of interaction quantity and well-being outcomes, concluding that the more social interactions, the better. For example, the more social activities people engage in, the more positive affect they experience (Clark, & Watson, 1988; Lucas, Le, & Dyrenforth, 2008; Watson et al., 1992); the more time people spent socializing, the happier they are (Diener & Seligman, 2002); and the more friends people have, the less loneliness they feel (Luhmann & Hawkley, 2016). This assumption of linearity has resulted in the idea of "the more, the better" that has dominated the studies of social interactions and well-being for decades. In the current research, we challenge the assumption of linearity and propose that the effect of interaction quantity is in fact nonlinear: At the low end of the spectrum, increasing the quantity of social interactions indeed promotes well-being; but at the high end of the spectrum, increasing interaction quantity may have little impact, or even possibly detrimental effects, on well-being. To evaluate the possibility of nonlinearity, we set out to examine the effect of interaction quantity across its full spectrum.

It is important to examine the full spectrum of interaction quantity for two reasons. First, while the low end of the spectrum—when people have no or limited social contact—

has been extensively studied, little empirical attention has been given to the other end of the spectrum where levels of interaction quantity are relatively high. It therefore remains unclear how high (vs. moderate) quantities of interactions potentially affect well-being. Second, recognizing the benefits of social relationships, the promotion of social contact has become the focus of many social policies (Umberson & Montez, 2010). While these policies can be effective when target groups have relatively small quantity of social interactions, they may not be as effective, or possibly even backfire, when interaction quantity among such target groups surpasses moderate levels.

Our goal is therefore to determine how well-being changes as a nonlinear function of interaction quantity across the full spectrum of interaction quantity. Below we first review existing evidence in the literature that supports a linear effect of interaction quantity on well-being; we then turn our attention to evidence that implies a nonlinear relation.

Interaction quantity and well-being: evidence of a linear relation

An extensive number of studies have shown that increasing interaction quantity promotes well-being. However, the most compelling evidence for such a positive association is found in studies focusing on the low end of the interaction quantity spectrum. These studies consistently link low levels of interaction quantity with poor well-being outcomes. For example, being excluded from social interactions induces stress and pain, lowers basic need satisfaction (e.g., belonging, self-esteem), leads to self-regulation failures, impairs cognitive abilities, and triggers aggressive responses (Bernstein et al., 2013; Eisenberger et al., 2003; Gaertner & Iuzzini, 2005; Twenge et al., 2001; Twenge et al., 2003; Warburton et al., 2006; Williams 2009). Further, chronic social exclusion forces individuals into isolation, leading to the feelings of helplessness, worthlessness, alienation, and depression (Riva et al., 2017). Similarly, chronically lacking social contacts often leads to loneliness, which has been associated not only with worse psychological health (inducing stress, depressive symptoms,

diminishing optimism and self-esteem, impairing cognitive functioning) but also worse physical health, predicting higher blood pressure, increased risk for heart diseases, and early mortality (Cacioppo & Patrick, 2008; Cacioppo, Hawkley, et al., 2006; Cacioppo, Hughes, et al., 2006; Hawkley & Cacioppo, 2010; Tilvis et al., 2004). Finally, solitary confinement—an extreme form of low interaction quantity—leads to a multitude of pathological reactions, such as impaired concentration, loss of appetite, hallucinations, illusions, lethargy, and suicidal thoughts (Smith, 2006).

It is therefore unsurprising that some social interactions, as compared to no social interactions at all, contribute to higher well-being. For example, people report higher subjective well-being when interacting with others, as compared to time spent in solitude (e.g., Mehl et al., 2010; Milek et al., 2018). This holds even when the interactions are brief, casual, and with acquaintances or strangers (Epley & Schroeder, 2014; Kahneman et al., 2004; Sandstrom & Dunn, 2014).

Interaction quantity and well-being: proposal for a nonlinear relation

There is strong evidence that an increase in interaction quantity at the low end of its spectrum is linked with better well-being. But do the results necessarily imply that further increases in interaction quantity maintain the same beneficial effects as well? Can the linear trend be extrapolated to the high end of the spectrum, or is there a threshold (or "breaking point") after which increased interaction quantity is no longer beneficial for, or possibly even detrimental to, well-being? Below we introduce two competing hypotheses regarding the nonlinear relation between interaction quantity and well-being.

Diminishing Returns Hypothesis. It is possible that the positive impact of interaction quantity on well-being is restricted to the low end of the spectrum, with benefits of additional social interactions substantially reduced at the high end. This hypothesis is consistent with several well-established theories. For example, the economic law of

diminishing marginal utility states that as consumption of a commodity increases, the additional happiness or satisfaction derived from each additional unit consumed declines (Gossen, 1854/1983). Social Impact Theory (Latane, 1981) states that the impact of others on a target individual follows a similar nonlinear trend: the larger the number of group members attempting to influence an individual's behavior or attitudes, the stronger the influence; however, as the number of group members increases, the added value of every new member's impact declines. Specific to the benefits of social contact, the Need to Belong theory hints at the possibility of nonlinearity by stating that human beings strive for "a minimal quantity of" social relationships (Baumeister & Leary, 1995, p. 497).

Consistent with these theoretical ideas, some studies have suggested that the effect of interaction quantity on well-being follows the principle of diminishing returns. For example, the association between time spent socializing and subjective well-being was only positive up to a point, beyond which social time was no longer associated with well-being (Kushlev et al., 2018). Similarly, social contact frequency was no longer associated with physical health once social contact reached a moderate level (Stavrova & Ren, 2020). Moreover, being included by more group members in a group interaction decreased aggression, but each additional "includer" has a smaller incremental effect for reducing aggression (DeWall et al., 2010). Finally, being socially included in an interaction resulted in more positive outcomes, as compared to being excluded; but being overincluded (e.g., being included to a greater extent than other group members) did not result in higher levels of positivity (Ren et al., 2021; van Beest & Williams, 2006; Wolf et al., 2015; Williams, Cheung, & Choi, 2000).

Inverted U Hypothesis. It is also possible that the effect of interaction quantity follows an inverted-U curve, whereby social interactions first benefit well-being, but after a certain point, the effect turns negative. This idea can be traced back to Aristotelian philosophy, which suggested that there might be "too much of a good thing" and it is the

moderate (rather than excessive or deficient) level of virtue, such as exercise or courage, that promotes well-being (Aristotle, trans. 1999). Importantly, this idea has been reflected in both psychological theories and research. For example, the Optimal Distinctiveness Theory (Brewer, 1991) states that individuals prefer moderately inclusive, rather than extremely inclusive or extremely exclusive, groups, yielding an inverted-U relation between group inclusiveness and group identification (for a review, see Leonardelli et al., 2010). More recently, several areas of psychological research have documented the inverted-U-shaped effect, including time spent volunteering and psychological well-being (Windsor et al., 2008), empathy and prosocial behaviors (Eisenberg, 2000), the number of choice options and choice satisfaction (Reutskaja & Hogarth, 2009). Building on the prevalence of the inverted-U-shaped effect, it has been argued that such a nonlinear relation may serve as a general principle in psychology (Grant & Schwartz, 2011).

The relation between interaction quantity and well-being may arguably follow a similar inverted-U curve. In support of this idea, it has been shown that socializing with family and friends was positively associated with affect balance; however, the association turned negative when the social time increased beyond 17 hours (Diener et al., 2008). Similarly, social contact frequency was associated with lower morality risk; but this association turned negative at the high end of contact frequency (i.e., socializing daily; Stavrova & Ren, 2020). Why might high interaction quantity reduce well-being? One possible explanation could be that the demands of social interactions, such as providing support and care, can be psychologically taxing (Cichy et al., 2014; Kahneman et al., 2004). In contrast, spending time away from social interactions may promote well-being in several ways, including fostering beneficial contemplative or spiritual thoughts (Long et al., 2003), decreasing high-arousal affect (Nguyen et al., 2018), and providing an opportunity to avoid or recover from unpleasant social encounters (Ren et al., 2021). Indeed, adolescents who

spent a moderate amount of time in solitude were found to be better adjusted than those who spent little time alone (Larson, 1990). Finally, not spending enough time alone has been linked with diminished well-being in the general population (Coplan et al., 2019).

Current Research

The present research directly tested these two competing hypotheses regarding the nonlinear relation between interaction quantity and psychological well-being: the Diminishing Returns Hypothesis and the Inverted U Hypothesis. We applied a variety of methods to diverse samples across a series of six studies. We first report a laboratory experiment using college students from the United States (Study 1, $N = 157$). We then present a cross-sectional dataset from a representative adult sample from 29 European countries (European Social Survey, 2018; Study 2, $N = 129{,}228$) and a social network study involving students across 57 middle schools in the United States (Study 3, $N = 22{,}163$). To further examine the hypotheses in everyday, naturalistic settings, we present two studies using daily diary design (Study 4, 2,562 observations from $N = 461$ participants recruited via Amazon Mechanical Turk) and experience sampling design (Study 5, 7,943 observations from $N = 272$ UK residents recruited via Prolific Academic). Finally, we report longitudinal evidence from a panel study tracking Dutch adults for 10 years (the Longitudinal Internet Studies for the Social Sciences, LISS Panel; Study 6, 42,386 observations from $N = 9{,}555$ participants).

We used various indicators of the key variables for interaction quantity and psychological well-being. Across the studies, interaction quantity (the predictor) was either manipulated (Study 1) or measured using well-defined indicators: the frequency of social contact (Studies 2 & 6), the number of peers interacted with at school (Study 3), the amount of time spent socializing (Study 4), and the number of target groups interacted with (Study 5). Psychological well-being (the outcome) was measured using established indicators, such as

happiness (Argyle, 2001; Studies 2, 4, 5, & 6), life satisfaction (Diener et al., 1985; Studies 1, 2, 5, & 6), and social well-being (the appraisal of one's relationship with others; Keyes, 1998; Larson, 1996; Studies 4, 5, & 6). In addition to these main variables, measures of the Big Five traits were included in Studies 1, 5, and 6. These datasets allowed us to explore whether personality traits moderated the nonlinear effect of interaction quantity on well-being. We provide a summary of these exploratory moderation analyses in a separate section after we report all six studies.

For all analyses, we rescaled all outcome variables to be between zero and one. Doing so eases interpreting the effects simply as the proportion difference of the outcome variable per unit change in the predictor variable (e.g., a coefficient of .10 is a 10% increase in happiness for every additional hour spent with others). Each effect size is followed by its 95% confidence intervals in brackets throughout the manuscript. All analyses were conducted in R version 4.0.0 (R Core Team, 2020) with packages lme4 (Bates et al., 2014), the lmerTest (Kuznetsova et al., 2015), nlme (Pinheiro et al., 2013), and the functions provided by Muggeo et al. (2014). All research materials, data, and analysis scripts are available at the Open Science Framework (OSF): https://osf.io/8r7gz/

Study 1

Our first study examined the nonlinear effect of interaction quantity on well-being using an experimental design. Participants were randomly assigned to receive a forecast about their future career that would involve interaction quantity at one of three levels: low, moderate, or high. Afterwards, participants reported their anticipated job satisfaction, need satisfaction at work, affect at work, and overall life satisfaction.

Method

Participants. College students from a research university in the United States participated in this study for course credits. Data was collected for three weeks and a sample

of 159 participants was obtained. One participant did not grant permission to use their data, and one participant indicated to the experimenter that they had difficulty following instructions in English, leaving 157 participants in the final sample (63 male, 94 female; M_{age} = 19.52 years, SD = 1.34). A power analysis based on Monte Carlo simulations (1,000 simulations, >80% power, α = .05, two-tailed test) using R package SIMR (Green & MacLeod, 2016) yielded a minimal detectable (unstandardized) effect size of 0.25 given the observed sample size when comparing moderate (vs. low) interaction quantity or high (vs. moderate) interaction quantity.

Procedure and materials. Participants were brought into a laboratory and directed to individual cubicles to complete the study on a computer. Participants were told that this was a study about personality and future career. First, to support the cover story, participants completed a personality test (Big Five Inventory; John & Srivastava, 1999). Participants then learned that, based on their responses to the personality test, they would receive a forecast about their future career. In reality, regardless of participants' personality scores, they were randomly assigned to receive a description of a job in which social interactions were either "rarely involved" (low quantity; n = 53), "involved to some extent" (moderate quantity; n = 52), or "constantly involved" (high quantity; n = 52). Importantly, aside from the manipulated interaction quantity level, all other aspects of the job were held constant across conditions (e.g., work pressure was the same in all conditions: "it could be quite demanding at times that you will have to work towards close-approaching deadlines"). See Supplementary Materials for the full text of the descriptions.

After receiving the forecast about their future career, participants completed manipulation check items, and four measures of psychological well-being (job satisfaction, need satisfaction at work, affect at work, and life satisfaction). Participants also filled out a few measures that are not relevant to the current research (e.g., their preferred leisure

activities). Next, participants reported demographics information. Finally, they were debriefed and thanked.

Manipulation check. Participants indicated their agreement with two items: (1) "I would be spending most of the time by myself during work hours." (2) "I would be spending most of the time interacting with others during work hours." (1 = *not at all*; 5 = *extremely*). A single manipulation check index of perceived interaction quantity was computed by reverse-coding the response to the first item, then taking the average of both items ($r_{\text{Spearman-Brown}}$ = .88; Eisinga et al., 2012).

Job satisfaction. Participants indicated their agreement with three items: (1) "I would enjoy the working environment." (2) "The job would be ideal for me." (3) "I would want to quit and find a different job." (1 = *not at all*; 5 = *extremely*). Item 3 was reverse coded and the average of the three items taken to provide a single index such that higher average responses reflected greater anticipated job satisfaction (α = .94).

Need satisfaction at work. Drawing on the belonging literature, we used a brief version of the need satisfaction scale (Williams, 2009), with one item per need, assessing participants' anticipated need satisfaction for belonging ("I would feel disconnected"), self-esteem ("My self-esteem would be high"), meaningful existence ("I would feel invisible"), and control ("I would feel I have control over my social situation"). All items were rated on a 5-point scale (1 = *not at all*, 5 = *extremely*). Items were recoded when necessary, and averaged to provide a single index for need satisfaction (α = .88).

Affect at work. We used 12 items to assess participants' anticipated affect at work: good, bad, angry, sad, stressed, excited, motivated, supported, unsatisfied, suffocated, frustrated, exhausted. All items were rated on a 5-point scale (1 = *not at all*, 5 = *very much*). Items were recoded when necessary, and averaged to provide a single index for affect with higher values indicating more positivity (α = .92).

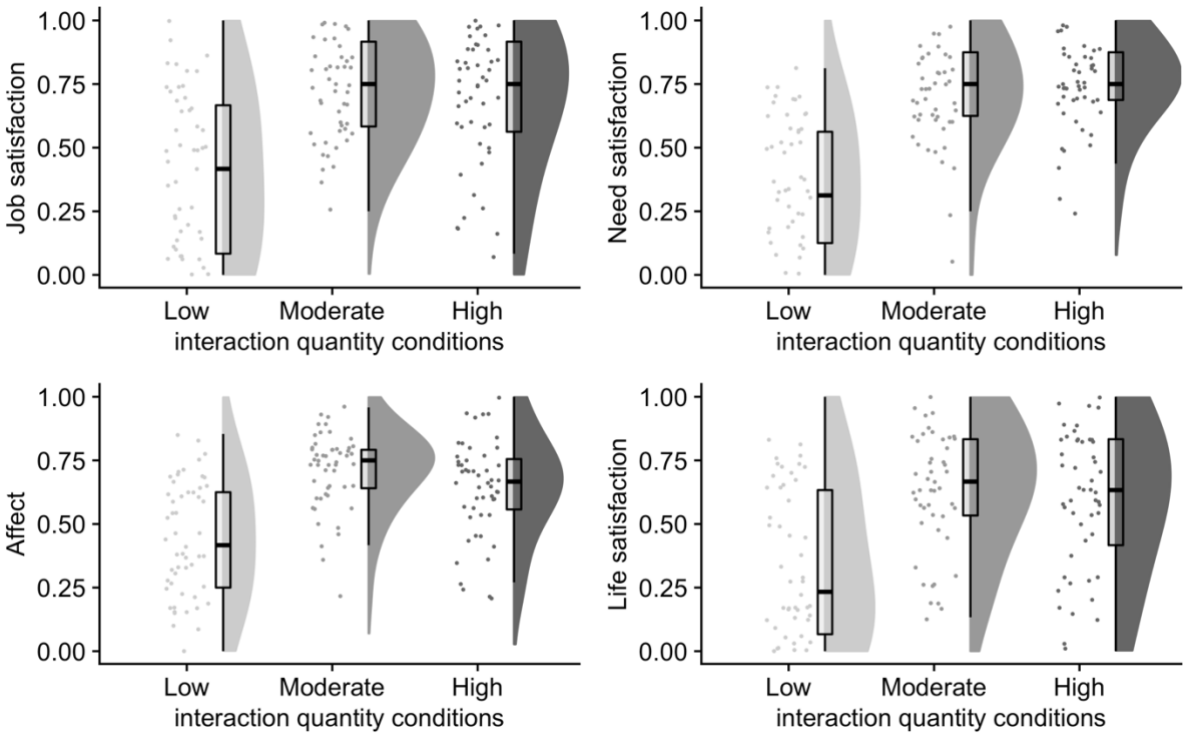
Life satisfaction. We adapted the Satisfaction with Life Scale (Diener et al., 1985) to measure participants' anticipated overall life satisfaction. The original scale consists of 5 items rated on a 7-point scale (e.g., "In most ways my life is close to my ideal." 1 = *strongly disagree*; 7 = *strongly agree*). All items were re-worded to subjunctive tense ("In most ways my life would be close to my ideal.") and their responses were averaged to form a single indicator of life satisfaction (α = .96).

Results

A visual inspection of the data is presented in Figure 1, using raincloud plots (a combination of raw data points, a boxplot, and a half violin plot illustrating the data distribution; Allen et al., 2019).

Figure 1

Interaction quantity and well-being outcomes (Study 1)

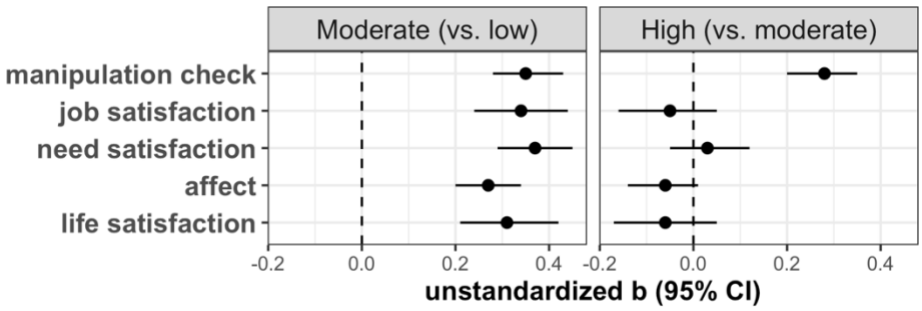


We tested the effect of the conditions on the index of manipulation check and the well-being outcomes. For all analyses, we estimated regression models with the experimental

conditions (two dummy coded variables) as predictors. The reference category depended on the effect of interest (i.e., moderate vs. low, high vs. moderate), and is specified in Figure 2, in which the unstandardized coefficients are plotted.

Figure 2

Regression models predicting each outcome variable from the conditions (Study 1)



As shown in Figure 2, our manipulation was successful with similar estimates across both comparisons. Across all four outcomes, participants' well-being increased from the low-quantity condition to the moderate-quantity condition as expected from the existing literature; however, there was no evidence suggesting that well-being levels differed between the moderate and high conditions.

Discussion

Study 1 provided initial support for the Diminishing Returns Hypothesis: Increasing interaction quantity from low to moderate improved well-being, but increasing interaction quantity from moderate to high did not further increase (or decrease) well-being. While this study provided an experimental test of our hypotheses (which suggested a causal relationship), using an undergraduate student sample and a laboratory task undermined its external validity. To address this limitation, in the next study, we conducted secondary data analyses of a large-scale dataset of nationally representative adult samples from 29 European countries.

Study 2

We used data from a large international survey project on Europeans' values and attitudes: the European Social Survey (ESS, 2018). Every two years since 2002, ESS recruits new nationally representative samples in 36 European countries. Participants are recruited using a random probability sample, with a minimal sample size of 1,500 respondents per country (or 800 in countries with the total population of less than 2 million). Respondents are interviewed in a face-to-face mode. The data can be downloaded from here: https://www.europeansocialsurvey.org/about/.

Method

Participants. We analyzed data from all waves that included our focal variables (interaction quantity and subjective well-being): waves 3 (year 2006), 6 (year 2012), and 7 (year 2014). After removing individuals with missing values on the key variables, the final sample consisted of 129,228 individuals (M_{age} = 47.76, SD_{age} = 18.47, 46.1% male) from 29 countries. See Supplementary Table 1 for the list of countries and descriptive statistics by country.

Measures.

Interaction quantity. We used one item to assess interaction quantity. Participants were asked to indicate how often they meet socially with friends, relatives, or work colleagues. Response options were: 1 = *never*, 2 = *less than once a month*, 3 = *once a month*, 4 = *several times a month*, 5 = *once a week*, 6 = *several times a week*, 7 = *every day*. Among this sample, the average social frequency was about once a week (M = 4.88, SD = 1.59). To identify potential influential outliers, histograms representing the distributions of the interaction quantity indicators in this study and all subsequent studies are presented in Supplementary Figure 6. For brevity, we will not repeat this information below, except when outliers were identified (Studies 3 and 5).

Psychological well-being. We used three measures to assess psychological well-being: happiness, life satisfaction, and affect during the past week. Happiness was measured with one item: "Taking all things together, how happy would you say you are?" (0 = *extremely unhappy*, 10 = *extremely happy*). Life satisfaction was measured with one item: "All things considered, how satisfied are you with your life as a whole nowadays?" (0 = *extremely dissatisfied*; 10 = *extremely satisfied*). Affect was measured using eight items. Participants indicated how much of the time during the past week: (1) they felt depressed, (2) they felt that everything they did was an effort, (3) their sleep was restless, (4) they felt lonely, (5) they felt sad, (6) they could not get going, (7) they felt happy, and (8) they enjoyed life. Responses were given on a 4-point scale (1 = *none or almost none of the time*, 2 = *some of the time*, 3 = *most of the time*, 4 = *all or almost all of the time*). Items were recoded when necessary and averaged to form a single index of affect with higher values reflecting more positivity (α = 0.84).

Covariates. We used the following socio-demographic and economic variables as covariates: gender (female, male), age (in years), education (number of years), employment status (categories: employed, unemployed, student, retired, other), marital status (categories: married or in a civil partnership, divorced or separated, widowed, and never married/never in a civil partnership), and household income ("Which of the descriptions on this card comes closest to how you feel about your household's income nowadays?" 1= *Living comfortably on present income*, 2 = *Coping on present income*, 3 = *Finding it difficult on present income*, 4 = *Finding it very difficult on present income*; recoded such that higher values correspond to a higher income[1]).

[1] This was the only measure of income that was included in all the waves without changes in phrasing or response options.

Analytic Plan

To evaluate the nonlinear relation between interaction quantity (predictor) and psychological well-being (outcome), we used two different analytic approaches. In the first approach, we fitted a quadratic regression model, commonly used for detecting nonlinear effects (e.g., Nickel et al., 2019; Vergauwe et al., 2018). To account for the clustered nature of the data (participants are clustered within both countries and waves), we estimated random-intercepts for each country and each wave in a cross-classified multilevel model. Because the variance of the random intercepts for waves was negligible (across models, variance <0.00017), for model parsimony, we refitted a model with only the random intercepts for each country. Models were estimated either without or with covariates: Model 1 included only the linear and quadratic (i.e., squared) terms of interaction quantity as predictors; Model 2 additionally included the covariates described above. The interaction quantity scores were mean-centered so that the linear and squared term of interaction quantity were orthogonal. Significant squared terms of interaction quantity would indicate the presence of a nonlinear effect.[2]

The first analytic approach detects the presence (or absence) of nonlinearity. However, this approach assumes a quadratic relationship that forces the parabola to bend at a single turning point and be symmetric around said point. This assumption prevents us from evaluating the two competing hypotheses regarding the shape of the curve. In fact, as demonstrated in simulation studies, the quadratic regression approach for testing a U-shaped effect has a high false positive rate (Simonsohn, 2018). To address this limitation, a "two-lines" approach that estimates separate line segments within two sub-intervals (low vs. high) of the predictor has been proposed as a valid method to evaluate the shape of the nonlinear curve (Simonsohn, 2018). This approach has been increasingly adopted in various areas of

[2] For completeness, inflection points are calculated and provided in Supplementary Materials.

psychological research (e.g., Gula et al., 2021; Jordan et al., 2019; Nickel et al., 2019; Nook et al., 2018; Zmigrod et al., 2019). In our analyses, we used segmented multilevel models (Muggeo et al., 2014), a "two lines" approach which takes into account the nested structure of the data. Using the functions in Muggeo et al. (2014), we first estimated the location of the so-called "breakpoint," and then the segment slopes before and after the breakpoint. We refer interested readers to Muggeo (2008) for technical details. Such an approach allowed us to evaluate the possibly different relations between interaction quantity and well-being at either the low or high values of interaction quantity. We expect the slope of the first line segment (at low values of interaction quantity) to be positive based on established evidence from past research, such that increasing interaction quantity from low to moderate is associated with higher well-being. Critically, for the second line segment (at high values of interaction quantity), a positive slope of reduced magnitude (or a slope that is statistically indistinguishable from zero) would support the Diminishing Returns Hypothesis, whereas a (statistically significant) negative slope would support the Inverted-U Hypothesis.

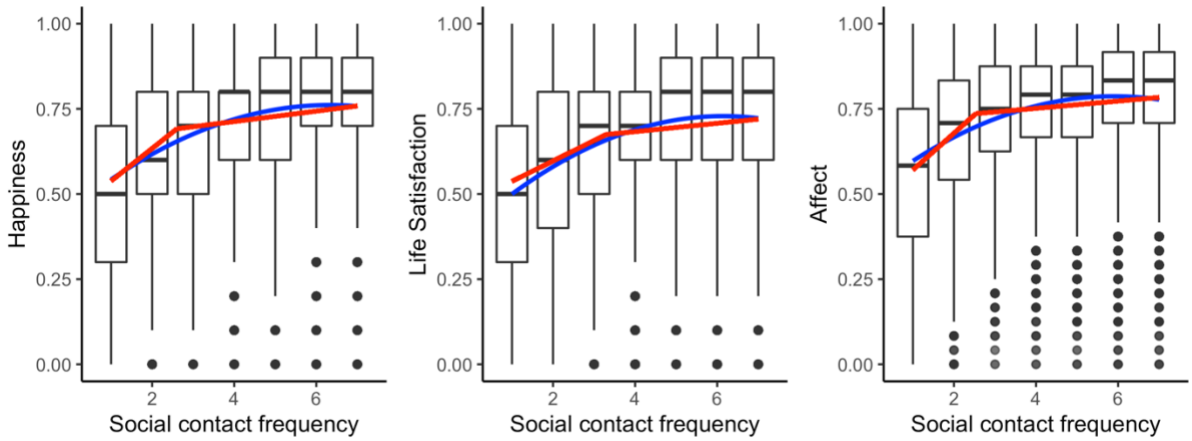
Results

A visual inspection of the data is presented in Figure 3. Below we present the results from each analytic approach in turn.[3]

[3] Because the interaction quantity indicator had seven discrete levels, we additionally used pairwise comparison tests (as implemented in the package LmerTest, Kuznetsova et al., 2017) to estimate the differences in the well-being outcomes between the levels. Results support the same conclusions of our primary analyses. See Supplementary Materials for details.

Figure 3

Interaction quantity and well-being outcomes (Study 2)

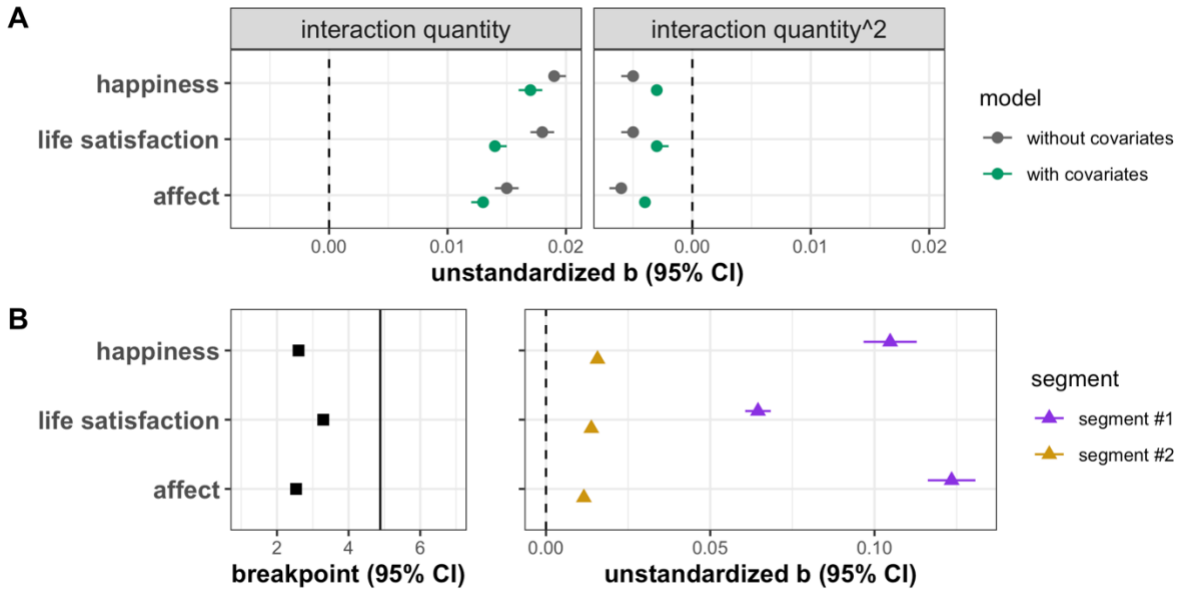


Note. The superimposed blue line represents the predictions from the quadratic model (without covariates); the red line represents the predictions from the segmented model. The horizontal axis represents social contact frequency (1 = *never*, 2 = *less than once a month*, 3 = *once a month*, 4 = *several times a month*, 5 = *once a week*, 6 = *several times a week*, 7 = *every day*).

Quadratic models. Across the outcome variables, the linear terms of interaction quantity were significant; critically, the quadratic terms of interaction quantity were also significant, providing support for the nonlinear effect of interaction quantity. These findings were robust to adjusting for the covariates listed above. The unstandardized regression coefficients are presented in Figure 4, Panel A.

Figure 4

Quadratic models (Panel A) and segmented models (Panel B) for each outcome variable (Study 2)



Note. 95% CI for all effects are plotted but may not be visible due to the small range relative to the size of the plotted point estimate. Breakpoints are plotted on the full range of interaction quantity (1 = *never*, 2 = *less than once a month*, 3 = *once a month*, 4 = *several times a month*, 5 = *once a week*, 6 = *several times a week*, 7 = *every day*). The solid vertical line represents the sample mean.

Segmented models. For each of the three outcome variables, a breakpoint for interaction quantity at around "once a month" (interaction quantity = 3) was detected. Across all three outcome variables, the slopes of the first line segments (before the breakpoint) were consistently positive; the slopes of the second line segments (after the breakpoint) continued to be positive, but their magnitudes were substantially reduced. For example, when considering happiness, the magnitude of the slopes was reduced from 0.11 (first segment) to 0.02 (second segment), a decrease by 82%. In other words, a unit increase in interaction quantity was associated with an 11% increase in happiness, but only up to "once a month'"; a unit increase in interaction quantity beyond "once a month" was associated with only a 2%

increase in happiness. All breakpoint estimates and segment slopes are presented in Figure 4, Panel B.

Discussion

Using nationally representative samples across 29 European countries, we uncovered a nonlinear association between interaction quantity and psychological well-being. The nonlinear pattern supports the Diminishing Returns Hypothesis rather than the Inverted U Hypothesis: increasing interaction quantity at the low end of the spectrum (from "never" to "once a month") was associated with greater well-being; this association became much smaller at the high end of the spectrum (beyond "once a month"), but did not turn negative.

Study 3

In Study 3, we analyzed a publicly available dataset of a social network experiment, conducted among student participants across 57 public middle schools in New Jersey, the United States (Paluck et al., 2019). This study extends the findings of Study 2 in two ways. First, instead of using a self-reported measure of interaction quantity, here we leveraged each school's network of peer interactions uncovered using a round robin design based on self- and other-reports, and calculated the number of unique ties (one tie indicates one peer interacted with) as a more objective indicator of interaction quantity. Second, we tested our hypotheses regarding the relation between interaction quantity and well-being in a non-adult population: middle school students.

Participants were surveyed twice: before (time 1) and after (time 2) an anti-conflict intervention (see Paluck et al., 2016, for details of the intervention). For the purpose of this research, we focused on time 1 data.

Method

Participants. A total of 24,471 students from 57 schools completed the survey. The social networks of each school were uncovered among 24,286 students after removing 185

students with missing identification numbers. For data analysis, 2,123 were further removed on the basis of having missing values on our key variables of interest. The final sample thus consisted of 22,162 students (49.8% female; M_{age} = 12.00, *SD* =1.06).

Procedure and measures. The data were collected at the beginning of a school year, about three weeks after school started. Students within each school completed a survey at the same time of a given day.

Interaction quantity. Each student was asked to report which other students (up to ten) in their school they chose to spend time with in the past few weeks (Paluck et al., 2016). Using this question, networks of social interactions within each school were uncovered: Two students were connected if at least one of them reported the other as an interaction partner (e.g., students A and B were connected if either A reported having spent time with B, or B reported having spent time with A, or both). The number of each student's social ties was used as an indicator of interaction quantity. Among this sample, the average number of ties was 11.48 (*SD* = 4.75, range: 0-41). Visually inspecting a histogram (Supplementary Figure 6) representing the distribution of the interaction quantity index shows a positively skewed distribution with clear outliers. Specifically, 99% of the students had 23 or fewer ties but 1% had at least 24 ties and as many as 41 ties; the interaction quantity index for these outlying individuals were truncated to 23 ties to reduce their influence on the results. In the following we report analyses after outliers were recoded, but note that the results were consistent in analyses before recoding the outliers (see Supplementary Materials).

Well-being at school. We combined three single-indicator variables to form a composite for students' overall well-being at school. Participants were asked to report whether they agree with the statements based on what they think: (1) "I feel like I belong at this school." (2) "I have stayed home from school because of problems with other students." (3) "During the past month, I have often been bothered by feeling sad and down". Each item

was measured using a dichotomous response format. The items were recoded when necessary and averaged to form a composite so that higher values reflected greater well-being.[4]

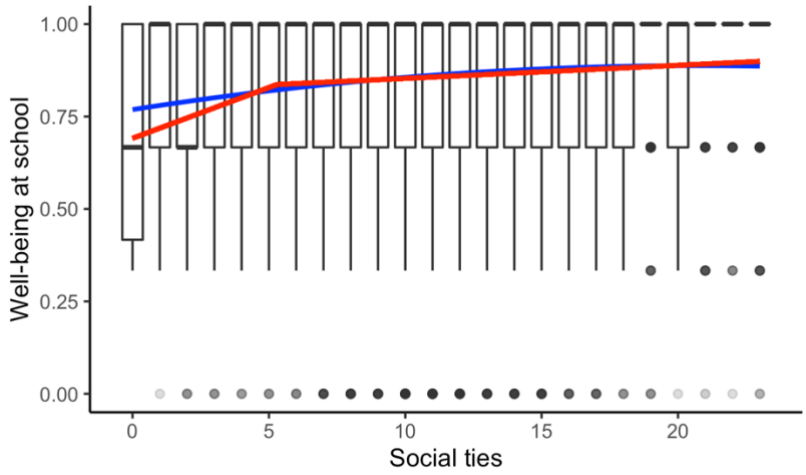
Covariates. We included basic demographic variables: age (in years), gender (female, male), grade (5th grade, 6th grade, 7th grade, 8th grade), ethnicity (white, nonwhite); and one variable that is a likely confounder of the number of social ties and students' well-being at school: whether or not they were new to the school.

Results

A visual inspection of the data is presented in Figure 5. Following the analytic plan of Study 2, we estimated both the quadratic regression model, and the segmented model. To account for the clustered nature of the data (students are clustered within schools), we fitted multilevel models with random intercepts for each school.

Figure 5

Interaction quantity and well-being at school (Study 3)



Note. The superimposed blue line represents the predictions from the quadratic models (without covariates); the red line represents the predictions from the segmented model.

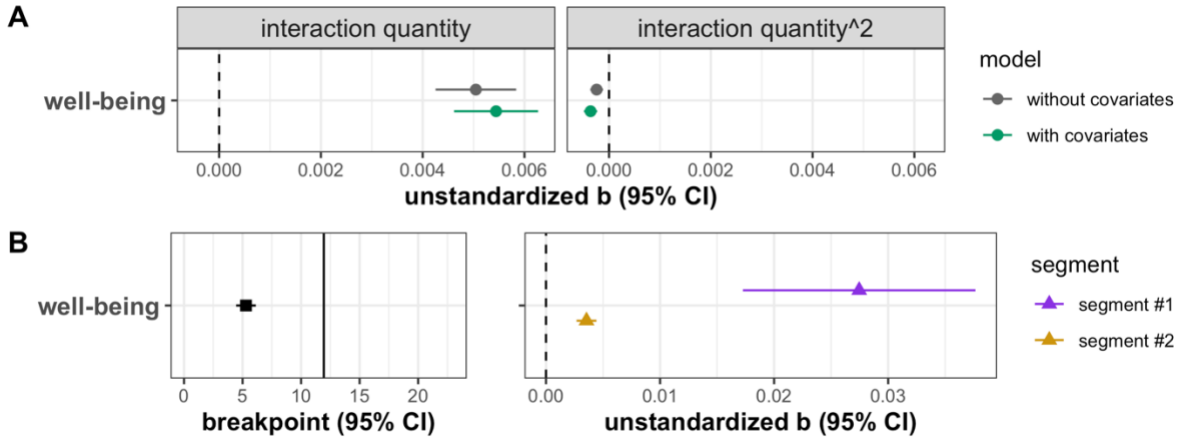
Quadratic models. The linear term of interaction quantity was significant; critically, the quadratic term was also significant, providing support for the nonlinear effect of

[4] Because this was a composite variable (a linear combination of three variables which do not necessarily correlate with one another; Bollen & Bauldry, 2011), Cronbach alpha was not computed.

interaction quantity. These findings were robust to adjusting for the covariates listed above. See Figure 6, Panel A.

Figure 6

Quadratic models (Panel A) and segmented models (Panel B; Study 3)



Note. 95% CI for all effects are plotted but may not be visible due to the small range relative to the plotted point estimate. The breakpoint is plotted on the full range of recoded interaction quantity (0-23). The solid vertical line represents the sample mean.

Segmented models. A breakpoint for interaction quantity at around five social ties was detected. The slope of the first line segment was positive; the slope of the second line segment was positive but smaller in magnitude. Concretely, up to five social ties, an increase of one social tie was associated with a 2.7% increase in well-being; beyond five ties, an increase of one social tie was associated with only a 0.4% increase in well-being. See Figure 6, Panel B.

Discussion

Using a sample of students from 57 middle schools, we uncovered a nonlinear association between students' interaction quantity at school and their overall well-being at school. The nonlinear pattern was consistent with the results of Studies 1 and 2 and supports the Diminishing Returns Hypothesis, rather than the Inverted U Hypothesis: increasing interaction quantity on the low end of the spectrum (from zero to five ties) was associated

with greater well-being; on the high end of the spectrum (beyond five ties), well-being benefits diminished.

Study 4

Moving beyond the laboratory experiment (Study 1) and single assessment methods (Studies 2 and 3), in Study 4, we investigated social interactions as they occurred in daily life using a diary method. Participants in this study reported how much time they spent with others, and their well-being, on a daily basis over a seven-day period. Using these data allowed us to understand the relation between interaction quantity and well-being as it occurred in vivo.

Method

Participants. We recruited participants on Amazon Mechanical Turk (MTurk). A total of 536 participants took part in an intake survey; 31 failed the attention check. The remaining 505 participants were invited to take part in a seven-day long diary study. Of these participants, 461 completed at least one daily assessment and constituted our final sample (243 male; M_{age}= 36.50, SD_{age} =11.51; one did not report age). Participants in our final sample completed an average of 5.56 assessments (*SD* = 1.88) and 50.1% of the sample completed all seven assessments. In total, 3,227 observations were recorded; 665 were further removed for having missing (*n* = 664) or erroneous values (*n* = 1; the time spent interacting with others was reported as 25 hours out of the past 24 hours) on the key variables of interest. Our analyses were based on 2,562 observations.

Procedure and measures. Every day, for a period of seven days, participants received a link to a daily assessment. The link was sent at 4pm Eastern Standard Time and was active for 24 hours. Most participants completed the daily assessment within 3.62 (*SD* = 4.76) hours after receiving the link.

Daily interaction quantity. Participants reported the number of hours within the past 24 hours they spent interacting with other people. Of all observations, the average number of social hours was 9.65 (*SD* = 5.95; range: 0-24).

Daily well-being. We used two measures to assess psychological well-being: happiness and social well-being. Happiness was measured by asking participants to indicate to what extent they "felt happy" within the past 24 hours. Social well-being was measured by asking participants to indicate to what extent they "felt lonely," "felt close to the people around you," and "felt annoyed with other people," within the past 24 hours. All measures used a 7-point scale (1 = *not at all*, 7 = *a lot*). Items for social well-being were reverse coded when necessary and averaged to provide a single index so that higher values reflected greater daily social well-being (α = 0.58).[5]

Covariates. Consistent with other studies, we included the standard demographic variables: age (in years), gender (female, male), relationship status (categories: living together with my partner or spouse, dating, single, other), employment status (categories: full-time employed, part-time employed, self-employed, student, retired, unemployed, housekeeper, other), the highest educational level attained (categories: did not complete high school, completed high school, have a college degree).

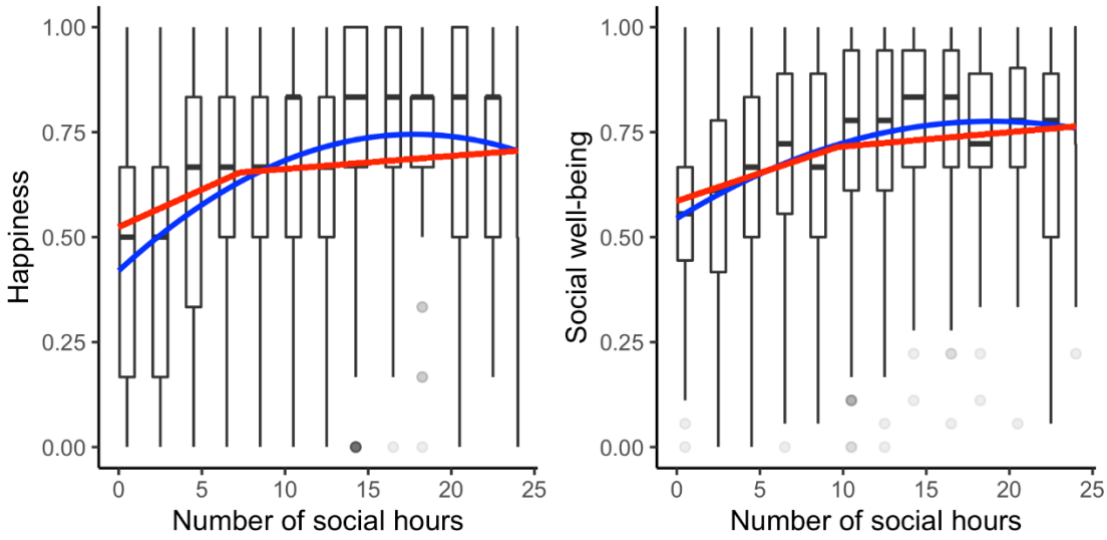
Results

A visual inspection of the data is presented in Figure 7. Following the analytic plan of Study 2, we estimated both the quadratic regression model, and the segmented model. To account for the repeated measures within each individual, we fitted multilevel models with random intercepts for each participant.

[5] Social well-being had relatively low estimates of internal consistency in Studies 4 and 5. This is not uncommon for short scales that cover a broad construct (e.g., Gosling et al., 2003).

Figure 7

Interaction quantity and well-being (Study 4)

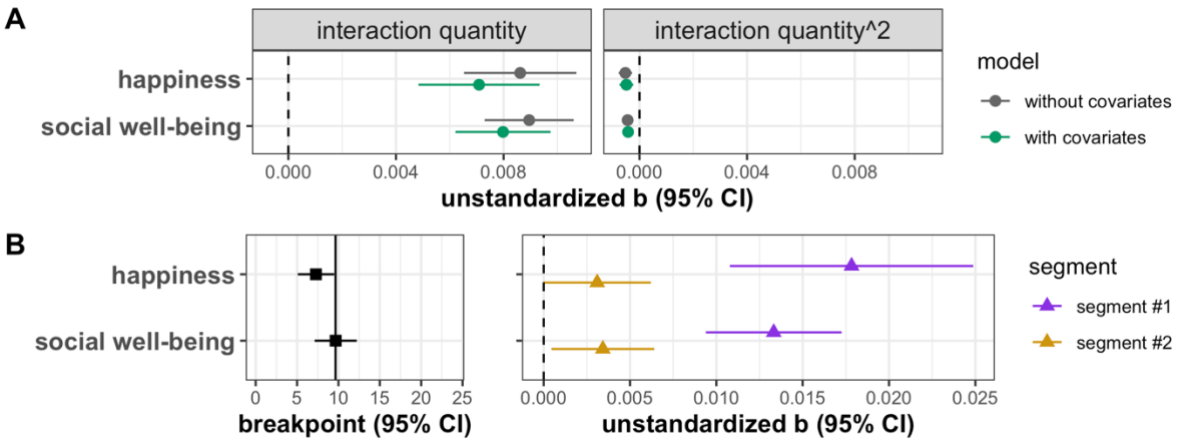


Note. The superimposed blue line represents the predictions from the quadratic models (without covariates); the red line represents the predictions from the segmented models.

Quadratic models. The linear terms of interaction quantity were significant; critically, the quadratic terms were also significant, providing support for the nonlinear effect of interaction quantity. These findings were robust to adjusting for the covariates listed above. See Figure 8, Panel A.

Figure 8

Quadratic models (Panel A) and segmented models (Panel B) for each outcome variable (Study 4)



Note. 95% CI for all effects are plotted but may not be visible due to the small range relative to the size of the plotted point estimate. Breakpoints are plotted on the full range of interaction quantity (0-24). The solid vertical line represents the sample mean.

Segmented models. For the happiness outcome, a breakpoint at seven hours was detected: the first line segment was positive, whereas the second line segment was not statistically significant. In other words, an increase of one hour spent interacting with other people, up to seven hours, was associated with a 1.8% increase in happiness; any increase in time spent socializing beyond seven hours was no longer associated with changes in happiness. For social well-being, a breakpoint at 10 hours was detected: although both line segments were positive, the magnitude reduced by 77%. In other words, an increase of one hour spent interacting with other people, up to 10 hours, was associated with a 1.3% increase in social well-being; whereas an increase of one hour beyond 10 hours was only associated with a 0.3% increase in social well-being. See Figure 8, Panel B.

Discussion

Using daily diary data, we replicated the nonlinear association between interaction quantity and well-being. Increasing interaction quantity on the low end of the spectrum (from

zero to 10 hours of socializing) was associated with greater well-being; on the high end of the spectrum (beyond 10 hours), well-being benefits of socializing were nearly negligible (social well-being) or statistically indistinguishable from zero (happiness). The results of this study provided further support to the Diminishing Returns Hypothesis, but not the Inverted U Hypothesis.

Study 5

Across Studies 1-4, we have observed no evidence for the potential negative impact of high (vs. moderate) interaction quantity under the Inverted U Hypothesis. One possible reason is that the indicators of interaction quantity used in the aforementioned studies (e.g., social contact frequency, number of social ties) are not particularly well-suited to capture the demanding aspects of social interactions, which may drain well-being (e.g., Cichy et al., 2014). Therefore, in Study 5, we used a different indicator of interaction quantity that might better reflect the demanding aspects of social interactions: the number of distinct social groups (e.g., romantic partner, friends, colleagues) one interacted with in a short period of time. Individuals usually have multiple identities linked to other target groups (Ashforth & Johnson, 2001), and interacting with a given target group activates the associated identity. For example, interactions with one's spouse could activate their identity as a romantic partner; interactions with one's children could activate their identity as a parent; and interactions with one's colleagues could activate their professional identity. Although having a greater number of social identities has been shown to enhance well-being (Iyer et al., 2009; Jetten et al., 2015), engaging in social interactions with a greater number of distinct target groups within a short period of time may drain well-being, as people would need to navigate multiple and potentially conflicting identities (Brook et al., 2008).

We used an experience sampling method. Participants reported the different social groups they interacted with in the past hour (the number of distinct target groups was

computed as the interaction quantity index), and their well-being in the past hour, up to five times per day, for seven days.

Method

Participants. We recruited a sample of United Kingdom residents on Prolific Academic for a week-long experience sampling study. A total of 454 participants completed the intake survey; 146 failed an attention check. On the following day, the remaining 308 participants were invited to take part in a seven-day long experience sampling study. Of these invited participants, 272 participants (88%) completed at least one assessment and constituted our final sample (68 male; M_{age}= 34.33, SD_{age} =12.47; seven did not report gender or age). Participants in our final sample completed an average of 29.2 assessments (*SD* = 7.76) and 67% completed 30 assessments or more out of a total of 35 possible assessments. In total, 7,943 observations were recorded.

Procedure and measures. Participants first completed an intake survey and were provided with instructions on how to access the study via a smartphone application for the daily surveys. For seven consecutive days following intake, participants received five time-triggered push notifications on the smartphone application per day to fill out momentary assessments. The notifications were sent randomly within each of the following time intervals: 9:20-11:40 (first assessment), 11:40-14:00 (second assessment), 14:00-16:20 (third assessment), 16:20-18:40 (fourth assessment), 18:40-21:00 (fifth assessment). Each survey stayed active for 80 minutes.

Momentary interaction quantity. Participants were asked to report whether they were interacting with others in the past hour, and if so, with whom they had been interacting. They were provided with a list of eight possible target groups and asked to check all that apply: spouse/partner, friend(s), colleague(s), client(s)/customer(s)/pupil(s)/student(s)/patient(s), child(ren) (also adoptive or stepchild(ren)), parents/relatives, supervisor/teacher/trainer, and

642 other. The number of target groups participants interacted with were used as an indicator of
643 the interaction quantity of the past hour. Of all observations, the average number of interacted
644 groups was 1.23 (*SD* = 0.93, range: 0-6). Visually inspecting a histogram (Supplementary
645 Figure 6) representing the distribution of the interaction quantity index shows a positively
646 skewed distribution with clear outliers. Specifically, 99% of the episodes involved three or
647 fewer groups but 1% involved four or more groups. Consistent with Study 3, the number of
648 episodes for the outlying individuals were truncated to 3 to avoid potentially influencing the
649 results. We report analyses after outliers were recoded, but note that the results were
650 consistent in analyses before recoding the outliers (see Supplementary Materials).

651 ***Momentary well-being.*** We used three measures to assess psychological well-being:
652 happiness, life satisfaction, and social well-being. Happiness was measured by asking
653 participants to indicate to what extent they "have felt happy" in the past hour. Life
654 satisfaction was measured by asking participants to indicate to what extent they "have felt
655 satisfied with life" in the past hour. Social well-being was measured using two items ("I have
656 felt lonely," and "I have felt connected"). A single index of social well-being was computed
657 by reverse-coding the response to the first item, then taking the average of both items
658 ($r_{\text{Spearman-Brown}}$ = .42; Eisinga et al., 2012). All measures used a 5-point scale (1 = *not at all*, 5
659 = *a great deal*).

660 ***Covariates.*** We included the standard demographic variables collected from the
661 intake survey: age (in years), gender (female, male), relationship status (categories:
662 married/living together with a partner, in a committed relationship but not living together,
663 dating, single), employment status (categories: work [home office], work [no home office],
664 unemployed, student, retired, other), the highest educational level attained (categories: less
665 than high school degree, high school graduate, some college but no degree, associate degree
666 in college, Bachelor's degree in college, Master's degree, Doctoral degree, Professional

667 degree), household income (12 options were provided, ranging from 1= Less than $10,000 to
668 12=$150,000 or more).

669 Because this dataset was collected in August 2020, during the ongoing pandemic of
670 COVID-19, we measured additional covariates that may have affected participants'
671 psychological well-being: perceived threat of COVID-19 to personal health, perceived threat
672 of COVID-19 to financial safety, perceived threat of COVID-19 to day-to-day life, diagnose
673 of COVID-19, suspicion of COVID-19 infection, living alone, and care-taking duties. The
674 first three items were measured using a 4-point scale (1 = *not a threat*, 4 = *major threat*); the
675 last four items were measured using a dichotomous response format (yes or no).

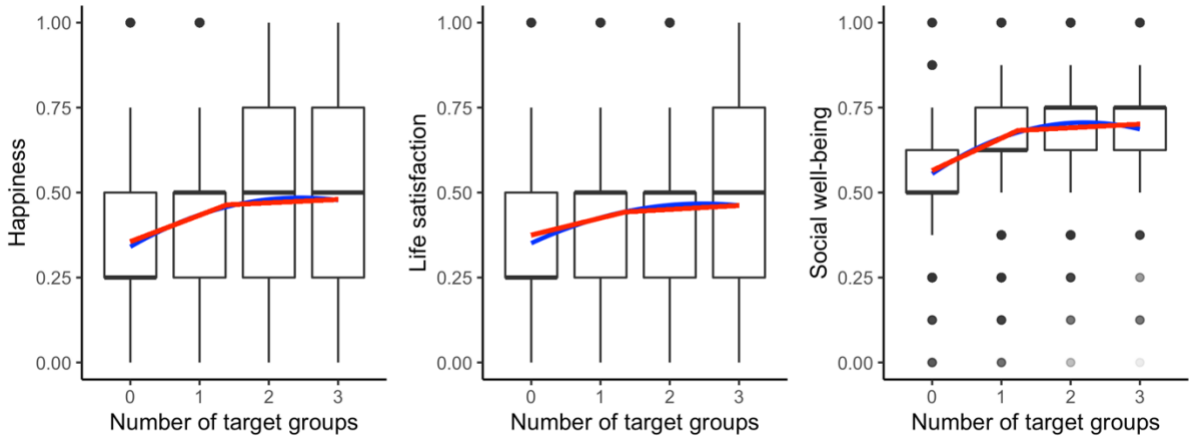
676 **Results**

677 A visual inspection of the data is presented in Figure 9. Following the analytic plan of
678 Study 2, we estimated the quadratic regression model and the segmented model[6]. To account
679 for the repeated measures within each individual, we fitted multilevel models with random
680 intercepts for each participant.

[6] Same as in Study 2, because the interaction quantity indicator had discrete levels, we conducted pairwise comparison tests. Results support the same conclusions of our primary analyses. See Supplementary Materials.

Figure 9

Interaction quantity and well-being (Study 5)

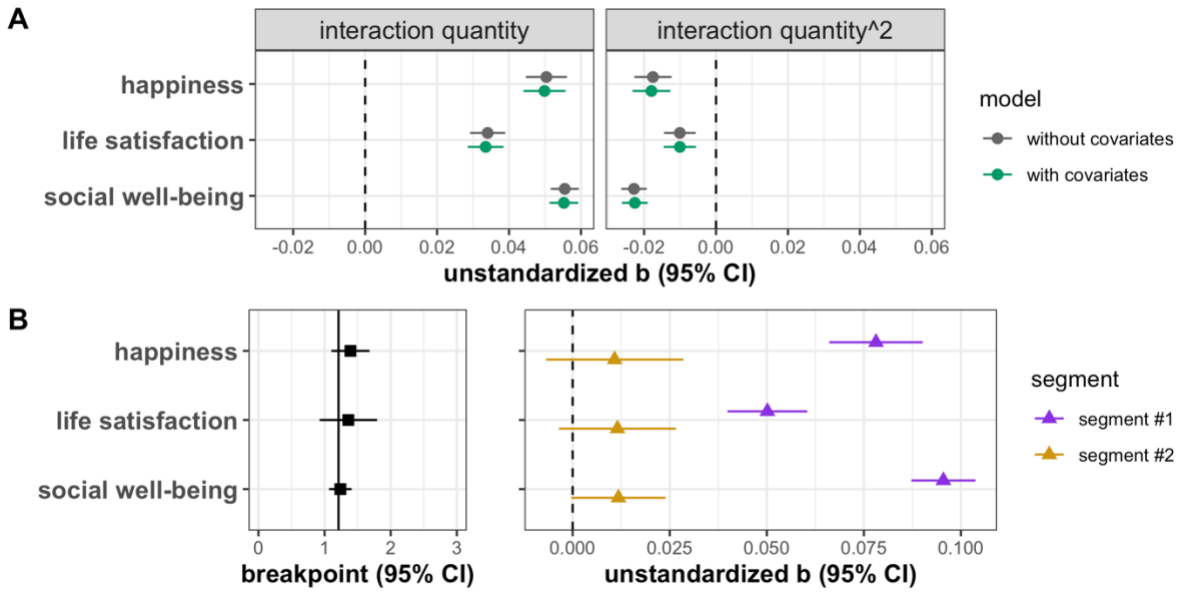


Note. The superimposed blue line represents the predictions from the quadratic models (without covariates); the red line represents the predictions from the segmented models.

Quadratic models. Both the linear and the quadratic terms of interaction quantity reached significance across all outcome variables. These results are robust to adjusting for covariates. See Figure 10, Panel A.

Figure 10

Quadratic models (Panel A) and segmented models (Panel B) for each outcome variable (Study 5)



Note. 95% CI for all effects are plotted but may not be visible due to the small range relative to the size of the plotted point estimate. Breakpoints are plotted on the full range of recoded interaction quantity (0-3). The solid vertical line represents the sample mean.

Segmented models. Consistently across all three outcome variables, a breakpoint between one and two target groups (on average, 1.4) was detected; the slope of the first segment was positive, whereas the slope of the second segment was statistically indistinguishable from zero. That is, interacting with one target group (as compared to no interactions) in a given hour was associated with better well-being during that time; but interacting with a greater number of groups was no longer associated with changes in well-being. See Figure 10, Panel B.[7]

Discussion

Using an experience sampling method, we sought to maximize the possibility of

[7] At the request a reviewer, we explored the lagged effect of interaction quantity on well-being. See Supplementary Materials.

detecting evidence in favor of an inverted-U trend by focusing on the number of different social groups people interact with in a given hour. Interacting with a greater number of social groups within a short period of time can be demanding and could potentially lead to reduced well-being. Nonetheless, consistent with the previous studies thus far, the nonlinear association between momentary interaction quantity and momentary well-being provided support for the Diminishing Returns Hypothesis but not the Inverted U Hypothesis: Increases in the number of social interaction groups beyond a certain point was no longer associated with changes in well-being outcomes.

Study 6

Studies 2-5 presented evidence for the concurrent associations between interaction quantity and well-being using cross-sectional survey data (Studies 2 and 3), or observing participants repeatedly over short periods of time (one week; Studies 4 and 5). Does the nonlinearity then extend to the associations between interaction quantity and well-being assessed over more extensive periods of time? In Study 6 we evaluated this possibility using a 10-year long panel study of a nationally representative panel study of Dutch adults: Longitudinal Internet Studies for the Social Sciences (LISS Panel). The data can be downloaded from https://www.lissdata.nl/about-panel.

Method

Participants. Every year, panel members complete surveys on different topics, referred to as modules, at different time points throughout the year. We combined data from two modules: Social Integration and Leisure, and Personality, collected from 10 waves (annually from 2008 to 2018). The measures of interaction quantity temporally preceded measures of psychological well-being within each year for almost all participants, with the exception of less than 1% of participants in only two particular years (see Supplementary Table 2 for more details). We removed these participants from our analyses to ensure the

temporal precedence of the predictor (interaction quantity) and outcomes (well-being). After removing the missing values on the key variables, our final sample consisted of 42,386 observations from 9,555 individuals ($M_{\text{age in 2008}}$ = 48.2, $SD_{\text{age in 2008}}$ = 17.78; 46.0% male).

Measures.

Interaction quantity. We combined three items to assess interaction quantity. Participants reported how often they spent an evening with family (excluding members of their household), someone from the neighborhood, and friends outside their neighborhood. Response options were: 1 = *almost every day*, 2 = *once or twice a week*, 3 = *a few times per month*, 4 = *about once a month*, 5 = *a number of times per year*, 6 = *about once a year*, 7 = *never*. All three items were reverse coded and averaged to form a composite with higher values reflecting higher quantity of social interactions.[8] Of all observations, the average social frequency was about once a month (M = 3.87, SD = 1.14).

Psychological well-being. We used three measures to assess psychological well-being: happiness, life satisfaction, and social well-being. Happiness was measured with the same item as in Study 2: "On the whole, how happy would you say you are?" (0 = *totally unhappy*, 10 = *totally happy*). Life satisfaction was measured with the same scale as in Study 1 (Satisfaction with Life Scale; Diener et al., 1985; α = .90). Social well-being was measured using one item: "How satisfied are you with your social contacts?" (0 = *not at all satisfied*, 10 = *completely satisfied*).[9]

Covariates. We included the standard socio-demographic and economic control variables: age (in years), gender (female, male), marital status (categories: married, divorced/separated, widowed, never married), employment status (categories: employed,

[8] Cronbach alpha was not computed for composite variables (see footnote 4).
[9] LISS panel also included measures of affect (Module: Personality). However, in years 2010, 2012, 2015 and 2017, these measures were only administered to the participants who did not respond to them in the previous waves (i.e., 2009, 2011, 2014 and 2016). Therefore, given the longitudinal nature of the present analysis, we included only the measures that were consecutively collected in all waves.

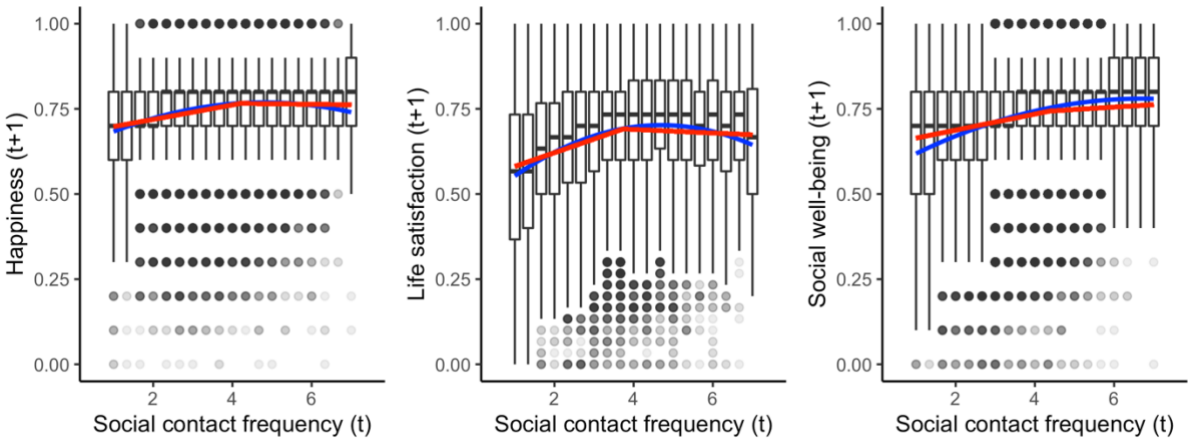
unemployed, in education, other), level of education (categories: higher secondary, higher vocational, university), and personal gross monthly income (12 response options were provided, ranging from 0 = *no income* to 12 = *more than 7,500 EUR*).

Results

A visual inspection of the longitudinal associations between interaction quantity at time *t* and well-being at time *t*+1 across all time points *t* is presented in Figure 11. Following the analytic plan of Study 2, we estimated both the quadratic model and the segmented model. To account for the repeated measures within each individual, we fitted multilevel models with random intercepts for each participant.

Figure 11

Interaction quantity at time t and well-being at t+1 (Study 6)



Note. The superimposed blue line represents the predictions from the quadratic models (without covariates); the red line represents the predictions from the segmented models. The horizontal axis represents social contact frequency at time *t* (1= *never*, 2 = *about once a year*, 3 = *a number of times per year*, 4 = *about once a month*, 5 = *a few times per month*, 6 = *once or twice a week*, 7 = *almost every day*).

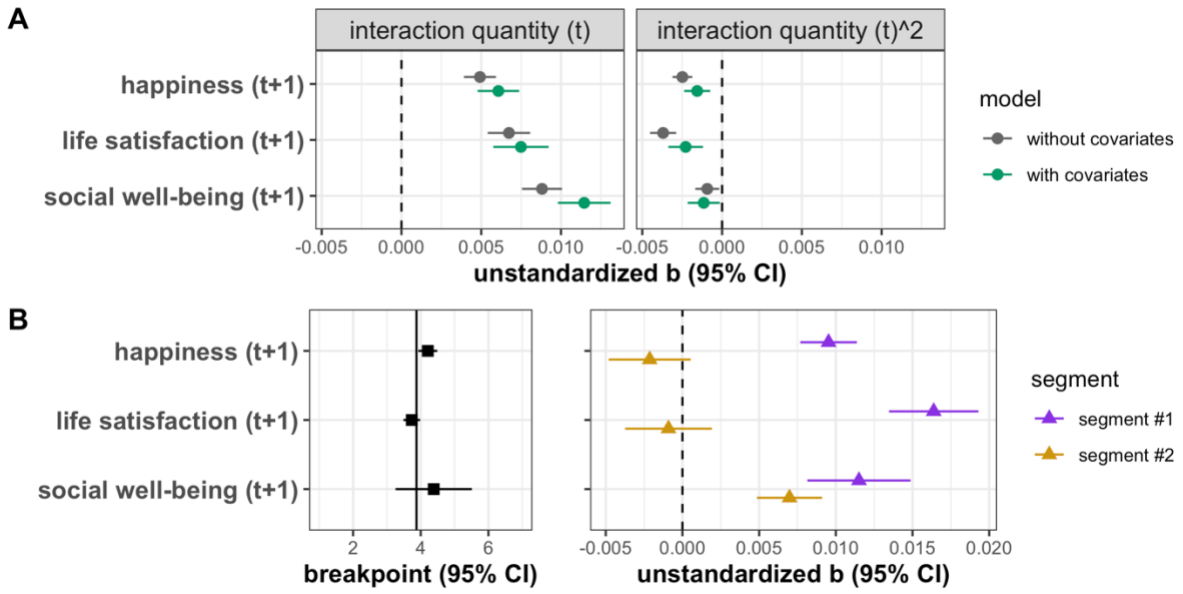
Quadratic models. To estimate the longitudinal effects of interaction quantity, in Model 1, we regressed each outcome at time *t+1* on the linear and quadratic terms of interaction quantity (mean-centered) at the previous time *t*, adjusting for the outcome at *t*, for

t = 1,…, 10. Each coefficient thus reflected a prospective or longitudinal effect of interaction quantity, that is, the effect of interaction quantity at time t on well-being at time t+1, adjusting for participants' well-being at time t. In Model 2, we further included the socio-demographic and economic control variables described above as covariates.

Results from both models revealed that, across all three outcome variables, interaction quantity at time t was indeed linearly associated with well-being at a later time $t+1$. Critically, the quadratic terms of interaction quantity at t were significant predictors of well-being at $t+1$, providing evidence of nonlinear effects. See Figure 12, Panel A.

Figure 12

Quadratic models (Panel A) and segmented models (Panel B) for each outcome variable (Study 6)



Note. 95% CI for all effects are plotted but may not be visible due to the small range relative to the size of the plotted point estimate. Breakpoints are plotted on the full range of interaction quantity (1= *never*, 2 = *about once a year*, 3 = *a number of times per year*, 4 = *about once a month*, 5 = *a few times per month*, 6 = *once or twice a week*, 7 = *almost every day*). The solid vertical line represents the sample mean.

Segmented models. For each of the three outcome variables, a breakpoint around "once a month" was detected: the first line segments had a positive slope, whereas the second line segment had a slope that was either of a smaller magnitude (social well-being), or statistically indistinguishable from zero (happiness and life satisfaction). See Figure 12, Panel B.

Discussion

Extending the results from previous studies in this report, our final study tested the nonlinear relation between interaction quantity and well-being assessed over an extensive period of time (i.e., 10 years): While increasing social contact frequency from "never" to "once a month" predicted greater well-being over time, further increases in contact beyond that point yielded either reduced or no additional benefits at all. These results provided additional support to the Diminishing Returns Hypothesis.

Exploring moderation by the Big Five traits

Across six studies, we have consistently shown that the effect of interaction quantity on well-being is nonlinear and follows the principle of diminishing returns. These analyses evaluated an average trend, but between-individual heterogeneity may exist in how social interactions shape their well-being. Is it possible the Diminishing Returns Hypothesis applies to some individuals while the Inverted U Hypothesis applies to others? And can the basic personality dimensions (e.g., Big Five) explain this variability? We explored these questions using the data from studies which included measures of the Big Five traits (i.e., Studies 1, 5, and 6; see Supplementary Materials for a full report of the analyses). We considered trait extraversion as the primary candidate moderator: people who score low in extraversion are less sociable, have a weaker desire for social attention, and may enjoy social interactions less than those who score high in extraversion (Srivastava et al., 2008; Wilt & Revelle, 2016), suggesting that less extraverted individuals may be more likely to experience reduced well-

being at high levels of interaction quantity (the Diminishing returns hypothesis). For completeness, we also explored other big five traits (i.e., agreeableness, conscientiousness, neuroticism, and openness) as potential moderators. Overall, we observed no evidence that any of the big five traits systematically moderated the nonlinear effect of interaction quantity on well-being outcomes. Importantly, the effect of interaction quantity followed a diminishing returns curve regardless of individual differences in the Big Five traits.

General Discussion

Social contact is considered to be one of the most important predictors of psychological well-being (e.g., Myers, 2000). However, is more social contact always better? While low (vs. moderate) quantity of social interactions has been consistently linked to poor well-being outcomes (e.g., Smith, 2006; Williams, 2009), it remains unclear whether increasing interaction quantity beyond a moderate level maintains a significant positive impact on well-being. Drawing on theories from psychology, philosophy, and economics, we proposed and tested two competing hypotheses regarding the nonlinear relation between interaction quantity and psychological well-being. The Diminishing Returns Hypothesis predicts that increasing interaction quantity beyond a moderate level has no or little well-being benefits; the Inverted U Hypothesis predicts that increasing interaction quantity beyond a moderate level will incur well-being costs. Across six studies, we obtained consistent evidence supporting the Diminishing Returns Hypothesis, demonstrating that the well-being benefits of social interactions are substantially reduced after a moderate amount of interactions are achieved.

The diminishing returns pattern was robust across a range of interaction quantity indicators (the frequency of social contact, the number of peers interacted with at school, the amount of time spent socializing, and the number of target groups interacted with), well-being indicators (e.g., happiness, life satisfaction, social well-being), samples (adults from

over 30 countries, middle school children), and methods (experimental, cross-national survey, daily diary, experience sampling, and longitudinal). Exploratory moderation analyses further established that the Diminishing Returns pattern holds regardless of individual variation on the Big Five traits.

Implications

Numerous existing studies have focused on the low end of the interaction quantity spectrum highlighting the negative impact on well-being outcomes due to the lack of social interactions. The current set of studies are among the first to systematically examine the effect of interaction quantity across the full spectrum from low to moderate to high. We consistently observed that increasing interaction quantity beyond a certain point had little to no impact on well-being. The present research thus suggests that interaction quantity has declining marginal utility for well-being and, more generally, supports the notion that the utility (well-being) one could derive from one single domain (e.g., social domain) of life can be limited (Sheldon & Niemiec, 2006).

Our work has novel contributions beyond extant theoretical frameworks. Although a nonlinear relation between interaction quantity and well-being may be inferred from several leading theories in psychology and related areas, most of these theories focus on other areas of research (e.g., consumption of a commodity, group inclusiveness) and therefore, are not directly appliable to the effects of social interactions. More importantly, the existing theories disagree about the shape of the nonlinear curve, with some supporting the principle of diminishing returns while others suggesting an inverted U effect. Here, we directly evaluated these two predictions, providing compelling evidence that moderate levels of interaction quantity are sufficient to make people happy and satisfied. Our studies further identified the locations of the breakpoints after which well-being benefits of social interactions fade,

showing novel results that help to quantify the minimal amount of social interactions people need.

More broadly, the current research contributes to an ongoing debate about the prevalence of the U-shaped effects in psychological research. The inverted-U-shaped effects have been theorized to be a general principle in various areas of human experience (Grant & Schwartz, 2011). While several studies support this notion (e.g., Eisenberg, 2000; Windsor et al., 2008), more recent evidence suggests the U-shaped effects are less prevalent than initially theorized. For example, some studies have failed to find support for such a nonlinear pattern with regard to the effects of several predictors of well-being including self-control (Wiese et al., 2018), conscientiousness (Nickel et al., 2019), and sexual frequency (Muise et al., 2016). Adding to this growing literature, the present research provides unique evidence that the inverted-U curve does not apply to another important predictor of well-being: the quantity of social interactions.

Finally, our findings may provide practical recommendations for organizations and policy makers interested in promoting well-being. Specifically, our research reveals that people do not need to have a great amount of social contact to achieve high levels of well-being. Therefore, policies that aimed at affording individuals with social contact opportunities should prioritize specific target groups whose existing levels of social contact are low. Target groups who are relatively socially active should be encouraged to allocate their time to other activities to further enhance well-being (Diener et al., 2008; Sirgy & Wu, 2009).

Limitations and future research

The current conclusions apply only to the levels of interaction quantity that are observable in natural settings. Across the non-experimental studies (Studies 2-6), the observed interaction quantity ranged from absolute solitude (i.e., no social interactions) to

socializing every day (Study 2), interacting with 23 peers at school in the past few weeks (Study 3), spending 24 hours with others in a 24-hour period (Study 4), interacting with three different groups of people in one hour (Study 5), and spending an evening socializing with others almost every day (Study 6; see Supplementary Materials for histograms of interaction quantity). It remains to be explored how higher levels of social interactions—beyond these upper bounds recorded in our studies—affect well-being. For example, a possible future study may build on our current Study 5 by having participants report the number of distinct social groups they have interacted with in a 24-hour period. Another possibility is to focus on holidays where people engage in a particularly high number of social interactions with several distinct groups (such as family, friends, romantic partners, religious organizations, charitable groups, among others).

Although the experimental design (Study 1) and longitudinal aspect (Study 6) of the current research can help to establish causality, most of our analyses are based on cross-sectional data. A laboratory experiment that manipulates interaction quantity in vivo would strengthen causal inference; however, we have several reservations about using this method to answer our research question. The first issue is feasibility. It is unfeasible to manipulate most of the indicators of interaction quantity we used in our studies (e.g., social contact frequency, hours spent socializing, number of social ties) in a lab setting. The second issue is ecological validity. Consider the following thought experiment, in which participants are randomly assigned to interact with a varying number of groups (e.g., 0, 2, 4, 6) during a one-hour long lab session. Social interactions in this study would be a result of experimenter's instructions (which is rarely the case in real life); participants would interact with partners they would not have met before, nor expected to meet again; the duration of these interactions would be limited to the duration of a lab session (e.g., one hour); researchers may run the risk of creating an artificially high level of interaction quantity (e.g., interacting with

six different groups in one hour) that does not occur in real life. In brief, we believe that manipulating participants' interaction quantity in a lab setting falls short of providing insights to our research question. We look forward to future development of innovative experimental manipulations and designs that would be suitable for testing the effect of interaction quantity on psychological well-being in a naturalistic environment. A promising direction is randomly assigning participants to maintain either a low, a moderate, or a high frequency of social contact over several weeks (see Jacques-Hamilton et al., 2018 for an example).

Future research is needed to understand the underlying mechanisms of the nonlinear effect of interaction quantity on well-being. We posit that there are both benefits (e.g., interactions increase a sense of belonging; Baumeister & Leary, 1995) and costs (e.g., providing emotional support can be psychological taxing; Cichy et al., 2014) associated with social interactions. At the low end of the interaction quantity spectrum, the costs are outweighed by the benefits, yielding a positive effect of interaction quantity on well-being. Yet, as interaction quantity increases, the benefits of any additional interactions diminish, whereas the costs of any additional interactions escalate (Grant & Schwartz, 2011). As such, beyond moderate quantities of social interactions, the costs and the benefits cancel each other out, and social interactions no longer further promote well-being. Why does the curve stay flat but does not turn negative? We put forward two possible explanations. One explanation is that the benefits associated with social interactions carry more weight in determining people's overall well-being than the associated costs. As evolutionary theories have suggested, people are motivated by multiple biologically significant goals (Kenrick, Griskevicius, et al., 2010; Kenrick, Neuberg, et al., 2010). Several of these goals, including affiliation, mate acquisition, and parenting, cannot be achieved without social interactions. In contrast, the costs associated with interactions (e.g., psychological taxing, little time alone; Cichy et al., 2014; Coplan et al., 2019) are unrelated to evolutionarily fundamental needs, and

therefore unlikely to negate or override the benefits. Another explanation is that while well-being may potentially turn negative at extremely high levels of interaction quantity, people can preemptively avoid such deteriorations by downregulating interaction quantity where possible. Compared to interaction upregulation (e.g., initiating interactions and establishing new connections in consent with others), interaction downregulation (e.g., foregoing interaction opportunities) is arguably less effortful, and more controllable (i.e., relying less on mutual agreement between interaction parties).

The present research focused on the quantity of social interactions. Future work may consider taking into account other attributes of social interactions that may affect well-being, such as the quantity of social interactions one may wish to have, the type of social relationship (e.g., friends, family, coworkers), and the quality of social interactions. Moreover, it remains an open question whether a nonlinear pattern applies to other aspects of social experience, such as the amount of "likes" received on social media (Wolf et al., 2015) and the number of group memberships (Iyer et al, 2009; Jetten et al., 2015).

Finally, we have shown that one does not need to maximize interaction quantity to be happy. But do people have an accurate understanding of this? Are people seeking more social contact than what they need in daily life? To answer these questions, it is important to examine people's lay beliefs about the effect of interaction quantity across its spectrum, and to what extent these lay beliefs are accurate. Given the social norm to be socially engaged and the stigma associated with solitary behaviors (Kerr & Levine, 2008; Rubin et al., 1991), people may hold inaccurate beliefs, assuming they have to be highly socially active to maximize their well-being. Assessing and dispelling these misguided beliefs could be a useful strategy for enhancing well-being.

Conclusion

Social contact promotes well-being. However, is more social contact necessarily better? To answer this question, the current research explored the effect of interaction quantity on well-being across the full spectrum from complete solitude to extreme interaction quantity. Across six studies using diverse methods, measures, and samples, we obtained compelling evidence supporting the diminishing marginal utility of interaction quantity on well-being: increasing interaction quantity is associated with higher well-being only up to a certain point; increasing interaction quantity beyond that point has a reduced or nearly negligible impact on well-being.

References

Argyle, M. (2001). The psychology of happiness. New York: Taylor & Francis.

Aristotle. (trans. 1999). *Nicomachean ethics (W.D. Ross, Trans.)*. Kitchener, Ontario, Canada: Batoche Books.

Ashforth, B. E., & Johnson, S. A. (2001). Which hat to wear? The relative salience of multiple identities in organizational contexts. In M. A. Hogg & D. J. Terry (Eds.), Social identity processes in organizational contexts (pp. 31–48). Philadelphia, PA: Psychology Press.

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2014). lme4: Linear mixed-effects models using Eigen and S4. https://cran.r-project.org/package=lme4

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117,* 497–529.

Bernstein, M. J., Claypool, H. M., Young, S. G., Tuscherer, T., Sacco, D. F., & Brown, C. M. (2013). Never let them see you cry: Self-presentation as a moderator of the relationship between exclusion and self-esteem. *Personality and Social Psychology Bulletin, 39,* 1293-1305.

Bollen, K. A., & Bauldry, S. (2011). Three Cs in measurement models: Causal indicators, composite indicators, and covariates. *Psychological Methods*, *16*, 265.

Brewer, M. B. (1991). The social self: On being the same and different at the same time. *Personality and Social Psychology Bulletin, 17,* 475-482.

Brook, A. T., Garcia, J., & Fleming, M. A. (2008). The effects of multiple identities on psychological well-being. *Personality and Social Psychology Bulletin, 34,* 1588-1600.

Cacioppo, J. T., & Patrick, W. (2008). Loneliness: Human nature and the need for social connection. WW Norton & Company.

Cacioppo, J. T., Hawkley, L. C., Ernst, J. M., Burleson, M., Berntson, G. G., Nouriani, B., & Spiegel, D. (2006). Loneliness within a nomological net: An evolutionary perspective. *Journal of Research in Personality, 40*, 1054-1085.

Cacioppo, J. T., Hughes, M. E., Waite, L. J., Hawkley, L. C., & Thisted, R. A. (2006). Loneliness as a specific risk factor for depressive symptoms: cross-sectional and longitudinal analyses. *Psychology and Aging, 21*, 140.

Cichy, K. E., Stawski, R. S., & Almeida, D. M. (2014). A double-edged sword: Race, daily family support exchanges, and daily well-being. *Journal of Family Issues, 35,* 1824-1845.

Clark, L. A., & Watson, D. (1988). Mood and the mundane: Relations between daily life events and self-reported mood. *Journal of Personality and Social Psychology, 54*, 296.

Coplan, R. J., Hipson, W. E., Archbell, K. A., Ooi, L. L., Baldwin, D., & Bowker, J. C. (2019). Seeking more solitude: Conceptualization, assessment, and implications of aloneliness. *Personality and Individual Differences, 148*, 17-26.

DeWall, C. N., Twenge, J. M., Bushman, B., Im, C., & Williams, K. (2010). A little acceptance goes a long way: Applying social impact theory to the rejection-aggression link. *Social Psychological and Personality Science, 1,* 168-174.

Diener, E. D., Emmons, R. A., Larsen, R. J., & Griffin, S. (1985). The satisfaction with life scale. *Journal of Personality Assessment, 49,* 71-75.

Diener, E., & Seligman, M. E. (2002). Very happy people. *Psychological Science, 13,* 81-84.

Diener, E., Ng, W., & Tov, W. (2008). Balance in life and declining marginal utility of diverse resources. *Applied Research in Quality of Life, 3,* 277-291.

Eisenberg, N. (2000). Emotion, regulation, and moral development. *Annual Review of Psychology, 51,* 665-697.

Eisenberger, N. I., Lieberman, M. D., & Williams, K. D. (2003). Does rejection hurt? An fMRI study of social exclusion. *Science*, *302*, 290-292.

Eisinga, R., Te Grotenhuis, M., & Pelzer, B. (2013). The reliability of a two-item scale: Pearson, Cronbach, or Spearman-Brown?. *International Journal of Public Health*, *58*, 637-642.

Epley, N., & Schroeder, J. (2014). Mistakenly seeking solitude. *Journal of Experimental Psychology: General*, *143*, 1980-1999.

ESS. (2018). European Social Survey Cumulative File, ESS 1-8 (2018). Data file edition 1.0. NSD - Norwegian Centre for Research Data, Norway - Data Archive and distributor of ESS data for ESS ERIC.

Gaertner, L., & Iuzzini, J. (2005). Rejection and entitativity: A synergistic model of mass violence. In K. D. Williams, J. P. Forgas, W. von Hippel (Eds.), *The social outcast: Ostracism, social exclusion, rejection, and bullying* (pp. 307-320). New York, NY: Psychology Press.

Gosling, S. D., Rentfrow, P. J., & Swann Jr, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, *37*, 504-528.

Gossen, H. H. (1854/1983). The laws of human relations and the rules of human action derived therefrom. Cambridge, MA: MIT Press.

Grant, A. M., & Schwartz, B. (2011). Too much of a good thing the challenge and opportunity of the inverted U. *Perspectives on Psychological Science*, *6*, 61-76.

Green, P., & MacLeod, C. J. (2016). SIMR: an R package for power analysis of generalized linear mixed models by simulation. *Methods in Ecology and Evolution*, *7*, 493-498.

Gula, B., Vaci, N., Alexandrowicz, R. W., & Bilalić, M. (2021). Never too much—The benefit of talent to team performance in the National Basketball Association:

Comment on Swaab, Schaerer, Anicich, Ronay, and Galinsky (2014). *Psychological Science, 32,* 301-304.

Hawkley, L. C., & Cacioppo, J. T. (2010). Loneliness matters: A theoretical and empirical review of consequences and mechanisms. *Annals of Behavioral Medicine*, *40,* 218-227.

Iyer, A., Jetten, J., Tsivrikos, D., Postmes, T., & Haslam, S. A. (2009). The more (and the more compatible) the merrier: Multiple group memberships and identity compatibility as predictors of adjustment after life transitions. *British Journal of Social Psychology*, *48,* 707-733.

Iyer, A., Jetten, J., Tsivrikos, D., Postmes, T., & Haslam, S. A. (2009). The more (and the more compatible) the merrier: Multiple group memberships and identity compatibility as predictors of adjustment after life transitions. *British Journal of Social Psychology*, *48,* 707-733.

Jacques-Hamilton, R., Sun, J., & Smillie, L. D. (2019). Costs and benefits of acting extraverted: A randomized controlled trial. *Journal of Experimental Psychology: General*, *148,* 1538-1556.

Jetten, J., Branscombe, N. R., Haslam, S. A., Haslam, C., Cruwys, T., Jones, J. M., ... & Thai, A. (2015). Having a lot of a good thing: Multiple important group memberships as a source of self-esteem. *PloS one*, *10,* e0124609.

John, O. P., & Srivastava, S. (1999). The Big Five trait taxonomy: History, measurement, and theoretical perspectives. Handbook of Personality: Theory and Research, 2, 102-138.

Jordan, K. N., Sterling, J., Pennebaker, J. W., & Boyd, R. L. (2019). Examining long-term trends in politics and culture through language of political leaders and cultural institutions. *Proceedings of the National Academy of Sciences*, *116,* 3476-3481.

Kahneman, D., Krueger, A. B., Schkade, D. A., Schwarz, N., & Stone, A. A. (2004). A survey method for characterizing daily life experience: The day reconstruction method. *Science, 306,* 1776-1780.

Kenrick, D. T., Griskevicius, V., Neuberg, S. L., & Schaller, M. (2010). Renovating the pyramid of needs: Contemporary extensions built upon ancient foundations. *Perspectives on Psychological Science, 5,* 292–314.

Kenrick, D. T., Neuberg, S. L., Griskevicius, V., Becker, D., & Schaller, M. (2010). Goal-driven cognition and functional behavior: The fundamental-motives framework. *Current Directions in Psychological Science, 19,* 63–67.

Kerr, N. L., & Levine, J. M. (2008). The detection of social exclusion: Evolution and beyond. Group Dynamics: Theory, Research, and Practice, 12, 39–52

Keyes, C. L. M. (1998). Social well-being. *Social Psychology Quarterly*, 121-140.

Kushlev, K., Heintzelman, S. J., Oishi, S., & Diener, E. (2018). The declining marginal utility of social time for subjective well-being. *Journal of Research in Personality, 74*, 124-140.

Kuznetsova, A., Brockhoff, P. B., & Christensen, R. H. B. (2015). lmerTest: Tests for random and fixed effects for linear mixed effect models (lmer objects of lme4 package). https://cran.r-project.org/package=lmerTest

Larson, J. S. (1996). The World Health Organization's definition of health: Social versus spiritual health. *Social Indicators Research, 38,* 181-192.

Larson, R. W. (1990). The solitary side of life: An examination of the time people spend alone from childhood to old age. *Developmental Review*, *10,* 155-183.

Latané, B. (1981). The psychology of social impact. *American psychologist, 36,* 343–356.

Leonardelli, G. J., Pickett, C. L., & Brewer, M. B. (2010). Optimal distinctiveness theory: A framework for social identity, social cognition, and intergroup relations. In Advances in experimental social psychology (Vol. 43, pp. 63-113). Academic Press.

Long, C. R., Seburn, M., Averill, J. R., & More, T. A. (2003). Solitude experiences: Varieties, settings, and individual differences. *Personality and Social Psychology Bulletin*, *29*, 578-583.

Lucas, R. E., & Dyrenforth, P. S. (2006). Does the existence of social relationships matter for subjective well-being? In K. D. Vohs & E. J. Finkel (Eds.), Self and Relationships: Connecting Intrapersonal and Interpersonal Processes (pp. 254–273). New York, NY: Guilford Press

Lucas, R. E., Dyrenforth, P. S., & Diener, E. (2008). Four myths about subjective well-being. *Social and Personality Psychology Compass, 2*, 2001-2015.

Lucas, R. E., Le, K., & Dyrenforth, P. S. (2008). Explaining the extraversion/positive affect relation: Sociability cannot account for extraverts' greater happiness. *Journal of Personality, 76*, 385-414.

Luhmann, M., & Hawkley, L. C. (2016). Age differences in loneliness from late adolescence to oldest old age. *Developmental Psychology*, *52*, 943.

Mehl, M. R., Vazire, S., Holleran, S. E., & Clark, C. S. (2010). Eavesdropping on happiness: Well-being is related to having less small talk and more substantive conversations. *Psychological Science, 21*, 539-541.

Milek, A., Butler, E. A., Tackman, A. M., Kaplan, D. M., Raison, C. L., Sbarra, D. A., ... & Mehl, M. R. (2018). “Eavesdropping on Happiness” Revisited: A Pooled, Multisample Replication of the Association Between Life Satisfaction and Observed Daily Conversation Quantity and Quality. *Psychological Science*, *29*, 1451-1462.

Muggeo, V. M. (2008). Segmented: an R package to fit regression models with broken-line relationships. *R news*, *8*, 20-25.

Muggeo, V. M., Atkins, D. C., Gallop, R. J., & Dimidjian, S. (2014). Segmented mixed models with random changepoints: a maximum likelihood approach with application to treatment for depression study. *Statistical Modelling*, *14*, 293-313.

Muise, A., Schimmack, U., & Impett, E. A. (2016). Sexual frequency predicts greater well-being, but more is not always better. *Social Psychological and Personality Science*, *7*, 295-302.

Myers, D. G. (2000). The funds, friends, and faith of happy people. *American Psychologist*, *55*, 56.

Nguyen, T. V. T., Ryan, R. M., & Deci, E. L. (2018). Solitude as an approach to affective self-regulation. *Personality and Social Psychology Bulletin*, *44*, 92-106.

Nickel, L. B., Roberts, B. W., & Chernyshenko, O. S. (2019). No evidence of a curvilinear relation between conscientiousness and relationship, work, and health outcomes. *Journal of Personality and Social Psychology*, *116*, 296–312.

Nook, E. C., Sasse, S. F., Lambert, H. K., McLaughlin, K. A., & Somerville, L. H. (2018). The nonlinear development of emotion differentiation: Granular emotional experience is low in adolescence. *Psychological Science*, *29*, 1346-1357.

Paluck, E. L., Shepherd, H. R., & Aronow, P. (2019). Changing climates of conflict: A social network experiment in 56 schools, New Jersey, 2012-2013. Inter-university Consortium for Political and Social Research [distributor].

Paluck, E. L., Shepherd, H., & Aronow, P. M. (2016). Changing climates of conflict: A social network experiment in 56 schools. *Proceedings of the National Academy of Sciences*, *113*, 566–571.

1138 Pinheiro, J., Bates, D., DebRoy, S., Sarkar, D., & Team, R. C. (2013). nlme: Linear and
1139 nonlinear mixed effects models. *R package version, 3*, 111.
1140 R Core Team (2020). R: A language and environment for statistical computing. R Foundation
1141 for Statistical Computing, Vienna, Austria. URL https://www.R-project.org/.
1142 Ren, D., Wesselmann, E. D., & van Beest, I. (2021). Seeking Solitude After Being
1143 Ostracized: A Replication and Beyond. *Personality and Social Psychology Bulletin,*
1144 47, 426-440.
1145 Reutskaja, E., & Hogarth, R. M. (2009). Satisfaction in choice as a function of the number of
1146 alternatives: When "goods satiate". *Psychology & Marketing, 26*, 197-203.
1147 Riva, P., Montali, L., Wirth, J. H., Curioni, S., & Williams, K. D. (2017). Chronic social
1148 exclusion and evidence for the resignation stage: An empirical investigation. *Journal*
1149 *of Social and Personal Relationships, 34*, 541-564.
1150 Rohrer, J. M., Richter, D., Brümmer, M., Wagner, G. G., & Schmukle, S. C. (2018).
1151 Successfully striving for happiness: Socially engaged pursuits predict increases in life
1152 satisfaction. *Psychological Science, 29*, 1291-1298.
1153 Rubin, K. H., Hymel, S., Mills, R. S. L., & Rose-Krasnor, L. (1991). Conceptualizing
1154 different developmental pathways to and from social isolation in childhood. In D.
1155 Cicchetti & S. Toth (Eds.), The Rochester symposium on developmental
1156 psychopathology, Vol. 2. Internalizing and externalizing expressions of dysfunction
1157 (pp. 91–122). Cambridge University Press.
1158 Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic
1159 motivation, social development, and well-being. *American Psychologist, 55*, 68.
1160 Sandstrom, G. M., & Dunn, E. W. (2014). Social interactions and well-being: The surprising
1161 power of weak ties. *Personality and Social Psychology Bulletin, 40,* 910–922.

Sheldon, K. M., & Niemiec, C. P. (2006). It's not just the amount that counts: Balanced need satisfaction also affects well-being. *Journal of Personality and Social Psychology, 91*, 331.

Simonsohn, U. (2018). Two lines: A valid alternative to the invalid testing of U-shaped relationships with quadratic regressions. *Advances in Methods and Practices in Psychological Science, 1,* 538-555.

Sirgy, M. J., & Wu, J. (2009). The pleasant life, the engaged life, and the meaningful life: What about the balanced life?. *Journal of Happiness Studies, 10,* 183-196.

Smith, P. S. (2006). The effects of solitary confinement on prison inmates: A brief history and review of the literature. *Crime and Justice*, *34,* 441-528.

Srivastava, S., Angelo, K. M., & Vallereux, S. R. (2008). Extraversion and positive affect: A day reconstruction study of person–environment transactions. *Journal of Research in Personality, 42,* 1613-1618.

Stavrova, O., & Ren, D. (2020). Is More Always Better? Examining the Nonlinear Association of Social Contact Frequency With Physical Health and Longevity. *Social Psychological and Personality Science,* 1948550620961589.

Sun, J., Harris, K., & Vazire, S. (2019). Is well-being associated with the quantity and quality of social interactions?. *Journal of Personality and Social Psychology*.

Tilvis, R. S., Kähönen-Väre, M. H., Jolkkonen, J., Valvanne, J., Pitkala, K. H., & Strandberg, T. E. (2004). Predictors of cognitive decline and mortality of aged people over a 10-year period. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *59*, 268-274.

Twenge, J. M., Baumeister, R. F., Tice, D. M., & Stucke, T. S. (2001). If you can't join them, beat them: Effects of social exclusion on aggressive behavior. *Journal of Personality and Social Psychology, 81*, 1058.

Twenge, J. M., Catanese, K. R., & Baumeister, R. F. (2003). Social exclusion and the deconstructed state: time perception, meaninglessness, lethargy, lack of emotion, and self-awareness. *Journal of Personality and Social Psychology, 85*, 409.

Umberson, D., & Karas Montez, J. (2010). Social relationships and health: A flashpoint for health policy. *Journal of Health and Social Behavior, 51,* S54-S66.

Van Beest, I., & Williams, K. D. (2006). When inclusion costs and ostracism pays, ostracism still hurts. *Journal of Personality and Social Psychology, 91*, 918-928.

Vergauwe, J., Wille, B., Hofmans, J., Kaiser, R. B., & De Fruyt, F. (2018). The double-edged sword of leader charisma: Understanding the curvilinear relationship between charismatic personality and leader effectiveness. *Journal of Personality and Social Psychology, 114*, 110.

Warburton, W. A., Williams, K. D., & Cairns, D. R. (2006). When ostracism leads to aggression: The moderating effects of control deprivation. *Journal of Experimental Social Psychology, 42*, 213-220.

Watson, D., Clark, L. A., McIntyre, C. W., & Hamaker, S. (1992). Affect, personality, and social activity. *Journal of Personality and Social Psychology, 63*, 1011.

Wiese, C. W., Tay, L., Duckworth, A. L., D'Mello, S., Kuykendall, L., Hofmann, W., ... & Vohs, K. D. (2018). Too much of a good thing? Exploring the inverted-U relationship between self-control and happiness. *Journal of Personality, 86*, 380-396.

Williams, K. D. (2009). Ostracism: A Temporal Need-Threat Model. *Advances in Experimental Social Psychology, 41*, 275-314.

Williams, K. D., Cheung, C. K., & Choi, W. (2000). Cyberostracism: Effects of being ignored over the Internet. *Journal of Personality and Social Psychology, 79*, 748-762.

Wilt, J., & Revelle, W. R. (2016). Extraversion. In The Oxford handbook of the five factor model. Oxford Univeristy Press.

Windsor, T. D., Anstey, K. J., & Rodgers, B. (2008). Volunteering and psychological well-being among young-old adults: How much is too much? *The Gerontologist, 48,* 59-70.

Wolf, W., Levordashka, A., Ruff, J. R., Kraaijeveld, S., Lueckmann, J. M., & Williams, K. D. (2015). Ostracism Online: A social media ostracism paradigm. *Behavior Research Methods, 47,* 361-373.

Zmigrod, L., Rentfrow, P. J., & Robbins, T. W. (2020). The partisan mind: Is extreme political partisanship related to cognitive inflexibility?. *Journal of Experimental Psychology: General, 149,* 407.