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The declining marginal utility of social time for subjective well-being

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ABSTRACT

Are people who spend more time with others always happier than those who spend less time in social activities? Across four studies with more than 250,000 participants, we show that social time has declining marginal utility for subjective well-being. In Study 1 (N = 243,075), we use the Gallup World Poll with people from 166 countries, and in Study 2 (N = 10,387) the American Time Use Survey (ATUS), to show that social time has declining returns for well-being. In Study 3a (N = 168) and Study 3b (N = 174), we employ the Experience Sampling Method (ESM) to provide initial evidence for both intra-domain (principle of diminishing satisfaction) and inter-domain mechanisms (principle of satisfaction limits). We discuss implications for theory, research methodology, and practice.

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1. Introduction

"Virtue is the golden mean between two extremes."

[*Aristotle*]

If one were to find the key to happiness, what would they discover behind the door that it opens? Mounds of gold? A handsome prince? Acceptance with no revisions in a top journal? Although money, love, and professional success would undoubtedly contribute to happiness, decades of research suggests that the key to happiness would first and foremost unlock a door that leads to a rich social life (Epley & Schroeder, 2014; Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004; Reis, Sheldon, Gable, Roscoe, & Ryan, 2000; Sandstrom & Dunn, 2014). Indeed, research has shown that our social activities and relationships are a necessary component of a happy life (Diener & Seligman, 2002). So consistent is the evidence for the role of social relationships in happiness that it is now taken as an established fact in the psychological literature—the more time we spend socializing, the greater our happiness. But if Aristotle was right, true happiness lies in the "golden mean" between deficiency and excess. Has modern psychological science found an exception to the wisdom of Aristotle, or can people get too much even when it comes to this key factor in promoting happiness?

When it comes to sources of subjective well-being, Aristotle is far from the only one to suggest that more doesn't always equal better. The economic *law of diminishing marginal utility*, for example, states the there is a decline in the value derived from consuming additional units of a particular commodity (Gossen, 1854/1983). Importantly, this principle has been shown to function with regards to the utility of money for subjective well-being (e.g., Veenhoven, 1991): Although an increase from $10,000 to $20,000 in income has a significant impact on subjective well-being, the same increase from $140,000 to $150,000 has little or no effect (Diener & Biswas-Diener, 2002; Kahneman & Deaton, 2010). A rich social life, however, is a much stronger predictor of subjective well-being than a big bank account (for reviews, see Diener, 2000; Diener et al., 2017). We set out to explore whether even one of the most important factors of a happy life, time spent in social activities or *social time*, is characterized by a declining marginal utility for subjective well-being.

1.1. Existing empirical evidence

Only one examination of declining marginal utility of time spent socializing for subjective well-being has been published to date (Diener, Ng, & Tov, 2008). In the first of two studies, participants were asked to imagine that they would live 90 years and then to report how many years of their lives they would give up to spend various fixed amounts of social time each day. To spend two hours a day socializing, people were willing to forgo almost

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22 years of their lives; that is, to die at 68. But to spend 8 h a day socializing, the same individuals were willing to give up fewer (18.9) years of their lives. In a second study, the researchers utilized data from one wave of the Gallup World Poll (2005–2006) to examine the relationship between affect and the time a person spends with his or her family and friends in a day. They found that those spending no time with family and friends felt substantially worse than those spending between 1 and 16 h a day; spending more than 16 h a day with family and friends, however, did not predict further increases in well-being.

The above studies provide some initial evidence for the declining marginal utility of time spent with family and friends for subjective well-being. This work, however, is limited in several ways. First, this research operationalizes social life narrowly as time spent with family and friends, leaving a host of features of one's social life untested (e.g., actively socializing with friends). Even if the total time spent with family is characterized by a declining marginal utility for subjective well-being, socializing with friends might still be a robust linear predictor. Second, the researchers utilized arbitrary categories (rather than continuous measures) of time. Third, this work did not empirically test any mechanisms to explain the observed declining marginal utility. Finally, while this research utilizes an impressively large sample, the small effects have yet to be replicated in other samples.

1.2. Theory and mechanisms

Although past research on the declining marginal utility of our social lives is limited in quantity and scope, relevant theoretical accounts suggest that people might indeed reap progressively less happiness from more social time. Due to adaptation effects (Helson, 1964), the utility of a particular activity for subjective well-being diminishes as people repeatedly engage in this activity (e.g., Lyubomirsky & Layous, 2013; Lyubomirsky, Sheldon, & Schkade, 2005; Quoidbach & Dunn, 2013; Sheldon, Boehm, & Lyubomirsky, 2013). Spending increasingly more time socializing should thus have progressively smaller additional benefits for subjective well-being. We refer to this mechanism as *the principle of diminishing satisfaction* (c.f., Sirgy, 2010, 2012; Sirgy & Lee, 2018; Sirgy & Wu, 2009). Specifically, this principle suggests that any diminishing returns of social activities for well-being should be mediated by diminishing returns of social activities for intra-domain predictors of well-being. A key predictor of subjective well-being in the context of social life is the satisfaction of social needs, such as relatedness and belonging (e.g., Baumeister & Leary, 1995; Cacioppo et al., 2006; Myers & Diener, 1995; Ryan & Deci, 2000; Sheldon, Elliot, Kim, & Kasser, 2001). Thus, social need satisfaction should mediate a declining marginal utility effect of social time on well-being.

The principle of diminishing satisfaction describes a possible *intra*-domain mechanism for a declining marginal utility effect of social time on well-being. The *principle of satisfaction limits* (Sirgy & Lee, 2018) offers another, *inter*-domain mechanism. According to the *bottom-up spillover model* of life satisfaction (e.g., Andrews & Withey, 1976; Campbell, Converse, & Rodgers, 1976), general satisfaction with life is determined by how satisfied people are with various life domains, including their social lives, but also their work lives, spiritual activities, and so forth. Critically, Sirgy and Wu (2009) proposed that the contribution of a single life domain to overall subjective well-being is limited (see also, Frisch, 2005; Sirgy & Lee, 2018). If Jane, for example, spends a lot of time with her friends, she might be extremely satisfied with her abundant social life. But she might still be less satisfied with her life overall than Jack who invests less in his social life than Jane but strives for more of a balance—distributing his energy in advancing his career, engaging in his beloved hobbies, and continuing his meditation practice, as well. Indeed, people who distribute their time more evenly across multiple life domains (e.g., work, socializing) are generally happier than those focusing on only a few life domains (e.g., Eakman, 2016; Hsieh, 2003; Rojas, 2006; Sirgy & Lee, 2018). Relevant theory and research on work-life balance also speaks to the negative consequences for well-being of such role conflict due to an overinvestment in a single life domain (Fu & Shaffer, 2001; Greenhaus & Beutell, 1985; Holahan & Gilbert, 1979; Kalliath & Brough, 2008; Netemeyre, Boles, & McMurrian, 1996; Sirgy & Lee, 2018; Sturges & Guest, 2004; Voydanoff, 2005). According to the principle of satisfaction limits, then, we can predict that the relationship between social need satisfaction and overall well-being should depend on social time—with a weakening contribution of social needs for general well-being at very high levels of need satisfaction.

In sum, the principle of diminishing satisfaction suggests diminishing benefits of social time for social needs satisfaction, pointing to a mediational role of social needs in a diminishing utility of social time. The principle of satisfaction limits points to a separate mechanism, that is a moderational role of social time in the relationship between social need satisfaction and well-being. Notably, these mechanisms are not mutually exclusive and can operate in tandem.

1.3. The present research

1.3.1. Studies overview

The present research provides an extensive examination of the economic law of declining marginal utility in the context of social activity—one of the strongest and most well-established factors in promoting subjective well-being. Across four studies, we examine this central question by employing a variety of methods and samples: an international survey (Study 1; $N = 243{,}075$) and a U.S. survey (Study 2; $N = 10{,}387$) with large, representative samples, and two intensive experience sampling studies with university undergraduates (Study 3a, $N = 168$; Study 3b, $N = 174$).

Each of the present studies employs a unique methodological strategy, providing a robust test of curvilinearity in the relationship between social time and subjective well-being. In Study 1, we examine the relationship between social time and subjective well-being during a single day in people's lives. In Study 2, we use a different measure of daily social time obtained through the Day Reconstruction Method (DRM; Krueger et al., 2009). In Studies 3a and 3b, we employ the Experience Sampling Method (ESM; Larson & Csikszentmihalyi, 1983), polling participants five times a day over one week, while measuring social need satisfaction to explore the role of the proposed mechanisms. In Study 3a, we test the principle of diminishing satisfaction by examining the mediational role of social need satisfaction in the relationship between social time and episodic emotional well-being. In Study 3b, we additionally include validated measures of overall well-being—life satisfaction and general positive affect—enabling us to explore the role of the principle of satisfaction limits.

1.3.2. Analytic strategy

We tested for the presence of curvilinear relationships between social time and well-being using a multi-pronged statistical approach. First, in a stepwise approach, we predicted the well-being outcomes from social time (linear effect), and then added its orthogonal squared term (curvilinear effect). Because this statistical approach is sensitive to outliers, we systematically explored whether the form of the curved relationship is robust to respecification of the model after excluding the most influential observations (if any). Details of these additional analyses, as well as tests of model assumptions, are provided at RPubs: http://rpubs.com/KKushlevPhD.

Table 1
Between-Country (Below Diagonal) and Within-Country (Above Diagonal) Correlations (Study 1).

M(SD)	Social Time 5.34(4.88)	Social Time Squared	Soc. Time Squared (semi-partial)	Life Evaluation 5.40(2.18)	Positive Experience 0.70(0.27)
Social Time		0.69***	0.00	0.05***	0.11***
Soc. Time Squared	0.04		0.72***	0.03***	0.06***
Soc. Time Squared (semi-partial)	0.00	0.999***		−0.05***	−0.11***
Life Evaluation	0.38***	−0.14	−0.16†		0.22***
Positive Experience	0.21*	0.02	0.01	0.56***	

Note. Social Time is operationalized as the amount of time spent with others in a 24-h period. *Soc. Time Sqr. (semi-partial)* represents the independent variance of *Social Time Squared* from *Social Time*; the correlations of *Soc. Time Sqr. (semi-partial),* thus estimates the curvilinear effect. Correlations were decomposed using methodology by Pedhazur (1997), whereby within-country correlations are calculated using each person's deviation score from their country's mean score on social time.
† $p < .10$.
* $p < .05$.
*** $p < .001$.

Table 2
Between-subjects correlations (Study 2).

M(SD)	Social Time 42.22 (88.63)	Social Time Squared	Social Time Squared (orthogonal)	Happy 4.42 (1.30)
Social Time	1			
Social Time Squared	0.81***	1		
Social Time Squared (orthogonal)	0.00	0.58***	1	
Happy	0.07***	0.04***	−0.03***	1

*** $p < .001$.

Table 3
Between-subjects (below diagonal) and within-subjects (above diagonal) correlations (Study 3).

M(SD)	Social Time 0.38 (0.21)	Social Time Squared	Social Time Sqr. (orthogonal)	Mood 4.81 (0.85)	Relatedness 4.39 (0.72)	Relatedness w/Socializing 5.47 (0.89)
Social Time		0.38***	0.00	0.28***	0.53***	–
Social Time Squared	0.10		0.93***	0.08***	0.13***	–
Social Time Squared (orthogonal)	0.00	0.995***		−0.02	−0.07***	–
Mood	0.40***	−0.22***	−0.26***		0.51***	0.59***
Relatedness	0.46***	−0.10	−0.14*	0.71***		–
Relatedness While Socializing	0.16*	−0.16*	−0.18*	0.67***	0.63***	

Note. Social Time (between-subjects) is operationalized as the proportion of episodes spent socializing out of the total number of episodes for each participant. Pairwise deletion was applied. *Social Time* (within-subjects) is the person-mean centered occurrence of social episodes; thus, each person's socializing episodes are represented as a deviation from their own mean. *Social Time Squared. (semi-partial)* represents the independent variance of *Social Time Squared* from *Social Time*; the correlations of *Soc. Time Squared. (semi-partial)* thus represent the curvilinear effect. Correlations were decomposed using methodology by Pedhazur (1997).
* $p < .05$.
*** $p < .001$.

The above, classic statistical approach to curvilinearity allows us to model the quadratic relationship as a smooth curve. A different method of modeling curvilinear relationships is through segmented lines; that is, by estimating one or more piecewise linear relationships representing the different relationships between predictor and outcome within different ranges of the predictor (Bacon & Watts, 1971; Bates & Watts, 1988; Muggeo, 2003). In such *piecewise regression*, the lines representing the different relationships intersect at points, called breakpoints or bends. Thus, this piecewise approach allows us to establish at what point, if any, spending more time in social activities is no longer positively associated with subjective well-being. Indeed, these breakpoints are particularly relevant to our goal to explore the declining marginal utility of social time for well-being. In addition to providing a test of a declining marginal utility effect, this piecewise approach allows us to provide an estimate of the practical significance of any curvilinearity (i.e., the number/percentage of people that score beyond the breakpoint).

In order to estimate the piecewise relationships, we employ a nonparametric machine-learning technique: Multiple-Adaptive Regression Splines, or MARS (Friedman, 1991). Unlike parametric piecemeal regression models, where the number of curves/breakpoints is user-specified, MARS effectively 'adapts' to the data in order to model the specified relationship as a series of segmented lines that best fits the data. Specifically, MARS determines the optimal combination of predictors—or in our case, the optimal number of segments of a single predictor. Starting from the intercept-only model, MARS first adds linear, quadratic, and higher polynomial terms until error in the outcome is no longer substantially reduced (i.e., R-change < 0.001). To prevent overfitting, MARS supplements this forward method with a backward method, whereby terms deemed unlikely to generalize beyond the given data are consecutively removed until the most parsimonious and generalizable model is achieved. If a nonlinear relationship is found, MARS employs a recursive process to determine the optimal point(s) at which the relationship between predictor and outcome changes.

Table 4
Means, standard deviations, and correlations (Study 3b).

	Social Time	Soc. Time Squared	Soc. Time Sqr. (orthogonal)	Mood	Related	Related (Socializing)	Positive Affect	Life Satisfaction
M(SD)	0.62 (0.20)			4.87(0.83)	4.46(0.76)	4.84(0.87)	3.79(0.60)	3.67(0.78)
Social Time	1							
Social Time Squared	0.96**	1						
Social Time Squared (orthogonal)	0.00	0.26**	1					
Mood	0.29**	0.29**	0.07	1				
Relatedness	0.39**	0.40**	0.09	0.64**	1			
Relatedness When Socializing	0.26**	0.24**	−0.01	0.61**	0.85**	1		
Positive Affect	0.22**	0.19*	−0.11	0.46**	0.48**	0.48**	1	
Life Satisfaction	0.24**	0.21**	−0.08	0.39**	0.41**	0.41**	0.57**	1
Extraversion	0.30***	0.29***	0.03	0.20**	0.33***	0.26***	0.28***	0.31***
Agreeableness	0.04	0.04	−0.01	0.15*	0.16*	0.19***	0.24**	0.24**
Conscientiousness	0.07	0.06	−0.02	0.24**	0.19*	0.17**	0.18*	0.31***
Openness	0.16*	0.12	−0.13	0.20**	0.14	0.16*	0.16*	−0.01
Neuroticism	−0.03*	−0.02	0.05	−0.28***	−0.31***	−0.31***	−0.53***	−0.40***

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

Because these hinges, or spline functions, are determined through iterative partitioning of the data, the results of MARS have the added benefit of being less susceptible to outliers than regular polynomial regression. And because MARS does not rely on statistical significance to determine the best model, it can be a particularly useful technique for supplementing parametric testing based on p-levels, which are heavily influenced by sample size. Still, after estimating the segments nonparametrically with MARS, we also estimate the effect size and its 95% CI within each segment.

In Tables 1–4, we present Pearson correlations separately for each of the four studies. To provide standardized estimates of effect size for curvilinearity, these tables also include the orthogonalized squared term of social time. We present a summary of the polynomial regressions across all studies in Table 5 while providing the results of the segmented models in Table 6. In Table 5, we provide the standardized regression coefficients, while also presenting effect sizes in the form of variance explained, R^2. Because a key goal of the present research is to document how much researchers might be neglecting by only focusing on the linear effects of social time, we additionally estimate the variance explained by the curvilinear effect as a proportion of the variance explained by the linear effect, that is R^2_{curv}/R^2_{lin} (Table 5). As more practical measures of effect size, the breakpoints in the segmented models are also presented in Table 6. Finally, because the outcomes in Studies 1 and 3a had a clustered, multilevel structure,[1] we decompose the between-subjects and within-subjects correlations in Tables 1 and 3.

1.3.3. Data analysis

For our analyses, we used R (Version 3.4.3; R Core Team., 2017) and the R-packages *car* (Version 2.1.6; Fox & Weisberg, 2011), *class* (Version 7.3.14; Venables & Ripley, 2002), *dplyr* (Version 0.7.4; Wickham, Francois, Henry, & Müller, 2017), *earth* (Version 4.6.0; Hastie & Lumley, 2017), *ggeffects* (Version 0.3.0; Lüdecke, 2017a), *ggplot2* (Version 2.2.1.9000; Wickham, 2016), *gvlma* (Version 1.0.0.2; Peña & Slate, 2006, 2014), *knitr* (Version 1.18; Xie, 2015), *lattice* (Version 0.20.35; Sarkar, 2008), *lme4* (Version 1.1.15; Bates, Mächler, Bolker, & Walker, 2015), *MASS* (Version 7.3.48; Venables & Ripley, 2002), *Matrix* (Version 1.2.12; Bates & Maechler, 2017), *mda* (Version 0.4.10; Hastie & Tibshirani, 2017), *mgcv* (Version 1.8.22; Wood, 2003, 2004, 2011; Wood, Pya, & Säfken, 2016), *MuMIn* (Version 1.40.0; Bartoń, 2017), *papaja* (Version 0.1.0.9655; Aust & Barth, 2017), *plotmo* (Version 3.3.4; Milborrow, 2017), *plotrix* (Version 3.7; Lemon, 2006), *psych* (Version 1.7.8; Revelle, 2017), *rgl* (Version 0.98.22; Adler & Murdoch, 2017), *segmented* (Version 0.5.3.0; Muggeo, 2003, 2008), *sjPlot* (Version 2.4.0.9000; Lüdecke, 2017b), *standardize* (Version 0.2.1; Eager, 2017), and *visreg* (Version 2.4.1; Breheny & Burchett, 2017).

2. Study 1: Gallup World Poll

In Study 1, we utilized The Gallup World Poll as a replication, extension, and refinement of Diener et al. (2008). First, we include data collected over ten annual waves (2006–2016), compared to only a single wave used in Diener et al. (2008). Second, we analyze the social time data in a continuous, rather than categorical manner. Finally, we examine positivity of daily experience by using a greater array of items in order to provide more reliable composites (c.f., Oishi, Schimmack, & Diener, 2012).

[1] All multilevel analyses were conducted on R version 3.4.1, using (1) StatsBy package for disaggregating correlations, (2) lme4 package for the multilevel models, (3) MuMIn for isolating R^2-Marginal (the variance explained by the fixed component of a predictor.

Table 5
Polynomial modeling: linear and curvilinear effects.

	Linear			Curvilinear			
	b (SE)	*β*	R^2_{lin}	*b (SE)*	*β*	R^2_{curv}	R^2_{curv}/R^2_{lin}
Study 1							
Life Evaluation	0.019 (0.0008)	0.043	0.002	−0.002 (0.0001)	−0.038	0.002	0.985
Positive Daily Experience	0.006 (0.0001)	0.112	0.015	−0.0007 (0.00001)	−0.105	0.008	0.565
Study 2							
Happiness (DRM)	0.061 (0.009)	0.070	0.005	−0.009 (0.003)	−0.034	0.001	0.237
Study 3a							
Mood (ESM)	0.664 (0.292)	0.404	0.164	−50.03 (0.33)	−0.258	0.067	0.408
Study 3b							
Mood (ESM)	0.297 (0.311)	0.286	0.082	0.938 (0.038)	0.066	0.004	0.053
Positive Affect	0.685 (0.227)	0.224	0.050	−0.093 (0.756)	−0.107	0.011	0.188
Life Satisfaction	0.952 (0.267)	0.238	0.057	−0.071 (0.991)	−0.080	0.006	0.106

Notes. The standardized regression coefficients are calculated using the standardized *x* and *y*. The R^2 for multi-level models (Study 1) is the marginal variance explained, defined as the variance explained by fixed effects (i.e., not including variance explained by random parameters); R^2-marginal was estimated using R-package MuMIn 1.40.0.

Table 6
Piecewise modeling: multi-adaptive regression splines (MARS) and segmented linear regression.

	Breakpoints		Cases Above		Regression Below		Regression Above	
	N	*Value*	*N*	*Percent*	*b (SE)*	*[95% CI]*	*b (SE)*	*[95% CI]*
Study 1								
Life Evaluation	1	5.0 h	106,850	44.2%	0.11 (0.004)	0.07 [0.063; 0.073]	−0.00 (0.001)	0.00 [−0.007; 0.004]
Positive Daily Experience	1	3.0 h	163,392	68.1%	0.03 (0.001)	0.15 [0.149; 0.160]	0.00 (0.000)	0.00 [−0.005; 0.007]
Study 2								
Happiness (DRM)	1	2.55 h	971	9.0%	0.11 (0.022)	0.05 [0.032; 0.073]	0.00 (0.020)	0.01 [−0.056; 0.070]
Study 3a								
Mood (ESM)	1	25.0%	113	67.26%	0.05 (0.014)	0.47 [0.229; 0.715]	0.00 (0.005)	0.09 [−0.101; 0.274]
Study 3b								
Mood (ESM)	1	34.3%	158	90.8%	−0.01 (0.017)	−0.09 [−0.658; 0.484]	0.02 (0.004)	0.27 [0.114; 0.419]
Positive Affect (General)	1	64.0%	91	52.3%	0.01 (0.004)	0.25 [0.041; 0.469]	−0.00 (0.006)	−0.05 [−0.257; 0.164]
Life Satisfaction	1	40.9%	149	86.1%	0.03 (0.014)	0.42 [0.015; 0.819]	0.01 (0.005)	0.14 [−0.021; 0.302]

Notes. Results from statistical models with less than 20 subjects are not shown.

2.1. Method

We used data from the Gallup World Poll of people in 166 nations conducted each year between 2006 and 2016. Of the total respondents (N = 1,559,010), a subsample of 243,075 (M_{age} = 40.14, SD = 17.49; 54.1% female) were asked a question operationalizing social time: How much time they had spent with family and friends on the day before the interview, $M(SD)$ = 5.34 (4.88); 4 invalid cases who reported above 24 h were removed. For that same day, respondents were also asked to indicate whether or not (i.e., *yes* or *no*), they had a series of ten positive experiences on the day before. These items included: *smiling/laughing*; feeling *enjoyment, love, well-rested, respected*, and *proud*; having *good tasting food*; doing *something interesting*; being *able to choose one's activities*; and, desire to *have more days like that* (see Supplementary Online Materials-SOM for exact phrasing of each item). Following Oishi et al. (2012), we combined all ten items into a composite of *positivity of daily experiences*, α = 0.79; *M(SD)* = 0.70 (0.27). This composite thus represents standard items used to measure positive affect (e.g., PANAS; Watson, Clark, & Tellegen, 1988), as well as closely related constructs (Biswas-Diener, Kashdan, & King, 2009), such as autonomy, interest, and enjoyment (e.g., PANAS-X; Watson & Clark, 1999). In addition to these daily state measures, participants also reported how they currently evaluated their lives using the Cantril Ladder—a self-anchoring scale from 0 (*worst possible life*) to 10 (*best possible life*), *M(SD)* = 5.40(2.18); see Table 1 for correlations between all variables.

2.2. Results

2.2.1. Curvilinear models

Because participants are clustered within country, we used multilevel modeling to estimate the effects. Using step-wise models, we predicted each of the three components of subjective well-being from the time per day people spent with family and friends only (Step 1) and then adding its orthogonal squared term (Step 2).[2]

Consistent with past research, we found positive linear relationships across outcomes, such that more time with family and friends predicted both better life evaluation, β = 0.04, R^2 = 0.002, p < .001, and higher positivity of daily experience, β = 0.11, R^2 = 0.015, p < .001. These small positive relationships, however, were qualified by significant curvilinear effects both for life evaluation, β = −0.04, R^2 = 0.002, p < .001, and for positivity of daily experience, β = −0.11, R^2 = 0.008, p < .001 (see Table 5 for details). More time with family and friends is not progressively better for psychological well-being (see Fig. 1). Of course, these curvilinear effects could be due to other factors, such as differences in income or age. Poorer individuals, for example, might be spending more time with their family than they would like, but only because they cannot afford to live alone. Thus, we controlled for household income, as well as sex and age (by adding their fixed effects to the models).

[2] Level 1: $Y_{ij} = b_{0j} + b_{1j} * X_{ij} + b_{2j} * X^2_{ij} + error_{ij}$; Level 2: $b_{0j} = r_{00} + error_{0j}$, *where* i = person level; j = country level; note that only fixed effects were estimated.

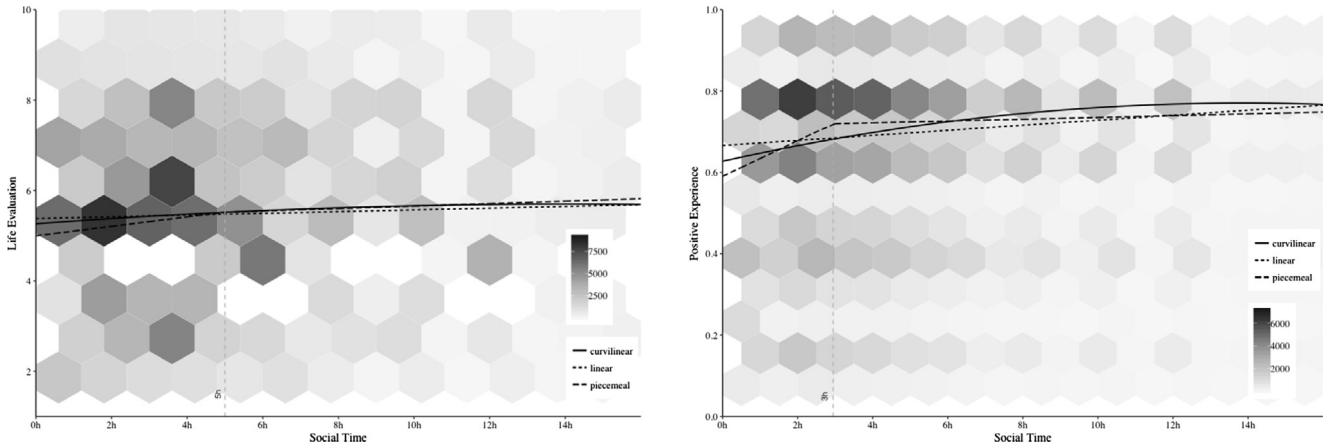

Fig. 1. Linear, quadratic, and piecemeal relationships of time spent with family/friends with life evaluation (left panel) and positive daily experience (right panel) in Study 1 (Gallup World Poll 2008–2016). Density distributions are represented as hexagonal heatmap, whereby the plane is divided in equally sized regular hexagons with the intensity of the greyscale indicating the number of cases observed in each hexagon; the size of the hexagons was calibrated for each dependent variable to minimize extraneous empty space due to the scale used. The y-axes show the full scale used to measure the dependent variables. The x-axes represent the hours in a single day people reported spending with their family and friends; the x-axes were truncated at 16 h so as to avoid misrepresenting the relationships due to relatively rare cases. The vertical dotted lines represent the breakpoints in the piecemeal relationships, that is value of social time at which more social time no longer predicts higher subjective well-being. See SOM (Fig. S1) for regular scatterplots with density distributions and smooth best-fitting loess lines for the full range of observed values of social time.

The curvilinear effects of time spent with family and friends on all outcomes remained stable to controlling for these variables in the case of both life evaluation, $\beta = -0.03$, $p < .001$, and positive experience, $\beta = -0.90$, $p < .001$. Further, we found weak evidence and inconsistent patterns of moderation by age, sex, and income of the linear and quadratic effects across life evaluation and positive daily experiences.[3]

Though robust to controlling for third variables, the observed linear and quadratic effects were both statistically small. Because we observed smaller linear effects of social time than documented in past research (e.g., Baumeister & Leary, 1995; Reis et al., 2000), it would be informative to evaluate the size of the curvilinear effect relative to the linear effect. Indeed, the primary theoretical goal of the present research is to establish how much additional variance in well-being is explained by the curvilinear effect of social time over and above its linear effect (see Table 5). As compared to the variance explained by the linear effect, the curvilinear effect explained as much variance in life evaluation ($R^2_{curv}/R^2_{lin} = 0.99$) and a little more than half as much variance in the positivity of daily experiences ($R^2_{curv}/R^2_{lin} = 0.57$).

Even though the multilevel modeling takes into account the nested design of the data, whereby individuals are clustered within countries, the models presented so far do not decompose within and between country effects. Thus, the effects we observed could be due to either differences between countries or differences between individuals, or to both. In Table 1, therefore, we present the decomposed effects between and within countries. Correlations were decomposed using methodology by Pedhazur (1997), whereby between-country correlations are simply the correlations between the countries' means scores on each variable (N = 166), whereas within-country correlations are the correlations between individuals' deviation scores from their country's mean on each variable (N = 243,075).

As seen in Table 1, the within-country effect of social time on life evaluation—that is the effect of variation between individuals, while holding constant variation between countries—was $r = 0.05$ for the linear effect and $r = -0.05$ for the quadratic effect (see Table 1 for details of both within-country and between-country effects). Of course, as the measure of social time represents the time spent with family and friends in a single day of people's lives, it is not surprising that the effects on global life evaluation were not as large as we should expect based on past research and theory. Indeed, the within-country effects of social time on positivity of daily experience were somewhat larger, for both the linear effect, $r = .11$, and for the quadratic effect, $r = -0.11$. This linear effect is still substantially smaller than we should expect from a measure of one of the strongest and more reliable positive predictors of well-being. We suspect that the relatively small effects may thus be due to the fidelity of Gallup's single-item, self-report measure of social time. Though our theorizing concerns effects primarily at the level of individuals, the between-country effects are also presented in Table 1.

2.2.2. Piecewise models

We now adopt a piecewise approach in order to model the relationship between social time and well-being as a segmented line, representing a series of linear relationships at different values of social time. To model the breakpoints, we use a nonparametric machine-learning technique: Multivariate Adaptive Regression Splines, or MARS (Friedman, 1991). As seen in Fig. 1, the segmented lines are close to the curved line of the quadratic effect, indicating a reassuring consistency in the form of the relationship between social time and well-being across fundamentally different statistical models. Specifically, MARS estimated one breakpoint in the segmented relationship between social time and each of the well-being outcomes. The total variance explained by this model

[3] Income moderated the linear effect of social time on life evaluation, $\beta = 0.012$, $p < .001$, whereas age, $\beta = 0.001$, $p > .250$, and sex (1-Male; 2-Female), $\beta = -0.002$, $p > .250$, did not. In contrast, sex, $\beta = 0.009$, $p < .001$, but not income, $\beta = 0.004$, $p = .065$, or age, $\beta = 0.004$, $p = .067$ moderated the linear effects on daily positive experiences. Thus, richer individuals displayed a stronger positive relationship between social time and life evaluation than poorer individuals, while females displayed a stronger positive relationship between social time and positive daily experience than males. The quadratic effect on life evaluation was moderated by age, $\beta = -0.008$, $p < .001$, as well as income, $\beta = -0.011$, $p < .001$, but not by sex, $\beta = 0.002$, $p > .250$. Thus, the concave curvilinear effects of social time on life evaluation was more pronounced for females than for males and for richer compared to poorer individuals. Finally, only age emerged as a significant moderator of the quadratic effect of social time on positive experiences, $\beta = -0.008$, $p < .001$, whereas sex, $\beta = -0.001$, $p > .250$, and income, $\beta = -0.004$, $p = .064$, did not. Thus, older individuals were characterized by a stronger concave curvilinearity between social time and positive experiences than younger people.

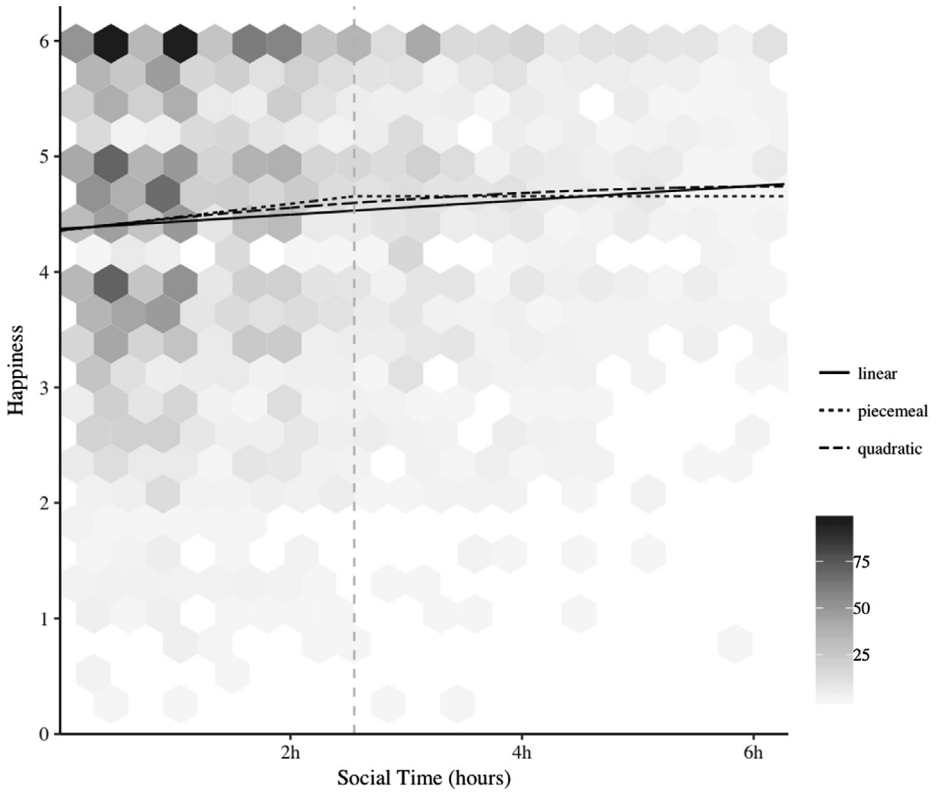

Fig. 2. Linear, quadratic, and piecemeal relationships between daily happiness and time spent socializing/communicating, Study 2 (ATUS-2013). Density distribution is represented as hexagonal heatmap, whereby the plane is divided in equally sized regular hexagons with the intensity of the greyscale indicating the number of cases observed in each hexagon; the size of the hexagons was calibrated to minimize extraneous empty space due to the measurement scales. The y-axis shows the full scale used to measure the dependent variable. The x-axis represents the time (in hours) during a 24-h period people spent socializing and communicating with others; values on the x-axis falling outside the Tukey fences (i.e., value of first quintile minus 1.5 × the interquartile range and/or value of third quintile plus 1.5 × the interquartile range) are not shown so as to avoid misrepresenting the curve of the quadratic relationship. The vertical dotted line represents the breakpoint in the piecemeal relationship, that is value of social time at which more social time no longer predicts higher daily happiness. See SOM (Fig. S2) for regular scatterplots with density distributions and smooth best-fitting loess lines for the full range of observed values of social time. Additional plots showing robustness to removal of influential cases are available at http://rpubs.com/KKushlevPhD/JRP-SOM-Study2.

across the linear and curvilinear effects was R^2 = 0.013, GR^2 = 0.013 for life satisfaction and R^2 = 0.028, GR^2 = 0.028 for positivity of daily experiences.[4] We are not, of course, primarily interested in these estimates of total variance explained, but rather in the estimates of the breakpoints, which provide the most practical measure of effect size. As shown in Table 6 and Fig. 1, social time up to 5 h a day predicted better life evaluation b = 0.11, β = 0.07; people who spent more than 5 h a day with family and friends experienced no further increases in life evaluation, b = 0.00, β = 0.00; more than a hundred thousand people or 44.2% of the sample fell into this category. Similarly, social time up to 3 h a day predicted higher positivity of daily experience, b = 0.03, β = 0.15; people who spent more than 3 h a day with family and friends experienced no further increases in positivity, b = 0.00, β = 0.00; more than 160,000 individuals, or 68.1% of the sample, fell into this category. See Table 6 for details, including 95% confidence intervals.

2.3. Discussion

In a large sample of participants across the globe, we found evidence to qualify a relationship—that between well-being and time spent with family and friends—largely assumed across social and personality psychology to be positive and linear. We see evidence that Aristotle's principles of golden mean and the economic law of diminishing returns apply even when considering one of the strongest and most consistent predictors of subjective well-being. Though statistically small, the curvilinear effect was substantial as compared to the linear effect, underscoring the theoretical importance of these findings. At the practical level, we observed that half of the people polled fell into the category of individuals who spend time with family and friends that bears no additional benefits to their well-being.

The diversity of people in this global sample supplies an equally diverse set of third possible variables that may account for the observed curvilinear effects. While the effects held when controlling for some likely confounds, it is not possible to control for all confounds across such a diverse set of countries as those included in Study 1. Another limitation of Study 1 was that we used time spent with family and friends as a predictor, which could include not only pleasant socializing but also any time spent in the same room without any social interaction. We attempt to address these central limitations in Study 2.

3. Study 2: American time-use survey

In Study 2, we explored the nature of the relationship of social time to subjective well-being in a narrower population: a national U.S. sample from the American Time Use Survey (ATUS; Hofferth,

[4] Note that these estimates are a measure of the total effects (i.e., they do not model out the random effect of country as in the mixed linear models presented in Table 5). GR^2 is an estimate of the generalizability of the model by adjusting the R^2 for the noise present in the data that is unlikely to generalize to new data. The GR^2 will thus always be smaller than R^2, but a value of GR^2 that is close to that of R^2 as observed here is desirable.

Flood, & Sobek, 2015). The ATUS employs a streamlined version of the Day Reconstruction Method (DRM; Krueger et al., 2009), in which people reconstruct their previous day, episode by episode, reporting what they were doing and how they were feeling with reference to specific episodes (Kahneman et al., 2004). In a more stringent test of the curvilinearity between social time and well-being, the ATUS allows us to examine the effects of time spent socializing, taking into account only episodes when socializing is the primary activity (rather than the effects of time spent merely in the presence of others as in Study 1).

3.1. Method

3.1.1. Participants

We analyzed data from a large cross-section of the U.S. population (N = 10,360)[5] from the 2013 wave of the ATUS (Hofferth et al., 2015). The U.S. Census Bureau conducts the ATUS by first selecting a large and diverse set of U.S. households, which approximates a nationally representative sample (55.6% female; M_{age} = 48, age range: 15–85). Next, households with Hispanic and Black members, as well as households with children, are oversampled in order to improve estimates for those groups: Race (White: 79.3%; Black: 14.8%; Asian: 3.5%); Ethnicity (Hispanic/Spanish/Latino: 14.1%). For each household, a designated person aged 15 or older is selected randomly to participate. Full information about the methodology of the ATUS, including sampling strategy, is available at https://www.bls.gov/tus/. The use of this dataset was exempt from review by the IRB at the authors' university.

3.1.2. Procedure

Respondents were contacted over the phone and asked to reconstruct what they did 'yesterday', episode by episode, from 4 am on the previous day to 4 am on the day of the interview. Weekdays and weekends were sampled equally (i.e., Saturday and Sunday represented 50% of the sampled days). Participants' descriptions of what they did during each episode were later activity-coded by trained coders, including for "socializing and communicating with others." The duration of episodes where that activity was primary was then used to compute the daily time each person spent socializing, $M(SD)$ = 42.22 min (88.63). We used this total time as our predictor. After reconstructing their day, participants were asked to rate how *happy* they felt on, from 0 (*not at all*) to 6 (*very*) during each of three randomly selected episodes. This was the only item assessing positive affect. These episodic measures were then used to compute the daily composites used in the analyses. We used this provided composite of daily happiness, $M(SD)$ = 4.42 (1.30).

Notably, the composite measure of time spent socializing is based solely on episodes when socializing is people's primary activity. As the ATUS codebook warns, this methodology is a limitation of the data as it systematically underestimates the amount of time people actually spend in various activities, especially activities that often co-occur with others. Thus, even though people often socialize while, for example, also eating, volunteering, working, watching TV, playing sports, or taking care of their children, none of these instances of social behavior are coded as social time because socializing is not the primary activity of the episode. Indeed, nearly two-thirds of individuals were classified as spending no time whatsoever socializing (n = 6620) compared to slightly more than one-third coded as socializing (n = 3740). For our purposes, this operationalization of social time allows an exceptionally stringent test of the curvilinearity hypothesis as (1) it underrepresents higher amounts of time spent socializing that should theoretically contribute to the hypothesized curve; and (2) it overrepresents social time spent in activities where the people's primary goal was to socialize with others.

3.2. Results

3.2.1. Curvilinear modeling

Using step-wise regression models, we predicted happiness from time spent socializing (see Table 2 for correlations between key variables). At Step 1, we found that people who socialized more felt happier, β = 0.07, p < .001, R^2 = 0.005 (see Table 5 for details of all regression analyses).[6] Entering the orthogonal squared term of the predictor at Step 2, we found a significant concave curvilinear effect for happiness, β = −0.03, p < .001, R^2 = 0.001 (see Fig. 2). Controlling for age, sex, and education[7] could not explain the linear, β = 0.07, p < .001, or the curvilinear effects on happiness, β = −0.03, p < .001.[8] Furthermore, we found a consistent curvilinear relationship between time spent socializing and happiness for both weekdays, β = −0.03, p = .037, and weekends, β = −0.04, p = .011. Exploration of influential cases did indicate several particularly influential cases; the effects, however, held after excluding the most influential observations by studentized residual, Cook's distance, and leverage, β = −0.03, p = .003 (see details at http://rpubs.com/KKushlevPhD/JRP-SOM-Study2). Finally, while providing no informative variability, the over 6000 participants coded as not socializing could misleadingly increase power; we thus reran the central analyses without these cases, observing a similar curvilinear effect of time spent socializing on happiness among those who socialized at least some amount of time, β = −0.04, p = .008. Though robust to alternative model specifications, the observed linear and curvilinear effects were statistically small. Still, as compared to the linear effects, the curvilinear effect of social time on happiness explained about one quarter as much variance—a theoretically non-negligible comparative effect (see Table 5).

3.2.2. Piecewise modeling

Consistent with the curvilinear model described above, MARS (R^2 = 0.006, GR^2 = 0.006) estimated a breakpoint in the relationship between social time and daily happiness. As shown in Table 6, social time up to 2.5 h a day predicted higher daily happiness, β = 0.05; people who spent more than two and a half hours a day socializing experienced no further increases in happiness, β = 0.01 (see Table 6 for details and confidence intervals). This breakpoint is remarkably consistent with the breakpoint of three hours we observed in Study 1 for the corresponding measure, positivity of daily experiences. The group of people who spent more than 2.5 h a day socializing comprised of almost one thousand individuals.

[5] Eighteen additional participants had no data no relevant well-being data and are not included in the present study.

[6] Note that these effects are smaller than we would have expected based on past research on the emotional benefits of socializing, suggesting smaller curvilinear effects, as well. We suspect that this might be in part due to the fact that the well-being outcomes were measured only during three episodes of the day.

[7] Income had a large number of missing cases, which are dependent on participants' age and other factors (https://www.bls.gov/tus/documents.htm). Thus, we did not include it as a covariate. Past research has shown that income is not related to daily happiness both in the ATUS (e.g., Kushlev, Dunn, & Lucas, 2015) and the German Socio-Economic Panel (GSOEP; Hudson, Lucas, Donnellan, & Kushlev, 2016).

[8] While age moderated the linear effect, β = 0.02, p = .008, age did not moderate the quadratic effect, β = 0.00, p > .250. Thus, the positive linear relationship between social time and happiness was significantly stronger in older individuals than in younger individuals. Sex (1-Male; 2-Female) moderated the quadratic effect, β = −0.02, p = .040, but not the linear effect, β = −0.01, p = .222, indicating that the concave curvilinear relationship between social time and happiness is more pronounced for females than for males. Years of education did not moderate either the linear, β = 0.00, p > .250, or the quadratic effect, β = −0.01, p > .250.

3.3. Discussion

Study 2 replicated and extended the findings of Study 1 in a U.S. sample by using a measure of time spent socializing as the primary activity rather than time spent in the presence of others. Proportionally, the variance explained by the curvilinear effect was a little more than one-fourth the size of variance explained by the linear effect—compared to about half the size of that explained by the linear effect in Study 1 for positivity of daily experiences. This makes intuitive sense as we should expect a relatively stronger linear relationship between socializing and well-being than between simply spending time with others and well-being. In absolute terms, the observed effects—both linear and curvilinear—were again statistically small. Particularly, the linear effect was again smaller than we should expect from existing theory and research on the critical role of social life and social needs in well-being (e.g., Baumeister & Leary, 1995; Reis et al., 2000; Ryan & Deci, 2000). We suspect that these smaller-than-expected effects may be due to the operationalization of the key variables. Thus, for example, the operationalization of social time likely did not capture many of the small but enjoyable instances of socializing when people are sharing food with others, spending a day with their family and kids in the park, or casually chatting with colleagues at work. Additionally, the predictor and outcome were reference-mismatched: happiness was measured only for a small subsample of three episodes, whereas socializing time was calculated based on all reported episodes across the past 24 h. Despite the statistically small effects we detected, the curvilinear effect proved to be theoretically significant, explaining one quarter as much variance as the linear effect. The effect also proved to be practically significant, with almost one thousand individuals falling into the category of people who spent more than 2.5 h socializing.

In sum, Studies 1 and 2 provided initial evidence for the presence of curvilinearity in the relationship between social time and well-being in large nationally representative samples (with a combined size of more than 250,000 individuals). But in these studies, we were limited, of course, to using the provided measures, which provided somewhat imprecise operationalizations of both social time and well-being. In addition, the available measures in those studies did not allow us to test the proposed theoretical mechanisms for the curvilinear effects. Accordingly, in Studies 3a and 3b, we ran two experience sampling (ESM) studies, which, albeit much smaller than Studies 1 and 2, allowed us to obtain more precise measures of social time and subjective well-being while also measuring social need satisfaction in order to explore the proposed theoretical mechanisms. In Study 3a, we focus on testing the principle of diminishing satisfaction, whereas in Study 3b we focus on testing the principle of satisfaction limits.

4. Study 3a: Experience sampling

In Study 3a, we conducted a week-long experience sampling study, polling participants five times a day, thus sampling experiences over a larger period of time than in Studies 1 and 2. We operationalized time spent socializing by deriving an objective composite of the proportion of episodes participants reported socializing over the week. For each episode, we also measured mood (feeling good vs. bad) and relatedness (feeling close to others vs. feeling distant from others). The inclusion of this relatedness measure provides us with the opportunity to test the proposed intra-domain mechanism: the principle of diminishing satisfaction. Based on the principle of diminishing satisfaction, we would expect that as people spend ever greater proportion of their time socializing, they would reap ever lower returns for relatedness—a domain-specific outcome; this diminishing satisfaction of social needs should, in turn, at least partially mediate any curvilinear effect between social time and overall weakly mood. Accordingly, we formed weekly person-level composites of relatedness, reported specifically during social episodes and of emotional well-being reported across all episodes.

After having established a consistent presence of a curvilinearity across larger nationally representative samples earlier, our primary goal here is to see if we can detect evidence for a mediation by relatedness of the curvilinear between social time and well-being as predicted by the principle of satisfaction limits. Thus, due to practical considerations (i.e., limited participant pool credits in the context of this time-intensive study), we were not able to power this study for the consistent detection of small effects as observed in Studies 1 and 2. Specifically, sensitivity analyses indicated that our sample of 168 participants allows us to detect medium or larger effect sizes with 80% power, $\rho = 0.21$. Thus, given the effect sizes observed earlier, this study is somewhat underpowered to detect effects, especially the relatively smaller curvilinear effects. Of course, as the goal of this study is to obtain measures of higher fidelity than those available in Studies 1 and 2, it is possible that the effects would be larger, including a linear effect that reflects existing research and theory.

4.1. Method

In total, 168 students at a public university in the U.S. participated for class credit (Median age = 18; 62.5% women). After providing informed consent, participants completed a demographic survey. Over the following seven days, participants received five text messages per day containing a link to a brief survey (for a total of 35 episodes). The prompts were sent semi-randomly within five equally divided intervals between 9 am and 9 pm, and participants were instructed to respond as quickly as they safely could. The survey links expired after 1 h, and each survey was administered at least 2 h after the previous prompt to prevent overlap. The median number of episodes reported by participants was 25 (i.e., 71% response rate). The total number of episodes reported across participants was 4060. Participants reported socializing in 1550 of those episodes, or approximately 4 in 10 of those episodes.

Participants were asked to report whether in the past 15 min they had been socializing in person (37.5% of the episodes include socializing). For the same time period, participants reported how they had been feeling from 1 (*bad*) to 7 (*good*), *M(SD)* = 4.81 (0.85); this mood measure provided our key measure of emotional well-being. To measure relatedness, we asked people how—1 (*distant*) to 7 (*close*)—they felt to others in the past 15 min, *M(SD)* = 4.39 (0.72). The survey also contained filler measures (e.g., other activities such as eating) and other measures (e.g., distraction) that are beyond the scope of the present research. Full survey and data are available on the Open Science Framework[9] (OSF; see Table 3 for descriptives and correlations of all measures). This study was approved by IRB (2015043100).

4.2. Results

4.2.1. Analytic strategy

For each participant, we estimated the proportion of episodes spent socializing out of the total number of episodes throughout the week. We adopted this person-level approach in this multilevel data (i.e., multiple episodes nested within person) because episode-level analyses do not allow us to examine the role of the

[9] Study 3a, materials & data: https://osf.io/ekfh8/?view_only=6202ee3a048c4d909d62c4ead7cdde36.

quantity of social time (as they are coded as either 1 or 0). That said, we present both between-subjects and within-subjects correlations in Table 3.

4.2.2. Curvilinear modeling

We first predicted mood from the proportion of episodes that people spent socializing in person (Step 1). Consistent with past research, we found that people who socialized more felt better on average, $\beta = 0.40$, $p < .001$, $R^2 = 0.15$. Notably, the size of this effect was much larger than observed in Studies 1 and 2, and thus, more in line with existing theory and research (e.g. Baumeister & Leary, 1995). We then entered the orthogonal squared term of social time at Step 2, and found the expected curvilinear effect, $\beta = -0.26$, $p < .001$, $R^2 = 0.07$ (see Fig. 3 and Table 5 for details). Controlling for age and gender did not explain this curvilinear effect, $\beta = -0.26$, $p < .001$. Removing the three most influential cases by leverage, Cook's distance, and studentized residuals also had little effect on the observed curvilinear relationship, $\beta = -0.19$, $p < .008$; removing influential cases also improved satisfaction of the regression model assumptions (for details, see http://rpubs.com/KKushlevPhD/JRP-SOM-Study3a). Thus, using a conceptually similar, but operationally different measure of social time from Study 1 and 2, we again found evidence of a curvilinear effect. Notably, though the effects were substantially larger than in Studies 1 and 2, the relative variance explained by the curvilinear effect over and above the linear effect was consistent with the previous studies (see Table 5).

4.2.3. Piecewise modeling

Consistent with the curvilinear model described above, the MARS model ($R^2 = 0.23$, $GR^2 = 0.20$) estimated one breakpoint in the relationship between social time and mood. As shown in Table 6, spending up to 25% of one's time socializing with others in person predicted better mood, $\beta = 0.47$; people who spent more than 25% of their time socializing experienced little further improvement in their mood, $\beta = 0.09$ (see Table 6 for details and confidence intervals). The majority of the sample ($n = 113$) fell into this group of people who spent more than 25% of their reported episodes socializing.

4.2.4. Principle of diminishing satisfaction

Consistent with existing theory and research, the proportion of time spent socializing was a strong linear predictor of relatedness during social episodes, $\beta = 0.16$, $p < .001$, $R^2 = 0.03$. As predicted by the principle of diminishing satisfaction, however, this relationship was qualified by a significant curvilinear effect of the proportion of time spent socializing on relatedness, $\beta = -0.21$, $p = .042$, $R^2 = 0.04$. Piecewise MARS modeling ($R^2 = 0.21$, $GR^2 = 0.19$) indicated a breakpoint at 39% of time spent socializing on relatedness. Thus, social time does indeed seem to have diminishing marginal utility for social need satisfaction as assessed by our relatedness measure.

In order to more directly test the mediational role of relatedness in the observed curvilinear effect between social time and well-being, we used instantaneous direct effects through MEDCURVE for SPSS (Hayes & Preacher, 2010). This procedure allowed us to

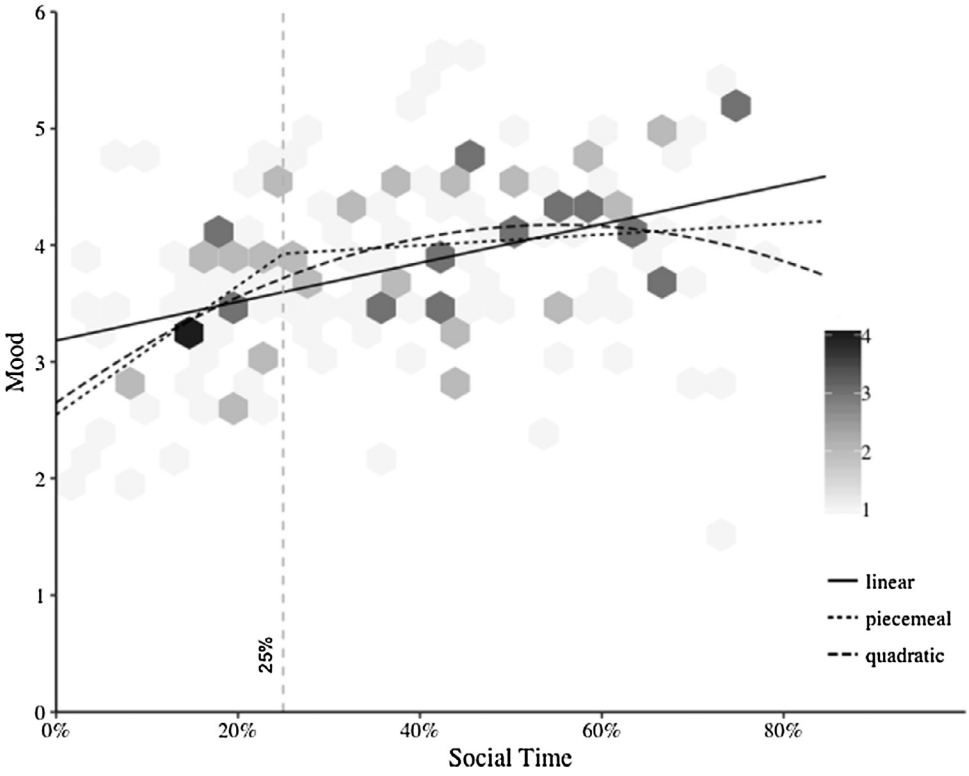

Fig. 3. Linear, quadratic, and piecemeal relationships between mood and proportion of episodes spent socializing in person, Study 3a (ESM). Density distribution is represented as hexagonal heatmap, whereby the plane is divided in equally sized regular hexagons with the intensity of the greyscale indicating the number of cases observed in each hexagon; the size of the hexagons was calibrated to the unique values of the y scales. The y-axis shows the full scale used to measure the dependent variable. The x-axis represents the time (in hours) during a 24-h period people spent socializing and communicating with others; values on the x-axis falling outside the upper Tukey fence (i.e., value of third quintile plus 1.5 × the interquartile range) are not shown so as to avoid misrepresenting the curve of the quadratic relationship. The vertical dotted line represents the breakpoint in the piecemeal relationship, that is value of social time at which more social time no longer predicts better mood. See SOM (Fig. S3) for regular scatterplots with density distributions and smooth best-fitting loess lines for the full range of observed values of social time. Additional plots showing robustness to removal of influential cases are available at http://rpubs.com/KKushlevPhD/JRP-SOM-Study3a.

quantify the indirect effect of social time on subjective well-being through relatedness at low, medium, and high proportions of social time. As a reminder, we use the composite of relatedness reported only during episodes of socializing as the mediator to predict the mood reported across all episodes during the week. This mismatching of the reference points of the mediator and the predictor should minimize the chance of detecting spurious mediational relationship due to nonessential collinearity between relatedness and mood, which are normally strong covariates. We specified curvilinear relationships from social time to both socializing-specific relatedness and overall mood (outcome), and a linear relationship between socializing-specific relatedness and overall mood. All confidence intervals for the indirect effects were obtained using bootstrapping with 5000 samples. All three variables were standardized to derive more interpretable measures of effect size.

For relatively low proportion of time socializing (-1 *SD*), adding more social time strongly predicted subjective well-being through relatedness, $\theta = 0.36$, 95% CI [0.11; 0.66]. Spending some time socializing impacts subjective well-being by increasing social need satisfaction. For medium proportion of time socializing (mean), the instantaneous indirect effect remained significant but was about three times weaker compared to the effect at low levels, $\theta = 0.11$, 95% CI [0.02; 0.22]. For people spending relatively high proportion of their time socializing (+1 *SD*), the indirect effect became non-significant and even trended in a negative direction, $\theta = -0.13$, 95% CI [–0.36; 0.07]. Consistent with the principle of diminishing satisfaction, then, we found evidence that the declining marginal utility of social time for well-being is mediated by intra-domain satisfaction within the social domain.

4.3. Discussion

In Study 3a, we found further evidence for the declining marginal utility of social interactions. Using ESM to provide a snapshot of people's socializing and emotional well-being over an entire week, we found that those who spent proportionally more time socializing felt happier but only to a point—after which more socializing was not associated with feeling progressively better. Notably, in absolute terms, both the linear and curvilinear effects were larger in Study 3 than they were in Studies 1 and 2; in relative terms, the curvilinear effect contributed a similar amount of additional variance explained over and above the linear effect as in Studies 1 and 2, providing a remarkable consistency in the theoretical significance of the curvilinear effects.

Study 3a allowed us to examine and provide initial evidence for an intradomain mechanism, the principle of diminishing satisfaction but did not allow a test of the principle of satisfaction limits, which posits that the contribution of satisfaction within one life domain to overall subjective well-being is limited. In the present study, however, we did not assess overall subjective well-being through validated questionnaires of life satisfaction and general positive affectivity. This choice was in part due to practical considerations (i.e., limited number of participant pool credit in the context of this already time-intensive study design). Additionally, to the extent that making people reflect on how satisfied they are with their life at baseline could have colored the way they answer the primary ESM measures of mood (c.f., Schwarz, 1999), the primary goal of the present study—to obtain as accurate as possible measure of mood in order to estimate accurate effect sizes and test the intradomain mechanism—could have been compromised. But for a test of the principle of satisfaction limits, we need to examine whether as time spent socializing increases, the satisfaction of the social need of relatedness has a declining marginal utility for general well-being (e.g., life satisfaction, general positive affect). Thus, focusing on testing the principle of satisfaction limits, in Study 3b we use the same ESM design as Study 3a while also including validated measures of subjective well-being at baseline.

5. Study 3b: Experience sampling

In Study 3b, we conducted the same experience sampling study as in Study 3a, measuring mood, relatedness, and the occurrence of socializing five times a day over one week. Going beyond Study 3a, people also provided measures of general well-being at baseline, allowing a test of the interdomain mechanism proposed by the principle of satisfaction limits. As in Study 3a, sensitivity analyses indicated that the sample of 174 participants in the present study allowed us to detect medium or larger effect sizes with 80% power, $\rho = 0.21$. Thus, this study is again somewhat underpowered to detect effects, especially the relatively small curvilinear effects on general well-being outcomes, such as life satisfaction and general positive affect. That said, after having established a consistent presence of a curvilinearity across larger nationally representative samples earlier, our primary goal here is to see if we can detect moderation by social time of the relationship between relatedness and general well-being.

5.1. Method

In total, 174 students at a public university in the U.S. participated for class credit (Median age = 19; 54.6% women). After providing informed consent, participants completed a baseline survey, which included measures of life satisfaction, *M(SD)* = 3.67 (0.78) (Satisfaction With Life Scale; Diener, Emmons, Larsen, & Griffin, 1985) and positive affect, *M(SD)* = 3.79(0.60) (SPANE; Diener et al., 2010); both were assessed on 1-to-5 point scales. Additionally, we measured the Big Five personality traits on a 7-point (1-*Strongly Disagree*; 7-*Strongly Agree*) using items from the Ten-item Personality Inventory, TIPI (Gosling, Rentfrow, & Swann, 2003): extraversion, *M(SD)* = 4.60(1.24), $\alpha = 0.88$, agreeableness, *M(SD)* = 4.88(.89), $\alpha = 0.66$, conscientiousness, *M(SD)* = 5.02(0.97), $\alpha = 0.69$, openness, *M(SD)* = 4.90(0.79), $\alpha = 0.51$, and neuroticism, *M(SD)* = 3.56(1.08), $\alpha = 0.74$. As each item of the TIPI contains two personality words (e.g., e.g., extroverted, enthusiastic), we split those into separate items in order to be able to obtain estimates of internal consistency (i.e., Cronbach alpha). Extraversion—the most relevant personality trait to the present investigation—showed good reliability. Intercorrelations are available in Table 4.

Over the seven days following the baseline survey, participants received five text messages per day containing a link to a brief survey. The procedure and episodic measures were identical to Study 3a (see Table 4 for means and standard deviations and correlations). Full survey and data are available on OSF.[10] This study was approved by IRB (2015043100).

5.2. Results

5.2.1. Principle of satisfaction limits

We found the expected linear relationships of social time with general positive affect, $\beta = 0.22$, $p = .003$, and with life satisfaction, $\beta = 0.24$, $p = .002$. We observed the expected negative curvilinear trends for general positive affect. $\beta = -0.11$, $p = .150$, and for life satisfaction, $\beta = -0.08$, $p = .281$ (see Fig. 4); though larger in absolute terms than the effects observed in Studies 1 and 2 (see Table 5), these curvilinear effects did not reach statistical significance. As statistical significance can be a misleading indicator of curvilinear-

[10] Study 3b, materials & data: https://osf.io/2u7hv/?view_only=77fa18cc0bd44138a1eacd5ead5c9865.

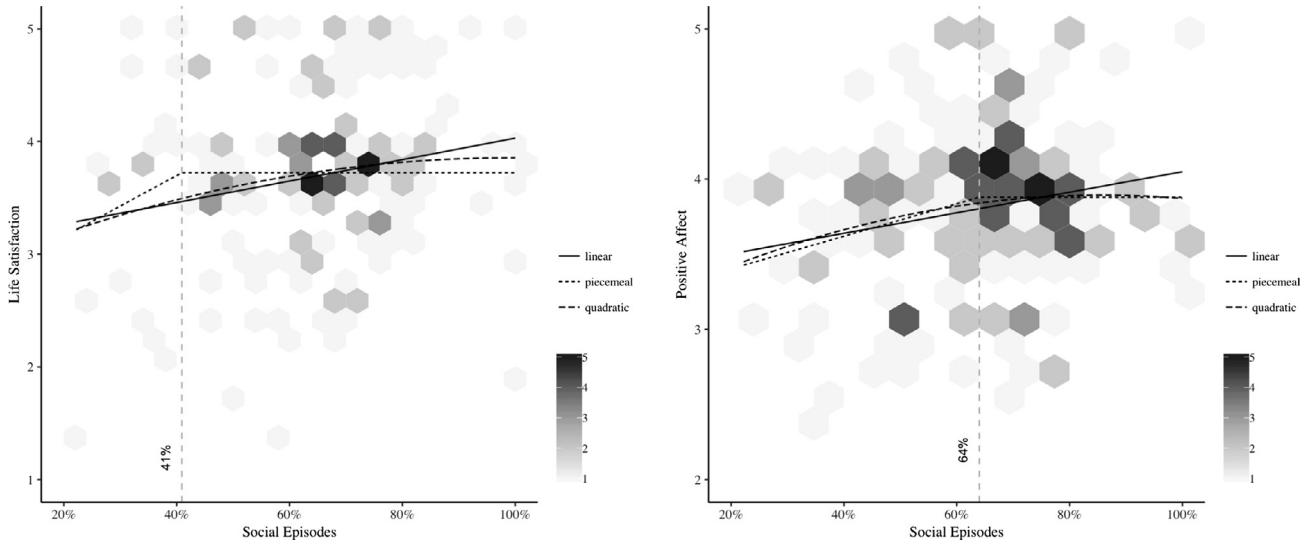

Fig. 4. Linear, quadratic, and piecemeal relationships of proportion of episodes spent socializing with general positive affect (left panel) and life satisfaction (right panel), Study 3b (ESM). Density distribution is represented as hexagonal heatmap, whereby the plane is divided in equally sized regular hexagons with the intensity of the greyscale colors indicating the relative number of cases observed in each hexagon; the size of the hexagons was calibrated to the unique values of the y scales. The y-axis shows the full scale used to measure the dependent variable. The x-axis represents the percentage of episodes over one week during which people socialized with others in person; values on the x-axis falling outside the Tukey fences are not shown so as to avoid misrepresenting the curve of the quadratic relationship. The vertical dotted line represents the breakpoint in the piecemeal relationship, that is value of social time at which more social time no longer predicts higher subjective well-being. See SOM (Fig. S4) for regular scatterplots with density distributions and smooth best-fitting loess lines for the full range of observed values of social time.

ity in a relatively underpowered study, we turn to the nonparametric MARS, which indicated a breakpoint of 64% of time spent in social episodes for general positive affect ($R^2 = 0.06$, $GR^2 = 0.04$) and a breakpoint of 41% for life satisfaction ($R^2 = 0.06$, $GR^2 = 0.03$). Notably, the majority of the sample fell into these categories of people (see Table 6). Overall, we find consistent but statistically inconclusive patterns for the presence of curvilinearity.

The key purpose of the present study was not to establish the presence of curvilinearity, but rather to explore whether the relationship between relatedness and general measures of subjective well-being is moderated by the amount of social time. In other words: Does the relationship between relatedness and overall subjective well-being become increasingly curvilinear as people spend more time socializing? To answer this question, we use the following regression equation: $y = a + b_1x + b_2x^2 + b_3m + b_4mx + b_5mx^2$, where x is relatedness and m is social time; the critical test of hypothesis is provided by b_5, the coefficient for the moderation by social time of the curvilinear relationship between relatedness and the well-being outcome (y). Using this equation, we find evidence for a moderated curvilinear relationship between relatedness and general positive affect, $b = -0.42$ (0.21), $p = .046$ ($\beta = -0.14$, $R^2 = 0.02$). As predicted by the principle of satisfaction limits, the relationship between relatedness and general positive affect grows increasingly weaker as the time spent socializing increases (see Fig. 5). This interaction seemed robust to removal of the most influential cases (see http://rpubs.com/KKushlevPhD/JRP-SOM-Study3b-PA for details). As shown in the perspective plot (Fig. 5), the data seem to suggest that the least happy people are those who spend a great amount of their time in face-to-face social interactions, yet do not feel related to others. In contrast, the happiest people seem to be those who spend relatively little time socializing with others, yet feel a strong sense of relatedness.

When predicting life satisfaction in the same equation, we also found evidence consistent with the principle of satisfaction limits, $b = -0.54$ (0.28), $p = .057$ ($\beta = -0.14$, $R^2 = 0.02$), though this test did not reach conventional levels of statistical significance (see http://rpubs.com/KKushlevPhD/JRP-SOM-Study3b-LS for details and plots). Overall, while underpowered, the present study seems to be consistent with the predictions of the principles of satisfaction limits.

5.2.2. The principle of diminishing satisfaction: Replication

Unlike in Study 3b, we did not detect a curvilinear effect on mood as measured at the episodic level in this sample (Table 5). Thus, we proceeded to test whether there may be any mediation of the curvilinear trend between social time and general positive affect. As before, we used instantaneous direct effects through MEDCURVE for SPSS (Hayes & Preacher, 2010) to explore whether the observed mediational pattern in Study 3a would withstand this stronger test. Indeed, for those socializing relatively little on average (−1 *SD*), socializing more predicted greater subjective well-being through greater relatedness, $\theta = 0.16$, 95% CI [0.01; 0.31]. For those socializing at medium levels (mean), socializing had a somewhat weaker effect but still significant effect, $\theta = 0.11$, 95% CI [0.03; 0.21]. For people socializing a great deal (+1 *SD*), the indirect effect reduced further and, again, became statistically non-significant, $\theta = 0.07$, 95% CI [−0.07; 0.23].

5.2.3. Personality traits

As shown in Table 4, social time was positively associated with extraversion, providing reassurance of the validity of our measure of social time. Openness was the only other personality trait that was positively associated with our measure of social time. In contrast, none of the five personality traits was associated with the orthogonalized curvilinear term. We proceeded to explore whether curvilinearity may depend on extraversion. For example, it is possible that people high in extraversion may have a higher saturation point, at which social time is no longer beneficial for their well-being (compared to more introverted individuals). Extraversion, however, did not moderate the curvilinear effect of social time on general positive effect, *b(SE)* = −0.13(0.57), $p = .827$, life satisfaction, *b(SE)* = 0.53(0.74), $p = .479$), or mood, *b(SE)* = −0.69(0.79), $p = .383$. In contrast, extraversion did moderate the linear relationship between social time and mood, *b(SE)* = 0.47(0.23), $p = .043$; predictably, the linear effect was stronger for those high in extraversion (+1SD above the mean), *b(SE)* = 1.75(.47), $p < .000$,

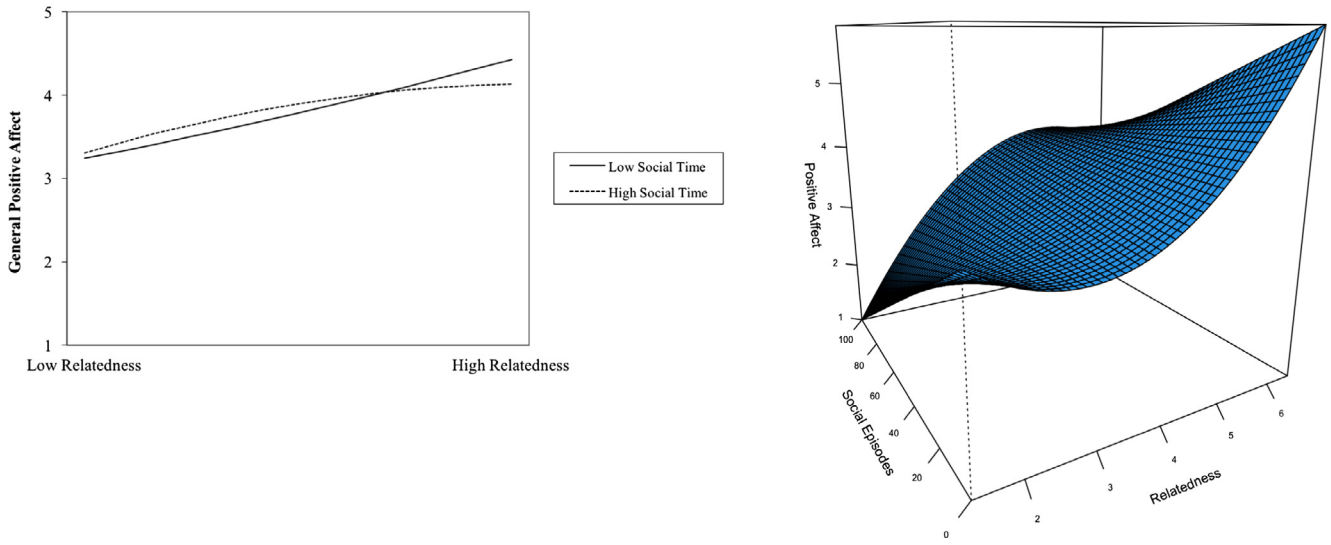

Fig. 5. The relationship between relatedness and general positive affect is moderated by social time. The relationship between relatedness and general positive affect is represented as a simple interaction plot at high and low levels of social time (left plot), as well as a perspective plot demonstrating the exact nature of the interaction. The specified model met all regression assumptions and the plotted relationships were robust to excluding for the most influential cases. Additional details, including interactive plots are available on Rpubs: http://rpubs.com/KKushlevPhD/JRP-SOM-Study3b-PA. The plots for the nonsignificant interaction effect on life satisfaction are available at http://rpubs.com/KKushlevPhD/JRP-SOM-Study3b-LS.

than for those low in extraversion (−1SD above the mean), *b(SE)* = 0.59(.40), $p = .140$. Interestingly, we found no moderation by extraversion of the relationship of social time with general positive affect, *b(SE)* = −0.09(.17), $p = .582$, or with life satisfaction, *b(SE)* = −0.09(0.22), $p = .689$.

5.3. Discussion

Study 3b provided support for both the intra-domain and inter-domain mechanisms for the diminishing marginal utility of social time for well-being. According to the principle of satisfaction limits, people should reap progressively lower benefits for overall well-being of satisfaction within a single life domain. Indeed, for those highly engaged in social activities, relatedness became less strongly predictive of overall subjective well-being. It is also notable that the curvilinear effect of social time on mood was inconsistent with the rest of the patterns observed both in this study and in the previous studies. Of course, as this is a relatively small sample, this effect on mood—as well as all other curvilinear and interaction effects reported—need to be interpreted with caution. Indeed, curvilinear effect, which can be particularly sensitive to outliers, influential cases, and mean levels, can be expected to become unstable in small samples. For example, we observed a notably higher mean level of percentage of social episodes in this study compared to the one observed in Study 3a, which, we suspect, may be due to the different times of the academic year when the data were collected for each study. Still, taken together, the evidence of Study 3b seems to be consistent with the patterns observed in our earlier well-powered studies.

6. General discussion

Across four studies and a variety of measures and methodologies, we found consistent evidence that time spent in social activities has declining marginal utility for subjective well-being. We found evidence for a curvilinear relationship, such that social time is beneficial for subjective well-being only up to a point, beyond which more social time is associated with no additional gains. In Study 1, people across 166 nations who spent more than three hours a day with their family and friends experienced no higher positivity of their daily experience. In Study 2, respondents in a large U.S. sample showed a similar curvilinear pattern for the time they spent actively socializing with others over the past day, with a similar breakpoint of two and a half hours. In Study 3a, students who spent more than 25% of their time socializing over a week did not experience any better mood compared to their peers. In Study 3b, we did not replicate this effect on mood, but we found some evidence for curvilinearity between social time and more general measures of well-being, including life satisfaction and general positive affect. Though these effects in Study 3b did not reach statistical significance, nonparametric segmented modeling indicated breakpoints at 64% and 41% for positive affect and life satisfaction.

Based on theories of the balanced life (e.g., Sirgy, 2012; Sirgy & Lee, 2018; Sirgy & Wu, 2009), we also explored two possible mechanisms to explain the observed diminishing returns of social time for well-being. In Study 3a, we found evidence that people who spent a progressively greater proportion of their time socializing reaped increasingly lower benefits for satisfying their social needs (e.g., relatedness, sense of community). Furthermore, social time had a progressively weaker effect on mood specifically through relatedness. In Study 3b, we found a similar mediation by relatedness for general positive affect. This provided evidence for the intra-domain mechanism predicted by the principle of diminishing satisfaction, whereby people get progressively fewer returns on subjective well-being because of diminishing satisfaction within the social domain.

In Study 3b, we also found evidence for an inter-domain mechanism predicted by the principle of satisfaction limits, whereby the contributions of satisfaction within a single life domain to overall well-being is limited. In particular, we found evidence that this principle seems to apply to time spent socializing, notwithstanding the strong linear association between socializing and well-being (Reis et al., 2000). To optimize well-being, then, people might want to avoid spending too much time in any single life domain, including the social domain. Following this initial evidence into the inter-domain dynamics of the diminishing returns of social time for well-being, future research can work to explore the role of other factors. It would be interesting, for example, to examine the

interplay between the satisfaction of social versus psychological needs that are primarily satisfied in other domains, such as competence at work or school (c.f., Sheldon & Niemiec, 2006). Another factor that may play a moderator role that deserves attention in future research is the congruence between desired and actual time spent in social activities (c.f., Matuska, 2012; Sheldon, Cummins, & Kamble, 2010). Based on the consistent curvilinearity we observed across our studies, however, we suspect that even those who want and can spend all their time in social activities may hit a plateau in terms of the benefits they reap for their subjective well-being.

6.1. Effect sizes and significance

6.1.1. Theoretical significance

While consistent across diverse samples, methodologies, and operationalizations, the curvilinear effects we observed were statistically small, especially in our two larger studies. Are the effects documented here, then, of any practical and theoretical significance? The evidence seems to suggest that the effects are, indeed, theoretically significant. First, the small statistical effects in Studies 1 and 2 should be interpreted in the context of the similarly tiny linear effects in those studies. Indeed, a relatively flat line representing a small linear effect would be necessarily limited in how curved it could become, at least when in the context of the predicted and observed declining marginal utility effect (i.e., a plateauing curvilinear line). The key measure of the theoretical significance of the observed curvilinearity, of course, is not the absolute size of the effect—which is directly impacted by the fidelity of the measures and other methodological peculiarities—but rather, its relative size with respect to the size of the corresponding linear effect. In Study 1, the curvilinear effect of time spent with family and friends explained about half as much variance in positive daily affect as the linear effect. In Study 2, where social time was operationalized by time spent socializing as a primary activity—a theoretically stronger linear predictor of well-being than simply time spent with others—the curvilinear effect explained only about one fourth as much variance as the linear effect. In Study 3a, where social time was operationalized as any episode when people engaged in socializing, even if it was not the primary activity, the relative variance explained by the curvilinear effect was somewhere in between that of Study 1 and Study 2 (explaining about two-fifths as much variance as the linear effect). Of course, other differences between the methodologies and samples of these studies could have contributed to these differences, and therefore, establishing the exact explanatory value of the curvilinear effects compared to the linear effects needs further investigation. What we can say with relative confidence based on the current research, however, is that by having ignored the declining marginal utility of social time for well-being, the field of psychology may have for decades been ignoring a non-negligible amount of variance that characterizes the true relationship between social time and well-being—a key theoretical contribution of the present work.

6.1.2. Practical significance

What about the practical significance of the observed declining marginal utility of social time? Because some of the measures of social time spanned presumably rather rare amounts of social time (e.g., up to 24 h a day in Study 1), we considered the possibility that our effects had little practical significance (e.g., impacting only the rare individuals who spend unusually large amounts of time in social activities). Our nonparametric segmented analyses with MARS, however, indicated this not to be the case. In fact, we found specific estimates of the points at which more social time stops predicting higher well-being, which varied from 2.5 h (Study 2) to 5 h (Study 1) and from one-fourth (Study 3a) to two-thirds (Study 3b) of time spent socializing. In all of those cases, we observed a sizable proportion of the samples falling above these critical breakpoints. Across all studies and measures, more than half the people (55%) fell into the category of those who spent more time socializing than the documented breakpoints; these individuals thus likely spent at least some of their social time reaping few added benefits for their well-being. And even when taking the more conservative estimates within each study for the individuals impacted, more than 100,000 individuals across the four studies spent more than the estimated optimal social time. If we presume that one of those hundred thousand individuals was a well-read social psychologist, we couldn't have blamed them for erroneously thinking that the social time they were spending was not enough if their goal were to maximize their well-being.

Of course, we need not and should not take the observed breakpoints too literally: There is likely nothing magical about 2.5 h of purposeful socializing or 3 h of time spent with family and friends. In fact, the exact number would vary by the criterion of well-being (e.g., affect vs. life satisfaction), the exact nature of the social time (e.g., with whom, where, when), as well as by myriad other factors, such as personality traits (e.g., extraversion), societal norms and expectations, and so forth. Although we did not find the curvilinear effects to be moderated by extraversion, Study 3b where we tested for this interaction was underpowered to detect such interactions, thus warranting further investigation of this possibility. While we hope researchers will explore the role of such factors in qualifying the optimal time to spend with social partners and in social activities, we would caution against trying to provide "user-friendly" estimates of optimal time that the media would love, potentially misleading the public. Taking our own advice, we note that the key lesson from our segmentation analyses is not in providing the exact optimal number of hours to socialize, but rather, in showing that the declining marginal utility of social time for well-being is far from a rare oddity; in reality, this curvilinearity seems to be a wide-spread phenomenon, impacting a sizable proportion of, if not the majority of, the population.

6.2. Implications

The present research has broader implications for the optimal ways to pursue greater happiness. A number of researchers have suggested that people can enhance their subjective well-being simply by restructuring their time so that they spend more time in rewarding activities—with socializing as the prime example (e.g., Kahneman et al., 2004; Lyubomirsky et al., 2005; Sheldon & Lyubomirsky, 2006). The present findings show that such recommendations are qualified by an important caveat: Reallocating one's time to social activities would only increase happiness for those who are not already spending a great amount of time in social activities to begin with. For those who already spend a good amount of time socializing, however, spending even more time in such activities might fail to produce the desired and expected boost to subjective well-being. In fact, the principle of satisfaction limits suggests that those who already spend much of their time in social activities might benefit not so much from more socializing, but rather from spending more time in other activities, even those considered less pleasurable such as working. Currently, many existing interventions designed to increase subjective well-being advise people to engage in more social interactions and invest more time in their relationships (e.g., Kushlev et al., 2017; Lyubomirsky & Layous, 2013; Quoidbach, Mikolajczak, & Gross, 2015; Seligman, Steen, Park, & Peterson, 2005; Sin & Lyubomirsky, 2009). Our findings suggest that rather than making such sweeping recommendations, these interventions need to first take into consideration the balance between social and other activities in people's lives (c.f., Sirgy & Wu, 2009).

The present findings also have implications for research, and in particular, how psychological researchers analyze and interpret data on the subjective well-being benefits of social life. First, rather than assuming that the presence of a linear effect indicates that more social time is progressively better for subjective well-being, researchers should first explore the presence of curvilinear effects. Similarly, experimental researchers seeking to explore the effects of increasing social interaction should examine moderation by baseline levels of social interaction. More generally, researchers should be careful in how they interpret their findings, staying away from sweeping statements about the benefits of social interaction.

6.3. Limitations

6.3.1. Correlation is not causation

Despite the consistent evidence for curvilinearity we observed using a triangulated multi-method approach, the present research is limited in several ways. First, because our studies are correlational, we cannot draw any strong conclusions about the effects of increasing or decreasing social time on well-being. We found that the effects held when controlling for multiple demographic and other factors, but it is not possible to rule out all potential confounds. The reverse direction of causality is also a possibility. For example, people who are depressed might be more likely to spend time at home with their family; thus, even if some individuals continue to reap benefits of ever more time spent with their family and friends, such depressed individuals might have effectively flattened the relationship between well-being and family time in Study 1. It is also possible that people who feel less happy seek to enhance their subjective well-being by socializing more, again flattening the relationship at higher levels of social time (Studies 2 & 3). Notably, however, these two possibilities seem to be somewhat at odds with one another—people who stay at home a lot with their families are probably not the ones that spend the most time socializing. Thus, the consistent findings across measures and methodologies speak in favor of the theorized direction of causality. The reverse direction of causality is also difficult to explain in view of the mediation and moderation effects we documented, as predicted by the principles of diminishing satisfaction and the principle of satisfaction limits. At the very least, then, the reverse direction of causality does not seem to offer the most parsimonious theoretical reason for the observed effects (c.f., Epstein, 1984). Still, future research could explore causality more directly by trying to manipulate the amount of time people spend in social interactions. This is not to say that experimental designs are inherently better than the approach adopted here: Experimental studies would, in general, have limitations of their own compared to the present studies, such as limited external validity, sample size, and population representativeness.

6.3.2. Between-subjects versus within-subjects curvilinearity

Another limitation of the present study is that the effects we observed are solely based on between-subjects comparisons. These between-subjects comparisons are ideal for testing the principle of satisfaction limits, which predicts curvilinearity between social time and general measures of well-being; that is, measures unlikely to vary meaningfully within-persons on a daily basis. Though such between-subjects comparisons can and did seem to capture the processes postulated by the principle of diminishing satisfaction, however, these intra-domain processes map better theoretically on within-subjects variations in social time. Thus, it would be important to see whether social time has declining marginal utility for well-being for individuals as they socialize more or less across different days.

At a first glance, it seems like our Study 3a could be positioned to explore such within-subjects effects because each person reported their well-being during multiple episodes. Other design characteristics of this study, however, prevented us from exploring within-subjects curvilinearity. Although we estimated the deconflated within-subjects effects (Table 3a), these effects can only be interpreted as the effects of socializing or not socializing on the good mood gained or lost during a particular episode (given people's own averages of socializing and mood). Precisely because we measured the presence of, rather than the quantity of, social time at the episodic level, the within-subject curvilinear effects in these analyses could not test the proposed curvilinear effects of social time. Thus, we considered the possibility of creating daily composites of social time quantity to explore within-subjects curvilinearity. While we can reasonably assume that our measure of socializing—the proportion of episodes socializing—was able to capture high socializers over a period of an entire week, this same measure likely provides a poor measure of socializing on a day-to-day basis. This is because participants could report a maximum of five 15-min episodes per day, thus capturing a mere 1.25 h of people's daily activities. In addition, we only had 7 days of within-subjects observations. The ideal study design to test curvilinearity due to within-subjects variations would, therefore, be a daily diary study with full-day measures of social time measured during a sufficient number of days to allow enough variation to detect a potential within-subjects effect (e.g., a month).

Though Study 3a was not designed to test the within-subjects curvilinearity, a closer look at Studies 1 and 2 reveals that those studies, though relying on between-subjects analyses, could provide some indication of whether a within-subjects curvilinear effect exists. Specifically, because these studies measured social time during a single day in people's lives—presumably a poor measure of stable individual differences—these two studies could be seen as providing some initial evidence that daily variation in social time might also be curvilinearly related to well-being. This possibility seems even more likely when we consider that, across both Studies 1 and 2, we observed curvilinearity in the relationship between social time and well-being when both social time and well-being were measured at the daily level. Despite these glimpses of a possible within-person curvilinearity effect, future research should explore this possibility more directly through experimental and long-term daily diary studies.

6.3.3. Quantity versus quality of social time

We began by highlighting some of the large body of evidence on the importance of a rich social life for well-being. The richness of one's social life is, of course, not determined solely by the quantity of time, but also by its quality (as well as other factors such as the quantity and quality of one's social relationships; Uchida, Endo, & Shibanai, 2012). We suspect that unlike quantity, the quality of time spent with others might not be characterized by the same curvilinearity with respect to well-being. In fact, a diminishing quality of social interactions as people spend more time in social activities may be another mechanism behind the curvilinear effects of quantity of social time. Every moment of the initial two hours of catching up with an old friend at dinner might bring increasing happiness to both companions. When the dinner drags on to three, and then four hours, however, the conversation might get less animated, the bursts of laughter a little less frequent, and the smiles a little more contrived. At this point, both companions could perhaps be gaining more enjoyment from solitary activities, such as streaming their favorite shows in the comfort of their home. It is our hope that the present investigation would prompt researchers to further explore this interplay between the quantity and quality of social time. In sum, as a first examination of the declining marginal utility of social time, the present research raises more questions than it answers—a fertile ground for future research.

6.4. Coda

Aristotle advised us that true happiness can be found in the golden mean between deficiency and excess. A quick look at the psychological literature, however, might lead one to believe that researchers have finally found an exception to this rule in the case of the utility of social life for subjective well-being. Pitting the wisdom of the great philosopher against the claims made in the psychological literature, we found consistent, converging evidence that even social life has a limited value for happiness.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.jrp.2018.04.004.

References

Adler, D., & Murdoch, D. (2017). *Rgl: 3D visualization using opengl*. Retrieved from <https://CRAN.R-project.org/package=rgl>.

Andrews, F. M., & Withey, S. B. (1976). *Social indicators of well-being: America's perception of life quality*. New York: Plenum Press.

Aust, F., & Barth, M. (2017). *papaja: Create APA manuscripts with R Markdown*. Retrieved from <https://github.com/crsh/papaja>.

Bacon, D. W., & Watts, D. G. (1971). Estimating the transition between two intersecting straight lines. *Biometrika, 58*(3), 525–534. https://doi.org/10.1093/biomet/58.3.525.

Bartoń, K. (2017). MuMIn: Multi-model inference Retrieved from <https://CRAN.R-project.org/package=MuMIn>.

Bates, D., & Maechler, M. (2017). *Matrix: Sparse and dense matrix classes and methods*. Retrieved from <https://CRAN.R-project.org/package=Matrix>.

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using lme4. *Journal of Statistical Software, 67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01.

Bates, D. M., & Watts, D. G. (1988). *Nonlinear regression analysis and its applications* (Vol. 2) New York: Wiley.

Baumeister, R. F., & Leary, M. R. (1995). The need to belong: Desire for interpersonal attachments as a fundamental human motivation. *Psychological Bulletin, 117*(3), 497–529. https://doi.org/10.1037/0033-2909.117.3.497.

Biswas-Diener, R., Kashdan, T. B., & King, L. A. (2009). Two traditions of happiness research, not two distinct types of happiness. *Journal of Positive Psychology, 4*(3), 208–211. https://doi.org/10.1080/17439760902844400.

Breheny, P., & Burchett, W. (2017). *Visreg: Visualization of regression models*. Retrieved from <https://CRAN.R-project.org/package=visreg>.

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*(6), 1054–1085. https://doi.org/10.1016/j.jrp.2005.11.007.

Campbell, A., Converse, P. E., & Rodgers, W. L. (1976). *The quality of American life: Perceptions, evaluations, and satisfactions*. New York: Russell Sage Foundation.

Diener, E. (2000). Subjective well-being. The science of happiness and a proposal for a national index. *The American Psychologist, 55*(1), 34–43. https://doi.org/10.1037/0003-066X.55.1.34.

Diener, E., & Biswas-Diener, R. (2002). Will money increase subjective well-being? A literature review and guide to needed research. *Social Indicators Research, 57*(2), 119–169. https://doi.org/10.1023/A:1014411319119.

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

Diener, E., Heintzelman, S. J., Kushlev, K., Tay, L., Wirtz, D., Lutes, L. D., & Oishi, S. (2017). Findings all psychologists should know from the new science on subjective well-being. *Canadian Psychology, 58*(2), 87–104. https://doi.org/10.1037/cap0000063.

Diener, E., Ng, W., & Tov, W. (2008). Balance in life and declining marginal utility of diverse resources. *Applied Research in Quality of Life, 3*(4), 277–291. https://doi.org/10.1007/s11482-009-9062-1.

Diener, E., & Seligman, M. E. P. (2002). Very happy people. *Psychological Science, 13*(1), 81–84. https://doi.org/10.1111/1467-9280.00415.

Diener, E., Wirtz, D., Tov, W., Kim-Prieto, C., Choi, D. W., Oishi, S., & Biswas-Diener, R. (2010). New well-being measures: Short scales to assess flourishing and positive and negative feelings. *Social Indicators Research, 97*(2), 143–156. https://doi.org/10.1007/s11205-009-9493-y.

Eager, C. D. (2017). *Standardize: Tools for standardizing variables for regression in r*. Retrieved from <https://CRAN.R-project.org/package=standardize>.

Eakman, A. M. (2016). A subjectively-based definition of life balance using personal meaning in occupation. *Journal of Occupational Science, 23*(1), 108–127. https://doi.org/10.1080/14427591.2014.955603.

Epley, N., & Schroeder, J. (2014). Mistakenly seeking solitude. *Journal of Experimental Psychology: General, 143*(5), 1980–1999. https://doi.org/10.1037/a0037323.

Epstein, R. (1984). The principle of parsimony and some applications in psychology. *The Journal of Mind and Behavior*, 119–130.

Fox, J., & Weisberg, S. (2011). *An R companion to applied regression* (2nd ed.). Thousand Oaks, CA: Sage. Retrieved from <http://socserv.socsci.mcmaster.ca/jfox/Books/Companion>.

Friedman, J. H. (1991). Multivariate adaptive regression splines. *The Annals of Statistics, 19*(1), 1–67. https://doi.org/10.1214/aos/1176347963.

Frisch, M. B. (2005). *Quality of life therapy: Applying a life satisfaction approach to positive psychology and cognitive therapy*. Hoboken, NJ: Wiley and Sons.

Fu, C. K., & Shaffer, M. A. (2001). The tug of work and family: Direct and indirect domain-specific determinants of work-family conflict. *Personnel Review, 30*, 502–522.

Gosling, S. D., Rentfrow, P. J., & Swann, W. B. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality, 37*(6), 504–528. https://doi.org/10.1016/S0092-6566(03)00046-1.

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

Greenhaus, J. H., & Beutell, N. J. (1985). Sources of conflict between work and family roles. *Academy of Management Review, 10*, 76–88.

Hastie, T., & Lumley, T. (2017). *Earth: Multivariate adaptive regression splines*. Retrieved from <https://CRAN.R-project.org/package=earth>.

Hastie, T., & Tibshirani, R. (2017). *Mda: Mixture and flexible discriminant analysis*. Retrieved from <https://CRAN.R-project.org/package=mda>.

Hayes, A. F., & Preacher, K. J. (2010). Quantifying and testing indirect effects in simple mediation models when the constituent paths are nonlinear. *Multivariate Behavioral Research, 45*(4), 627–660. https://doi.org/10.1080/00273171.2010.498290.

Helson, H. (1964). *Adaptation-level theory*. New York: Harper & Row.

Hofferth, S. L., Flood, S. M., & Sobek, M. (2015). *American time use survey data extract system: Version 2.5 [Machine-readable data-base]*. Minneapolis, MI: Maryland Population Research Center, University of Maryland, College Park, Maryland, and Minnesota Population Center, University of Minnesota. <http://doi.org/10.18128/D060.V2.5>.

Holahan, C. K., & Gilbert, L. A. (1979). Conflict between major life roles: Women and men in dual career couples. *Human Relations, 32*, 451–467.

Hsieh, C. M. (2003). Counting importance: The case of life satisfaction and relative domain importance. *Social Indicators Research, 61*(2), 227–240. https://doi.org/10.1023/A:1021354132664.

Hudson, N. W., Lucas, R. E., Donnellan, M. B., & Kushlev, K. (2016). Income reliably predicts daily sadness, but not happiness: A replication and extension of Kushlev, Dunn, and Lucas (2015). *Social Psychological and Personality Science, 7*(8), 828–836. https://doi.org/10.1177/1948550616657599.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences, 107*(38), 16489–16493. https://doi.org/10.1073/pnas.1011492107.

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. https://doi.org/10.1126/science.1103572.

Kalliath, T., & Brough, P. (2008). Work-life balance: A review of the meaning of the balance construct. *Journal of Management and Organization, 14*, 323–327.

Krueger, A. B., Kahneman, D., Fischler, C., Schkade, D., Schwarz, N., & Stone, A. A. (2009). Time use and subjective well-being in France and the U.S.. *Social Indicators Research, 93*(1), 7–18. https://doi.org/10.1007/s11205-008-9415-4.

Kushlev, K., Dunn, E. W., & Lucas, R. E. (2015). Higher income is associated with less daily sadness but not more daily happiness. *Social Psychological and Personality Science, 6*(5), 483–489. https://doi.org/10.1177/1948550614568161.

Kushlev, K., Heintzelman, S. J., Lutes, L. D., Wirtz, D., Oishi, S., & Diener, E. (2017). ENHANCE: Design and rationale of a randomized controlled trial for promoting enduring happiness & well-being. *Contemporary Clinical Trials, 52*, 62–74. https://doi.org/10.1016/j.cct.2016.11.003.

Larson, R., & Csikszentmihalyi, M. (1983). The experience sampling method. Naturalistic approaches to studying social interaction. *New Directions for Methodology of Social and Behavioral Science*, 41–56.

Lemon, J. (2006). Plotrix: a package in the red light district of R. *R-news, 6*(4), 8–12.

Lüdecke, D. (2017a). Ggeffects: Create tidy data frames of marginal effects for 'ggplot' from model outputs Retrieved from <https://CRAN.R-project.org/package=ggeffects>.

Lüdecke, D. (2017b). SjPlot: Data visualization for statistics in social science Retrieved from <https://CRAN.R-project.org/package=sjPlot>.

Lyubomirsky, S., & Layous, K. (2013). How do simple positive activities increase well-being? *Current Directions in Psychological Science, 22*(1), 57–62. https://doi.org/10.1177/0963721412469809.

Lyubomirsky, S., Sheldon, K. M., & Schkade, D. (2005). Pursuing happiness: The architecture of sustainable change. *Review of General Psychology, 9*(2), 111–131. https://doi.org/10.1037/1089-2680.9.2.111.

Matuska, K. (2012). Validity evidence of a model and measure of life balance. *OTJR: Occupation, Participation and Health, 32*(1), 229–237. https://doi.org/10.3928/15394492-20110610-02.

Milborrow, S. (2017). Plotmo: Plot a model's response and residuals Retrieved from <https://CRAN.R-project.org/package=plotmo>.

Muggeo, V. M. (2003). Estimating regression models with unknown break-points. *Statistics in Medicine, 22*, 3055–3071. https://doi.org/10.1002/sim.1545.

Muggeo, V. M. (2008). Segmented: An r package to fit regression models with broken-line relationships. *R News, 8*(1), 20–25. Retrieved from <https://cran.r-project.org/doc/Rnews/>.

Myers, B. D. G., & Diener, E. (1995). Who is happy? *Psychological Science, 6*(1), 10–19.

Netemeyre, R. G., Boles, J. S., & McMurrian, R. (1996). Development and validation of work-family conflict and family-work conflict scales. *Journal of Applied Psychology, 81*, 400–410.
Oishi, S., Schimmack, U., & Diener, E. (2012). Progressive taxation and the subjective well-being of nations. *Psychological Science, 23*(1), 86–92. https://doi.org/10.1177/0956797611420882.
Pedhazur, E. J. (1997). *Multiple regression in behavioral research* (3rd ed.). Orlando, FL: Harcourt Brace.
Peña, E. A., & Slate, E. H. (2014). *Gvlma: Global validation of linear models assumptions*. Retrieved from <https://CRAN.R-project.org/package=gvlma>.
Peña, E. A., & Slate, E. H. (2006). Global validation of linear model assumptions. *Journal of the American Statistical Association, 101*(473), 341–354 <https://dx.doi.org/10.1198%2F016214505000000637>.
Quoidbach, J., & Dunn, E. W. (2013). Give it up: A strategy for combating hedonic adaptation. *Social Psychological and Personality Science, 4*(5), 563–568. https://doi.org/10.1177/1948550612473489.
Quoidbach, J., Mikolajczak, M., & Gross, J. J. (2015). Positive interventions: An emotion regulation perspective. *Psychological Bulletin, 141*(3), 655–693. https://doi.org/10.1037/a0038648.
R Core Team. (2017). *R: A language and environment for statistical computing*. Vienna, Austria: R Foundation for Statistical Computing. Retrieved from <https://www.R-project.org/>.
Reis, H. T., Sheldon, K. M., Gable, S. L., Roscoe, J., & Ryan, R. M. (2000). Daily well-being: The role of autonomy, competence, and relatedness. *Personality and Social Psychology Bulletin, 26*(4), 419–435. https://doi.org/10.1177/0146167200266002.
Revelle, W. (2017). *Psych: Procedures for psychological, psychometric, and personality research*. Evanston, Illinois: Northwestern University. Retrieved from <https://CRAN.R-project.org/package=psych>..
Rojas, M. (2006). Life satisfaction and satisfaction in domains of life: Is it a simple relationship? *Journal of Happiness Studies, 7*(4), 467–497. https://doi.org/10.1007/s10902-006-9009-2.
Ryan, R. M., & Deci, E. L. (2000). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American Psychologist, 55*(1), 68–78. https://doi.org/10.1037//0003-066X.55.1.68.
Sandstrom, G. M., & Dunn, E. W. (2014). Social interactions and well-being: The surprising power of weak ties. *Personality and Social Psychology Bulletin, 40*(7), 910–922. https://doi.org/10.1177/0146167214529799.
Sarkar, D. (2008). *Lattice: Multivariate data visualization with r*. New York: Springer. Retrieved from <http://lmdvr.r-forge.r-project.org>.
Schwarz, N. (1999). Self-reports: How the questions shape the answers. *American Psychologist, 54*(2), 93. https://doi.org/10.1037/0003-066X.54.2.93.
Seligman, M. E. P., Steen, T. A., Park, N., & Peterson, C. (2005). Positive psychology progress: Empirical validation of interventions. *American Psychologist, 60*(5), 410–421. https://doi.org/10.1037/0003-066X.60.5.410.
Sheldon, K. M., Cummins, R., & Kamble, S. (2010). Life balance and well-being: Testing a novel conceptual and measurement approach. *Journal of Personality, 78*(4), 1093–1134. https://doi.org/10.1111/j.1467-6494.2010.00644.x.
Sheldon, K. M., Elliot, A. J., Kim, Y., & Kasser, T. (2001). What is satisfying about satisfying events? Testing 10 candidate psychological needs. *Journal of Personality and Social Psychology, 80*(2), 325–339. https://doi.org/10.1037/0022-3514.80.2.325.
Sheldon, K. M., Boehm, J., & Lyubomirsky, S. (2013). Variety is the spice of happiness: The hedonic adaptation prevention model. *The Oxford Handbook of Happiness* (pp. 901–914). <http://doi.org/10.1093/oxfordhb/9780199557257.013.0067>.
Sheldon, K. M., & Lyubomirsky, S. (2006). Achieving sustainable gains in happiness: Change your actions, not your circumstances. *Journal of Happiness Studies, 7*(1), 55–86. https://doi.org/10.1007/s10902-005-0868-8.
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*(2), 331–341. https://doi.org/10.1037/0022-3514.91.2.331.
Sin, N. L., & Lyubomirsky, S. (2009). Enhancing well-being and alleviating depressive symptoms with positive psychology interventions: A practice-friendly meta-analysis. *Journal of Clinical Psychology, 65*(5), 467–487. https://doi.org/10.1002/jclp.20593.
Sirgy, M. J. (2010). Toward a quality-of-life theory of leisure travel satisfaction. *Journal of Travel Research, 49*, 246–260. https://doi.org/10.1177/0047287509337416.
Sirgy, M. J. (2012). *The psychology of quality of life: Hedonic well-being, life satisfaction, and eudaimonia* (2nd ed.). Dordrecht, Netherlands: Springer Publishers.
Sirgy, M. J., & Lee, D.-J. (2018). The psychology of life balance. In E. Diener, S. Oishi, & L. Tay (Eds.), Handbook of well-being. Noba Scholar Handbook series: Subjective well-being. Salt Lake City, UT: DEF publishers.
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*(2), 183–196. https://doi.org/10.1007/s10902-007-9074-1.
Sturges, J., & Guest, D. (2004). Working to live or living to work? Work/life balance early in the career. *Human Resource Management Journal, 14*, 5–20. https://doi.org/10.1111/j.1748-8583.2004.tb00130.x.
Uchida, Y., Endo, Y., & Shibanai, Y. (2012). Well-being and social relationship styles: Effects of quantity and quality of social relationships. *The Japanese Journal of Experimental Social Psychology, 52*(1), 63–75. https://doi.org/10.2130/jjesp.52.63.
Veenhoven, R. (1991). Is happiness relative? *Social Indicators Research, 24*(1), 1–34. https://doi.org/10.1007/BF00292648.
Venables, W. N., & Ripley, B. D. (2002). *Modern applied statistics with s (Fourth.)*. New York: Springer. Retrieved from <http://www.stats.ox.ac.uk/pub/MASS4>.
Voydanoff, P. (2005). Toward a conceptualization of perceived work-family fit and balance: A demands and resources approach. *Journal of Marriage and Family, 67*, 822–836 <http://doi.org//10.1111/j.1741-3737.2005.00178.x>.
Watson, D., & Clark, L. A. (1999). *The PANAS-X: Manual for the positive and negative affect schedule-expanded form*. <http://www.psychology.uiowa.edu/Faculty/Watson/Watson.html>.
Watson, D., Clark, L. A., & Tellegen, A. (1988). Development and validation of brief measures of positive and negative affect: The PANAS scales. *Journal of Personality and Social Psychology, 54*(6), 1063–1070. https://doi.org/10.1037/0022-3514.54.6.1063.
Wickham, H. (2016). *Ggplot2: Elegant graphics for data analysis*. New York: Springer-Verlag. Retrieved from <http://ggplot2.org>.
Wickham, H., Francois, R., Henry, L., & Müller, K. (2017). *Dplyr: A grammar of data manipulation*. Retrieved from <https://CRAN.R-project.org/package=dplyr>.
Wood, S. N. (2003). Thin-plate regression splines. *Journal of the Royal Statistical Society (B), 65*(1), 95–114. https://doi.org/10.1111/1467-9868.00374.
Wood, S. N. (2004). Stable and efficient multiple smoothing parameter estimation for generalized additive models. *Journal of the American Statistical Association, 99*(467), 673–686. https://doi.org/10.1111/1467-9868.00374.
Wood, S. N. (2011). Fast stable restricted maximum likelihood and marginal likelihood estimation of semiparametric generalized linear models. *Journal of the Royal Statistical Society (B), 73*(1), 3–36. https://doi.org/10.1111/j.1467-9868.2010.00749.x.
Wood, S. N., Pya, N., & Säfken, B. (2016). Smoothing parameter and model selection for general smooth models. *Journal of the American Statistical Association, 111*(516), 1548–1563. https://doi.org/10.1080/01621459.2016.1180986.
Xie, Y. (2015). *Dynamic documents with R and knitr* (2nd ed.). Boca Raton, Florida: Chapman; Hall/CRC. Retrieved from <https://yihui.name/knitr/>.