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Is Well-Being Associated With the Quantity and Quality of Social Interactions?

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Social relationships are often touted as critical for well-being. However, the vast majority of studies on social relationships have relied on self-report measures of both social interactions and well-being, which makes it difficult to disentangle true associations from shared method variance. To address this gap, we assessed the quantity and quality of social interactions using both self-report and observer-based measures in everyday life. Participants ($N = 256$; 3,206 observations) wore the Electronically Activated Recorder (EAR), an unobtrusive audio recorder, and completed experience sampling method self-reports of their momentary social interactions, happiness, and feelings of social connectedness, 4 times each day for 1 week. Observers rated the quantity and quality of participants' social interactions based on the EAR recordings from the same time points. Quantity of social interactions was robustly associated with greater well-being in the moment and on average, whether they were measured with self-reports or observer reports. Conversational (conversational depth and self-disclosure) and relational (knowing and liking one's interaction partners) aspects of social interaction quality were also generally associated with greater well-being, but the effects were larger and more consistent for self-reported (vs. observer-reported) quality variables, within-person (vs. between-person) associations, and for predicting social connectedness (vs. happiness). Finally, although most associations were similar for introverts and extraverts, our exploratory results suggest that introverts may experience greater boosts in social connectedness, relative to extraverts, when engaging in deeper conversations. This study provides compelling multimethod evidence supporting the link between more frequent and deeper social interactions and well-being.

Keywords: social interactions, well-being, extraversion, experience sampling, naturalistic observation

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Social relationships are often touted as critical for well-being (Argyle, 2001; Myers, 2000). Indeed, a clear conclusion from previous research on social interactions and well-being is that people feel happier in moments when they are interacting with others, and that happier people tend to spend more time interacting with others. Across a range of methods, including not only retrospective and momentary self-reports (Kushlev, Heintzelman, Oishi, & Diener, 2018; Lucas, Le, & Dyrenforth, 2008; Rohrer, Richter, Brümmer, Wagner, & Schmukle, 2018; Srivastava, Angelo, & Vallereux, 2008; Watson, Clark, McIntyre, & Hamaker, 1992), but also mechanical clickers for counting social interactions as they occur (Sandstrom & Dunn, 2014b), and observer ratings based on unobtrusive audio recordings of everyday behavior (Mehl, Vazire, Holleran, & Clark, 2010; Milek et al., 2018), studies consistently show that the amount—or *quantity*—of social interactions one has is associated with greater well-being.

Less is known, however, about how much the *quality* of social interactions—including what happens during a social interaction

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Simine Vazire acquired funding. Simine Vazire and Kelci Harris designed and supervised data collection for the larger study. All authors conceptualized the current research goals. Jessie Sun supervised Electronically Activated Recorder coding, analyzed the data (with input from Kelci Harris and Simine Vazire), and drafted the manuscript. All authors provided critical revisions to the manuscript and approved the final manuscript for submission.

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and who it is shared with—matters for well-being. This literature is less conclusive because of its reliance on self-report measures of both the quality of social interactions and well-being. To address this gap, we use a multimethod approach that harnesses naturalistic observations of social interactions to clarify whether and which qualities of social interactions are related to within-person fluctuations and between-person differences in well-being. Finally, given the empirical and theoretical importance of trait extraversion to both social behavior and well-being, we examine whether the associations between the quantity and quality of social interactions and well-being are similar for introverts and extraverts.

Compared to experimental paradigms, our naturalistic method emphasizes ecological validity but prevents us from drawing causal conclusions. Still, grounded in the perspective that "it is necessary to know the thing we are trying to explain" (Asch, 1952/1987, p. 65; see also Rozin, 2001), we believe that establishing the robustness and magnitude of effects in the real world provides an important foundation for future experimental tests that can shed light on causal explanations. Effect sizes based on observations of real-world phenomena can also constrain theories about causal links between social interactions and well-being. Therefore, we focus on thoroughly describing the associations between several aspects of naturally-occurring variations in social interactions and well-being, rather than addressing issues of causality.

Is the Quality of Social Experience Related to Well-Being?

Not all social interactions are equal—rather, social interactions are flavored by attributes such as conversational features (e.g., conversational depth and self-disclosure), relational features (e.g., relationship type, closeness, acquaintanceship, liking), and the purpose of the social interaction (e.g., entertainment, work, chores), that make each social interaction unique. Theory and intuition both suggest that the quality of one's social interactions should matter for well-being, over and above the sheer amount of time spent in social interactions. For example, Baumeister and Leary (1995) argued that people have a universal basic need to form and maintain strong, stable interpersonal relationships. Crucially, according to Baumeister and Leary, mere social contact is not enough to fulfill this need to belong; instead, interactions should be not only frequent but also pleasant (or at least free from conflict), and people need to perceive a bond that involves "stability, affective concern, and continuation into the foreseeable future" (p. 500).

At first glance, it seems that a plethora of studies show that the quality of social experience is related to well-being. For example, people who report that their relationships are more satisfying and supportive tend to report greater subjective well-being (for a review, see Lyubomirsky, King, & Diener, 2005). However, such associations are based on self-reports of both relationship quality and subjective well-being, which raises concerns about potential artifacts (for methodological critiques, see Lucas & Dyrenforth, 2006; Lucas, Dyrenforth, & Diener, 2008). For example, people's positive perceptions of their lives could lead to halo effects in which they think that all domains of their lives (including their social relationships) are going well, regardless of whether things are objectively going well in those domains. Studies that use self-reports to measure both the quality of one's social interactions and well-being cannot easily disentangle true associations from associations due to this type of halo effect or other sources of shared method variance (e.g., response styles). Such studies likely produce inflated estimates of the association between the quality of social interactions and well-being.

To date, only a handful of studies have examined whether non-self-report measures or manipulations of social interaction quality are associated with well-being, and the results have been mixed. The strongest evidence for a link between the quality of naturalistic social interactions and well-being comes from studies that use the Electronically Activated Recorder (EAR; Mehl, 2017), a device that unobtrusively records audio snippets of people's everyday behaviors. Human coders subsequently code these recordings for audible behaviors, including the quantity and quality of social interactions. Using this method, Mehl and colleagues (2010) found that happier people tend to have more substantive conversations—an effect that was later replicated (Milek et al., 2018). Although the size of the association between life satisfaction and the percentage of substantive conversations was fairly small (r = .15; Milek et al., 2018), this finding is compelling because there is no method overlap between behavioral observations of conversational depth and self-reported life satisfaction.

Another important quality of a social interaction is one's relationship with the person with whom it is shared. Specifically, interactions with close others—although not without their own unique challenges—afford the opportunity for more responsive, accepting, and authentic interactions (at least as subjectively experienced), compared to interactions with distant others (Venaglia & Lemay, 2017). Yet, some studies suggest that even interactions with strangers and weak ties can be quite pleasant. For example, bus and train commuters who were instructed to interact with a stranger reported more positive experiences than those who were instructed to remain in solitude (Epley & Schroeder, 2014). Even having a brief but genuine social interaction with a Starbucks barista appears to have hedonic benefits, compared to completing the transaction as efficiently as possible (Sandstrom & Dunn, 2014a). These studies do not imply that closeness is irrelevant to well-being—only that minimal social interactions with those on the peripheries of our social networks can be surprisingly rewarding.

Fewer studies have examined whether interactions with close others are *more* rewarding than interactions with distant others, and have found mixed results. In the laboratory, participants who were randomly assigned to interact with a stranger felt just as happy as those assigned to interact with their romantic partner (Dunn, Biesanz, Human, & Finn, 2007). Similarly, a study of naturally occurring social interactions did not find systematically larger well-being benefits of interacting with strong ties than weak ties (Sandstrom & Dunn, 2014b, Studies 2a–2b). A recent experience sampling study, however, showed that people felt happier when they interacted with close others, compared to distant others—whether closeness was indexed by relationship type or subjective closeness (Venaglia & Lemay, 2017). Similarly, Mueller and colleagues (2019) found that people tended to feel happiest after interactions with friends, followed by interactions with family members, others, and colleagues. Thus, overall, it is unclear whether people benefit more from interacting with close (vs. distant) others.

In sum, very few studies have used non-self-report methods to examine the association between the quality of social experience and well-being, and existing studies have produced mixed results. The main goal of our study is to provide a strong test of the associations between the quality of social interactions and well-being, by using self- and observer-reports of multiple conversational and relational aspects of social interaction quality.

Trait Extraversion as a Potential Moderator

A second longstanding question is whether and how the associations between social interactions and well-being differ for those who are more or less extraverted ("extraverts" and "introverts", for short-hand). *Extraversion* describes the tendency to be talkative, assertive, outgoing, and sociable. Considerable evidence supports the theory that extraversion reflects reward sensitivity—the extent to which people are motivated to pursue rewards, and enjoy those rewards once they are attained (for reviews, see DeYoung, 2015; Smillie, 2013). Because many human rewards are social, extraverts, compared to introverts, should derive greater enjoyment from social interactions (the *social reactivity hypothesis*; Srivastava et al., 2008).

Yet, the social reactivity hypothesis has received only mixed support. Early studies found that extraverts and introverts experienced similarly large boosts in momentary positive affect when they spent more time socializing (Lucas, Le, & Dyrenforth, 2008; Srivastava et al., 2008). Similarly, commuters who were instructed to interact with a stranger reported more positive experiences than those instructed to remain in solitude, whether they were more or less extraverted (Epley & Schroeder, 2014). One recent study did find that extraverts had a stronger positive association between social time and average momentary mood than did introverts—but this did not generalize to global positive affect (Kushlev et al., 2018, Study 3b). Similarly, even though extraverts experienced a larger increase in positive affect after a "cocktail party" interaction than did introverts, a large proportion of introverts who had expected to feel worse after socializing actually felt better (Duffy, Helzer, Hoyle, Helzer, & Chartrand, 2018).

It is also unclear whether the quality of social interactions matters more for introverts. In her popular book *Quiet*, Susan Cain (2012) speculated that introverts "prefer to devote their social energies to close friends, colleagues, and family" and "have a horror of small talk, but enjoy deep discussions" (p. 11). Theoretically, however, extraversion involves an affiliative component characterized by the enjoyment of close interpersonal bonds, as well as a more general sensitivity to rewards (Depue & Morrone-Strupinsky, 2005; DeYoung, 2015; Smillie, 2013). These theoretical perspectives suggest that, if anything, extraverts should show a stronger association between deep social interactions and well-being, compared to introverts.

Here, the empirical evidence is once again inconclusive. A meta-analysis of four studies suggests that extraversion does not moderate the association between unobtrusively captured depth of conversation and self-reported life satisfaction (Milek et al., 2018). Nor are we aware of evidence that introverts benefit relatively more from interacting with close (vs. distant) others than do extraverts. One study of over 50,000 social interactions found no moderating role of extraversion on the within-person associations between the type of interaction partner and momentary happiness (Mueller et al., 2019). If anything, Sandstrom and Dunn (2014b; Study 2a) found that each additional interaction with a "weak tie" (but not a "strong tie") predicted a greater increase in belonging for introverts, compared to extraverts (but note that this interaction effect did not generalize to subjective well-being). Thus, our study also aims to address the open question of whether the associations between the quantity and quality of social interactions and well-being differ for introverts and extraverts.

The Present Study

There are still many open questions about how social interaction is related to well-being, and whether trait extraversion moderates any of the associations between aspects of social interactions and well-being. Our key goal is to examine whether self- and observer-based measures of the quantity and quality of social interactions converge on similar conclusions, in order to disambiguate true associations from methodological artifacts. To do so, we use an intensive multimethod approach to capture repeated self- and observer ratings of social interactions and self-reported well-being, and to examine effects at the within- and between-person levels. We measure naturally occurring fluctuations in social interactions and well-being in participants' everyday lives to provide an ecologically valid test of these associations.

To assess the quantity of social interactions, we use self- and observer-ratings of the presence or absence of social interactions. Assessing the quality of social interactions—especially using non-self-report methods, and in a way that clearly distinguishes between the quality of the social interaction and how the participant feels about the interaction—is much less straightforward. Here, we measure four variables that capture differences in the quality of social interactions. We use self- and observer-ratings of two conversational features (conversational depth and self-disclosure) that reflect deeper, more intimate interactions. We also use self-reports of two relational features (how much participants knew and liked their interaction partners). We opted not to analyze the observer ratings of these two relational features because we decided (without looking at the results) that these are inherently self-defined variables, and that observer ratings are very unlikely to contain valid variance not captured by self-reports. Of course, these four variables (conversational depth, self-disclosure, knowing, and liking) do not capture all of the ways that social interactions can differ. However, we believe that they are strong candidates for variables that (a) capture variability in the quality of everyday social interactions, (b) could potentially be related to well-being, and (c) can be validly measured repeatedly in everyday life, and, in the case of conversational depth and self-disclosure, with both self- and observer reports.

We examine how the quantity and quality of social interactions are associated with two distinct dimensions of well-being: feelings of happiness and of social connectedness (which both feature in several taxonomies of well-being; e.g., Butler & Kern, 2016; Huppert & So, 2013; Ryff, 1989). This allows for a more fine-grained understanding of the distinct correlates of different dimensions of well-being (e.g., Baumeister, Vohs, Aaker, & Garbinsky, 2013; Dwyer, Dunn, & Hershfield, 2017; Sun, Kaufman, & Smillie, 2018), while facilitating more general conclusions about the link between social interactions and well-being broadly construed (rather than only the affective component of well-being). Whereas happiness is a more general indicator of well-being that is influenced by many everyday experiences besides social interactions (e.g., Kahneman, Krueger, Schkade, Schwarz, & Stone, 2004), feelings of social connectedness are conceptually more closely linked to the quantity and quality of one's social interactions. Importantly, however, the feeling of social connectedness (as we operationalize it in this study) is also distinct from the quantity and quality of social interactions. Our social connectedness measure captures subjective feelings of connectedness versus loneliness, rather than the presence or absence of a social interaction, or features of the social interaction (e.g., the depth of the interaction, or how well the participant knew the interaction partner). In addition, people can feel more or less socially connected even when they are not interacting with others, whereas the quality of social interaction variables—by definition—only apply when a social interaction occurs.

We generally expected to see positive associations between all aspects of social interactions and well-being, but expected the effect sizes to be smaller for observer-based (vs. self-reported) measures of social interactions. Apart from these general expectations, we had no specific predictions about how effect sizes might vary across the analyses. We also had no predictions about the moderating role of extraversion (given the mixed findings reviewed above).

Method

Ethics and Open Practices Statement

We used data from the first wave of the longitudinal Personality and Interpersonal Roles Study (PAIRS). Data collection and coding procedures were approved by Institutional Review Boards at Washington University in St. Louis (IRB ID: 201206090; Study Title: Personality and Intimate Relationships Study) and University of California, Davis (IRB ID: 669518–15; Study Title: Personality and Interpersonal Roles Study).

Other published articles have used the PAIRS dataset (for a full list of citations, see https://osf.io/3uag4), including the experience sampling method (ESM) happiness and positive emotion variables (Sun, Schwartz, Son, Kern, & Vazire, 2019; Weidman et al., 2019; Wilson, Thompson, & Vazire, 2017), and the ESM quantity of social interaction, conversational depth, and self-disclosure variables (Wilson, Harris, & Vazire, 2015) used in this dataset. Of these, the most closely related paper (Wilson et al., 2015) examined between-person correlations among friendship satisfaction, the average quantity and quality of self-reported social interactions with friends, and trait extraversion, but did not include any EAR data or analyses examining within-person associations. This is the first article that we know of that examines associations between social interactions and well-being using both self- and observer-reports in everyday life, using any dataset. Note also that this dataset is not the same as the EAR datasets used in the research reviewed above (Mehl et al., 2010; Milek et al., 2018).

Below, we describe the measures and procedures relevant to the current article. Several parts of the description of procedures and analytic specifications have been closely adapted from a previous article that used different variables from the same dataset (Sun & Vazire, 2019). Codebooks for all measures in the larger study are available at https://osf.io/akbfj. Although ethical considerations prevent us from making the audio files publicly available, the quantitative data, R scripts, and Mplus input and output files required to reproduce the analyses reported in this paper are available at https://osf.io/23vpz. We did not preregister any of these analyses, as the data were collected years ago and we were familiar with the dataset and had run some analyses before starting this project. Thus, all results are exploratory and any interesting patterns should be interpreted with caution.

Participants and Procedure Overview

The study involved 434 students at Washington University in St. Louis, who were recruited in 2012 and 2013 via flyers and classroom announcements across the campus. Participants completed a measure of trait extraversion as part of a battery of questionnaires during an initial laboratory-based assessment ($20 compensation). For the next two weeks, they completed ESM measures of social interactions and well-being four times per day (for the opportunity to win $100; odds of winning were 1 in 10 if all ESM reports were completed). In addition, most participants ($N = 311$) wore the EAR for the first week ($20 compensation), providing audio recordings of their everyday lives that were later coded for social interaction variables.

We ended data collection when we reached the end of a semester and had recruited at least 400 participants. After exclusions (described below), the final subset of 256 participants (178 women, 77 men, one gender not reported) used in the current analyses ranged in age from 18 to 29 years ($M = 19.17$, $SD = 1.78$) and identified as Caucasian ($n = 144$), Asian ($n = 61$), Black ($n = 25$), American Indian or Alaska Native ($n = 1$), Other ($n = 18$), or did not disclose their ethnicity ($n = 7$). See the Appendix for a demographic comparison of participants who were included versus excluded from the current analyses.

ESM and EAR Procedures

ESM. The ESM portion of the study began after participants completed the laboratory-based assessment. Four times per day (at 12 p.m., 3 p.m., 6 p.m., and 9 p.m.) for 15 days, participants received a text message notification and were emailed a link to a survey that contained ESM measures of their social interactions and well-being in the hour that preceded the notification (11 a.m.–12 p.m., 2 p.m.–3 p.m., 5 p.m.–6 p.m., and 8 p.m.–9 p.m.).

ESM data exclusions. In line with exclusion criteria applied in previous papers that used the PAIRS ESM data (e.g., Finnigan & Vazire, 2018; Wilson et al., 2017), we excluded ESM reports (a) if they were completed more than 3 hr after the notification was sent, (b) if participants completed fewer than 75% of the items, (c) if participants used the same response option for at least 70% of the items, or (d) if participants indicated that they were asleep during the entire target hour. We also excluded practice ESM surveys that were completed during the participant's initial laboratory session. After these exclusions, 10,949 reports from 406 participants remained (across the 2-week ESM period, including the week in which participants were not wearing the EAR).

EAR data collection. During the first week (6–8 days) of the ESM protocol, 311 participants wore the EAR, implemented through the iEAR app using an iPod Touch device. The EAR component of the study was optional, was only offered during nonsummer months of the study, and was not an option when all of the researchers' iPod Touches were in use by other participants. The EAR was programmed to record 30 s audio snippets of participants' ambient sounds, every 9.5 min from 7 a.m. to 2 a.m. Participants were encouraged to wear the EAR as much as possible and to wear it clipped to a waistband or the outside of their pockets (i.e., not inside a bag or pocket). Although participants had no way to tell when the device was recording, they were told that they could decide to not wear the EAR at any time for any reason. After 3–4 days, participants returned to the lab to upload their data (due to device memory limitations), and then continued wearing the device before returning it after another 3–4 days.

EAR data exclusions. Upon returning the device at the end of the week, participants received a compact disk with their recordings, so that they could listen to and erase any files they did not want the researchers to hear. Only a few participants ($n = 15$) chose to erase a total of 99 files. After deleting these files, along with files from six participants who withdrew, and one participant who only had silent recordings (suggesting that the microphone malfunctioned), 152,592 usable recordings from 304 participants remained.

EAR codings. Research assistants from Washington University in St. Louis ($n = 8$) and University of California, Davis ($n = 137$) listened to the audio files recorded during the same hours as the ESM reports (11 a.m.–12 p.m., 2 p.m.–3 p.m., 5 p.m.–6 p.m., and 8 p.m.–9 p.m.), and coded participants' social interactions (and other variables), across two coding tasks (described below). Some research assistants were involved in both tasks, but were only assigned participants that they did not code in the other task. Thus, across the two tasks, the codings for each participant were provided by different sets of research assistants.

Hour-level codings. For the hour-level codings, for each of their assigned participants, coders listened to the six or seven 30 s files (3–3.5 min total) from each ESM-matched hour, coded whether or not the participant interacted with others, rated participants' conversational depth and levels of self-disclosure during that hour (if the participant was interacting with others), then moved onto the next ESM-matched hour for that participant.

Because research assistants joined and left the lab at different times, each participant was coded by a different set of coders. Initially, we aimed to have each participant coded by three coders. However, as the interrater reliabilities based on three coders were low, we decided to add three more coders, so that each participant was coded by at least six coders. Between the two sets of codings, we made minor changes to the coding protocol (see the online supplemental materials), in hopes of increasing intercoder reliability.

File-level codings. For the file-level codings, coders again listened to only the audio files that were part of each ESM-matched hour. However, unlike for the hour-level codings, they listened to and coded each file separately, coding whether or not the participant was interacting with others during each file (rather than providing a single binary judgment for the entire hour). For this coding task, all but four participants were coded by three or more coders.

EAR coding exclusions. Coders only rated participants' social interactions in hours and files that contained sufficient acoustic information. For the hour-level task, we only kept hours that at least three coders rated as being informative (i.e., no technical difficulties, and participants appeared to be awake and wearing the EAR; see the online supplemental materials for details). Based on these criteria, 807 out of 5,222 hr (15.45%) were uninformative (and excluded from further analyses). For the file-level task, we only kept files that at least two coders rated as being informative. Based on these criteria, 4,208 out of 31,417 files (13.4%) were uninformative (and excluded from further analyses).

Measures

See Table 1 for within- and between-person reliability coefficients for all composites.

Social interactions.

Quantity of interactions.

Self-reported. In the ESM surveys, participants completed the item, "From [11 a.m.–noon/2 p.m.–3 p.m./5 p.m.–6 p.m./8 p.m.–9 p.m.], were you interacting with other people?" (response options: no, one person, two people, three to five people, more than five

Table 1
Descriptive Statistics and Inter-Correlations Among All Observed Variables

Variable	Descriptive statistics						Between-person correlations										
	M	SD_{WP}	SD_{BP}	$1 - ICC(1)$	ω_{WP}	ω_{BP}	1	2	3	4	5	6	7	8	9	10	11
1. Binary interactions (ESM)	.78	.40	.13	.90													
2. Binary interactions (EAR)	.70	.44	.13	.93	.94	.98	.40										
3. Continuous interactions (EAR)	.33	.32	.09	.92	.93	.90	.35	.67									
4. Conversational depth (ESM)	3.11	0.96	0.45	.82			.04	−.05	.01								
5. Conversational depth (EAR)	2.71	0.42	0.15	.88	.70	.24	.01	−.08	.12	−.05							
6. Self-disclosure (ESM)	2.53	1.05	0.48	.83			.20	−.03	.07	.43	.10						
7. Self-disclosure (EAR)	2.36	0.54	0.19	.89	.78	.41	.10	−.06	.23	.10	.54	.32					
8. Knowing (ESM)	3.80	1.06	0.38	.89			.14	.16	.15	.28	−.15	.12	.01				
9. Liking (ESM)	4.21	0.76	0.36	.82			.27	.20	.26	.38	−.12	.21	.07	.62			
10. Happiness (ESM)	3.46	0.81	0.49	.73	.82	.98	.28	.21	.20	.27	−.09	.26	.01	.22	.35		
11. Social connectedness (ESM)	3.57	0.80	0.44	.77	.52	.48	.49	.33	.41	.33	−.05	.33	.08	.39	.54	.66	
12. Trait extraversion	9.29		2.84			.90	.27	.21	.19	.16	−.06	.17	.10	.16	.23	.35	.36

Note. Means were computed from the aggregate observed mean for each person. SD_{WP} = within-person SD; SD_{BP} = between-person SD; ω_{WP} = within-person omega reliability; ω_{BP} = between-person omega reliability; ESM = experience sampling method; EAR = Electronically Activated Recorder. $ICC(1)$, the intraclass correlation, represents the proportion of total variance ($\sigma^2_{BP} + \sigma^2_{WP}$) that is due to between-persons variability (σ^2_{BP}; i.e., mean-level differences on a variable across the week), so $1 - ICC(1)$ denotes the % of total variance due to within-person variability (σ^2_{WP}; i.e., fluctuations around a person's mean level). These between-person correlations are based on the aggregate observed mean for each person, which is why they are different from the latent self–observer agreement correlations reported in-text. Correlations $\geq |.15|$ are significant at $p < .05$, not corrected for multiple comparisons.

people). We recoded these responses into two categories that denote whether a social interaction occurred (coded as 1) or not (coded as 0) during the target hour. Because participants were not provided with an explicit definition of what counted as "interacting with other people," these self-reported social interactions could have included computer-mediated social interactions.

Observer-based. We had two observer-based measures of the quantity of social interactions. The first measure was a binary measure based on whether the participant had interacted at all in the target hour, analogous to the self-report measure described above. After listening to the six or seven 30 s files for the hour, EAR coders completed the same item as in the ESM survey, "Was the participant interacting with other people?" (response options: no, one person, two people, three to five people, more than five people), with respect to the entire hour. We recoded each coder's responses into two categories that denote the absence (coded as 0) or presence (coded as 1) of a social interaction during the target hour. Then, we aggregated the responses across coders by recoding the hour-level score to 0 (*no interaction*) if the majority of coders said that the participant did not interact during that hour, and to 1 (*interaction occurred*) if at least half of the coders said that the participant interacted during that hour.

The second measure provided a separate, continuous measure of social interaction during the same hours, using data from the file-level codings (i.e., codings of each of the six or seven 30 s sound files in a given hour). Coders completed the item, "During this file, was the participant interacting with other people?" (0 = no, 1 = yes) for each individual file (rather than the entire hour). We aggregated the scores across coders by recoding the file-level score to 0 (*no interaction*) if the majority of coders said that the participant did not interact in that file, and to 1 (*interaction occurred*) if at least half of the coders said that the participant interacted in that file. Then, we aggregated the file-level scores to a continuous hour-level score by taking the mean of all of the informative files in that hour (up to seven files). This continuous variable could range from 0 (*no social interactions in any of the sound files in that hour*) to 1 (*social interaction occurred in all six or seven files in that hour*).

Quality of interactions.

Self-reported. If participants indicated that they had interacted with at least one person in the target hour, they completed four additional 1-item measures about the quality of their interactions. Participants rated the depth of their own conversations ("How superficial (i.e., shallow) to substantive (i.e., deep) were the conversations?"; on a scale ranging from 1 [*very superficial*] to 5 [*very substantive*]), and how much they self-disclosed ("How much did you self-disclose?"; on a scale ranging from 1 [*not at all*] to 5 [*a lot*]) during the target hour. Participants also reported on two relational features—how much they knew and liked the people they interacted with ("How well do you [know/like] them?"; on a scale ranging from 1 [*not at all*] to 5 [*very well/very much*]).

Observer-based. If EAR coders indicated that the participant had interacted with at least one person in the target hour, EAR coders rated the depth of the participants' conversations ("How superficial (i.e., shallow) to substantive (i.e., deep) did the conversations sound?"; on a scale ranging from 1 [*very superficial*] to 5 [*very substantive*]), and how much the participant self-disclosed ("How much do you think the participant self-disclosed?"; on a scale ranging from 1 [*not at all*] to 5 [*a lot*]) during the target hour. Coders also had the option to select "No way to tell" (rather than a number on the 1–5 scale).

EAR coders also completed measures of how much participants knew and liked the people they were interacting with, but we chose not to analyze these measures as we thought that it would be difficult for EAR coders to tell how much participants knew and liked their interaction partners. Given the subjective nature of these variables, we decided that, unlike conversational depth and self-disclosure, which can be observed by others, the observer-based measures of knowing and liking one's interaction partner(s) would be unlikely to contain any valid variance not captured by self-reports.

Momentary well-being. As part of the ESM survey, participants completed self-report measures of their momentary feelings of happiness and social connectedness during the target hour (e.g., "from 11 a.m. to 12 p.m.").

Happiness. To measure feelings of happiness, we averaged two items: "How happy were you?" (on a scale ranging from 1 [*not at all*] to 5 [*very*]) and "How much positive emotion did you experience?" (on a scale ranging from 1 [*none at all*] to 5 [*a lot*]). All participants had data on the happiness item, but data on the positive emotion item was missing for 51 of the 256 participants, as this item was added after data collection had begun.

Social connectedness. To measure feelings of social connectedness, we averaged together two items: "did you feel 'close, connected' to others?" and, reverse-scored, "how lonely were you?" (on a scale ranging from 1 [*not at all*] to 5 [*very*]).

Trait extraversion. Participants completed the Big Five Inventory (BFI–44; John & Srivastava, 1999), which includes an eight-item measure of trait extraversion. Responses were made on a 15-point scale (ranging from 1 [*disagree strongly*] to 15 [*agree strongly*]). We computed z-scores for trait extraversion prior to using them in the moderation analyses. These z-scores were computed separately for participants who were included in the quantity of social interaction analyses and participants who were included in the quality of social interaction analyses (see final sample details below).

Data Included in Final Analyses

Quantity of interactions. To hold the time points constant across all quantity analyses, we first excluded observations that were missing either ESM or EAR data, resulting in 3,292 observations that had both ESM and EAR data. Then, we excluded 33 participants who had fewer than five observations, resulting in 3,206 observations across 256 participants for these analyses.

Quality of interactions. Participants and observers only reported on the quality of social interactions when the participant had been interacting. Participants and observers agreed about whether or not the participant had interacted with someone in the past hour 70.12% of the time (agreement is weakened by the fact that EAR coders only heard 3 to 3.5 min of the hour). To hold the time points constant across all quality analyses, we only included the 1,836 time points for which participants and observers agreed that the participant had interacted with someone. Then, we excluded 64 participants who had fewer than five social interactions, resulting in 1,641 observations across 192 participants for these analyses.

Data Analysis

The data had a multilevel structure, with observations (Level 1) nested within participants (Level 2). To model the within- and between-person associations that social interaction variables had with well-being, we used Muthén and Asparahouv's (2009) general multilevel structural equation modeling (MSEM) framework, implemented using Mplus Version 8.3 (Muthén & Muthén, 1998–2017) and facilitated by the R package *MplusAutomation* (Hallquist & Wiley, 2018). MSEM uses latent variable decomposition, which allows for Level 1 and Level 2 effects to be simultaneously estimated. We ran separate models for each of the nine predictors (self-reported and observer-rated binary interactions, observer-rated continuous interactions, self-reported and observer-rated conversational depth and self-disclosure, and self-reported knowing and liking) and the two well-being outcomes (feelings of happiness and social connectedness), with models either including or excluding trait extraversion as a moderator (described below).

Measurement models.

Latent variables. We modeled EAR-coded conversational depth and self-disclosure as latent variables, to account for intercoder unreliability in these predictors (see Figure 1). For these latent variables, we used coders as indicators. Some hours were coded by more than six coders, but to reduce model complexity, for the latent variables, we only included data from up to six coders (see the online supplemental materials for details). Thus, every variable had six indicators (with each indicator representing the observed score from a given coder, for a given participant). For a given participant (e.g., Participant 1), all ratings from coder 1 were from the same coder (e.g., Research Assistant 1). However, for a different participant (e.g., Participant 2), Coder 1 could have been a different research assistant (e.g., Research Assistant 2). To model the interchangeability of coders, we fixed all loadings for the six indicators to 1, constrained the six residual variances to be equal, and allowed the variance of the latent observer-rated variable to be freely estimated.

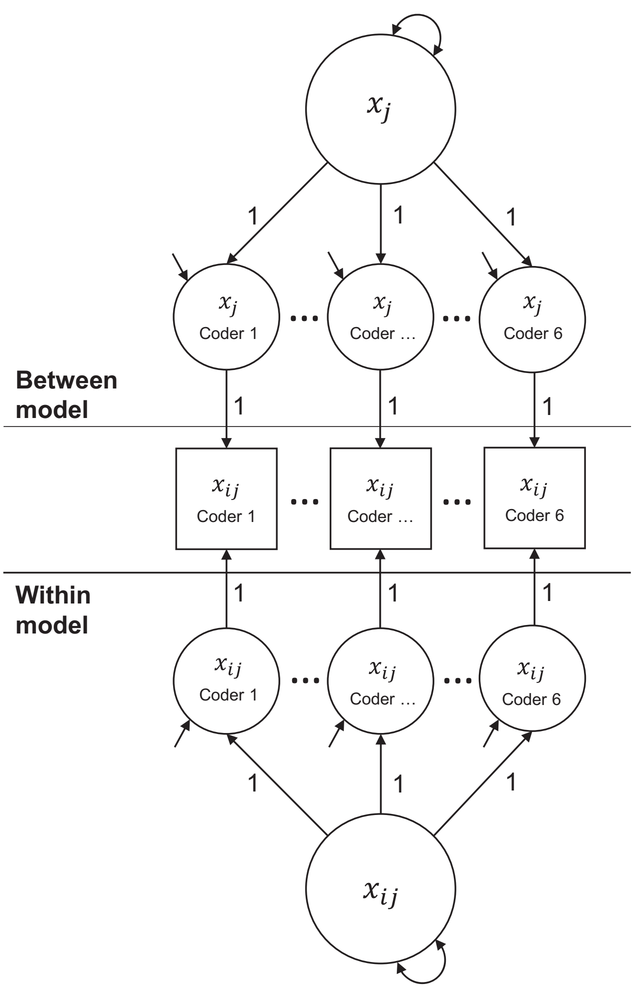

Figure 1. Measurement model for the Electronically Activated Recorder (EAR) observer-based conversational depth and self-disclosure variables. The six residuals at each level were constrained to equality (for each respective level).

Observed variables. All other variables were modeled as observed variables in the structural models described below. These included self-reported binary social interactions, conversational depth, and self-disclosure; observer-rated binary and continuous social interactions; self-reported happiness and social connectedness; and self-reported trait extraversion.

Reliability estimates. We conducted multilevel confirmatory factor analyses (MCFA; Geldhof, Preacher, & Zyphur, 2014; Shrout & Lane, 2012) to obtain level-specific omega (ω) reliability estimates for the EAR-coded social interaction variables and the ESM happiness and social connectedness variables. Because the ESM happiness and social connectedness variables each only had two indicators, we constrained the factor loadings for the two items to be equal at each level for these MCFA models. To estimate the reliability of the trait extraversion measure, we computed coefficient ω using the MBESS package (Version 4.4.3; Kelley, 2018). These reliability estimates are reported in Table 1.

Structural models. We illustrate the MSEMs in Figure 2. In all models, y denotes the outcome variable (happiness, social connectedness, or the individual "close, connected" and "lonely" items used in the supplemental analyses; see online supplemental materials), x denotes the social interaction predictor variable, and z denotes the moderator variable, trait extraversion. The subscripts i and j denote observations at time i for person j. For simplicity, Figure 2 does not depict the measurement model used for the EAR conversational depth and self-disclosure variables (shown in Figure 1).

Models for main effects. In the first set of models (see Figure 2, Models A–C), we regressed each well-being outcome onto each social interaction predictor at both the within- and between-person levels, with random intercepts and random slopes. This allows each participant to have a different mean level of well-being, and a different association between each social interaction variable and well-being.

For the quantity of social interaction analyses (see Figure 2, Model A), we estimated both the within- (β_{W1}) and between-person (β_{B1}) effects in the same model. For these analyses, the person-level estimates of well-being were based on latent variable decomposition. However, for the quality of social interaction analyses, we estimated the within- and between-person effects in two separate models (see Figure 2, Models B–C). Because the quality variables only applied when a social interaction occurred, using person-level estimates of well-being based on this subset of time points would only enable inferences about the association between the average quality of interactions and average well-being during social interactions (rather than overall well-being across all time points, including hours in which the participant was not interact-

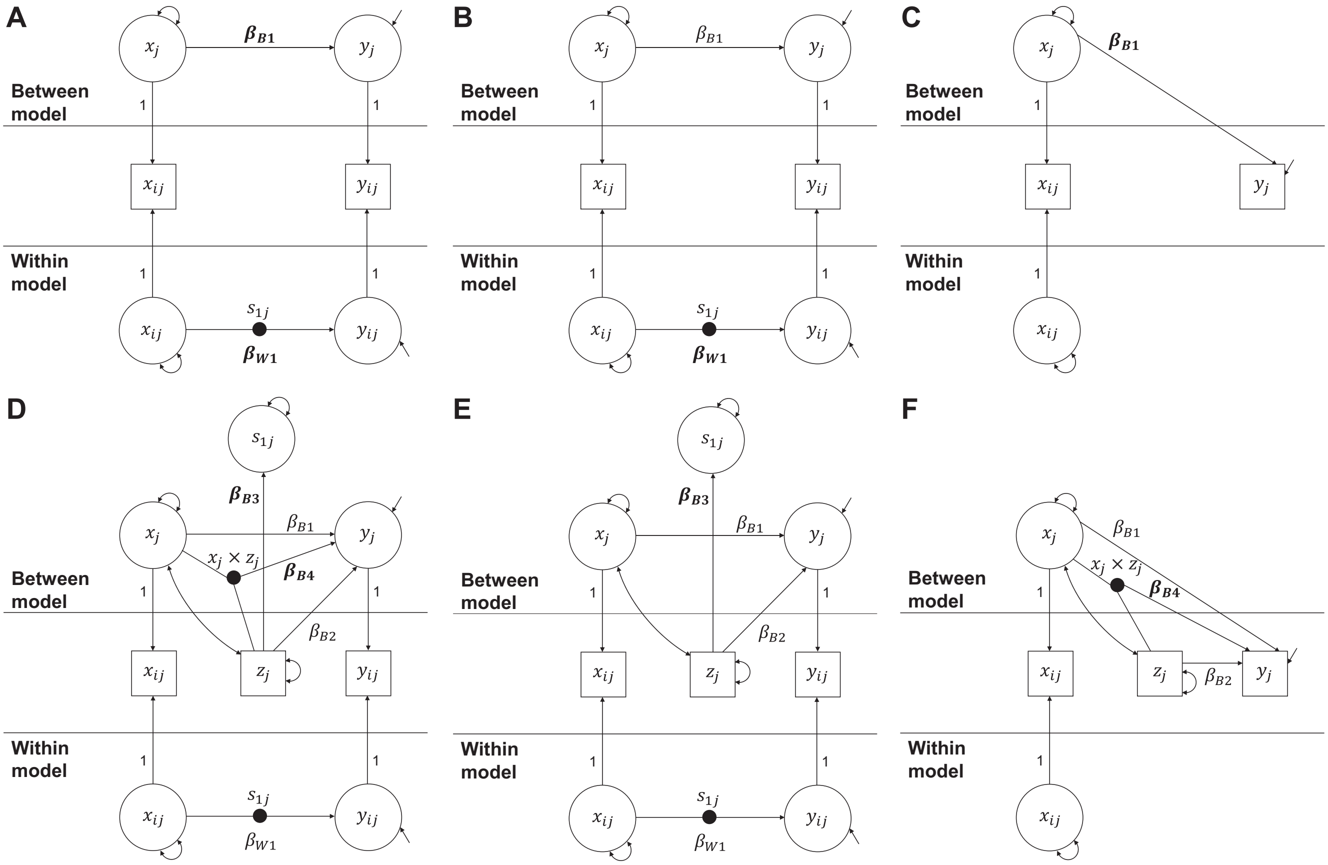

Figure 2. Path diagrams representing the multilevel structural equation models used in the study. Bold coefficients denote the key parameter(s) of interest in each model. Squares represent observed variables, circles represent latent variables, and filled-in circles represent random slopes (labeled as s_{1j}) or interactions (labeled as $x_j \times z_j$). Double-headed arrows represent variances and covariances.

ing). Thus, to draw inferences about the associations between the average quality of social interactions and overall well-being, we computed person-level happiness and social connectedness aggregate scores for each person using all 3,206 time points, and estimated the between-person effects predicting these observed scores. This ensures that the between-person effect (β_{B1}, Model C) represents the association that the quality of social interactions has with well-being across all time points, not only the time points in which participants were interacting with others (represented by the β_{B1} effect in Model B, which we are not interested in).

Models for interaction effects. In the second set of models (see Figure 2, Models D–F), we added trait extraversion as a moderator of the association between aspects of social interactions and well-being. As for the main effects, we used one model to estimate the cross-level and between-person interaction effects for the quantity of social interaction predictors (Model D), but used two separate models to estimate the cross-level (Model E) and between-person (Model F) interaction effects for the quality of social interaction predictors. For reasons described above, the between-person well-being variable was latent for the quantity of social interaction model (Model D) and observed (aggregated across all time points) for the between-person quality of social interactions model (Model F).

Trait extraversion was modeled as an observed, *z*-scored between-person variable (z_j). To estimate the cross-level interaction effect (β_{B3}), we regressed the random slope (s_{1j}) onto trait extraversion. To estimate the between-person interaction effect (β_{B4}), we constrained the mean of the latent between-person social interaction variable to zero (which centers the predictor). Then, we regressed the between-person well-being variable onto the interaction between trait extraversion and the latent between-person social interaction variable ($x_j \times z_j$). In all moderation models, we modeled the main effect of trait extraversion on average well-being (β_{B2}), as well as the covariance between trait extraversion and the social interaction predictor.

Estimation and inference criteria. We used the Bayes estimator in Mplus Version 8.3 (Muthén & Asparouhov, 2012), with the default set of diffuse (i.e., noninformative) priors. We use the 95% credibility interval (CI) around the standardized effects (β) as inference criteria for the range of plausible population values of the effect sizes.

We standardized the quality of social interaction effects against the standard deviations of both the predictor and the well-being outcome. The binary and continuous social interaction variables are on a readily interpretable metric, so we only standardized the within-person effects against the standard deviations of the well-being outcome variables (but standardized the between-person effects against the standard deviations of both the predictor and the well-being outcome). Thus, the within-person β for the binary social interaction variable represents the standard deviation increase in momentary happiness or social connectedness when participants were interacting versus when they were not, and the within-person β for the continuous variable represents the standard deviation increase in momentary happiness or social connectedness when participants were interacting in 100% of the files in the target hour versus when they were interacting in none of the files in that hour. All standardized effects were computed based on the standard deviations of the respective levels (i.e., within-person or between-person).

Results

Preliminary Analyses

Descriptive statistics and intercorrelations among all variables are shown in Table 1. Omega reliability estimates showed that 70% to 94% of the within-person fluctuations in each of the social interaction variables, as assessed by three to six EAR coders per participant, were due to meaningful fluctuations (rather than random noise). The two happiness items reliably assessed true fluctuations in momentary happiness (ω_{WP} = .82). Although the composite of the two social connectedness items had lower reliability (ω_{WP} = .52), we nevertheless chose to combine them for conceptual reasons (see Supplemental Table S1 in the online supplemental materials for item-level results). EAR coders also reliably assessed between-person differences in quantity of social interactions ($\omega_{BP} \geq .90$), but showed much lower reliability when assessing between-person differences in conversational depth (ω_{BP} = .24) and self-disclosure (ω_{BP} = .41). MSEM corrects for attenuation of point estimates due to measurement error, but greater measurement error results in less precise estimates.

Next, we assessed the extent of agreement between ESM self-reports and EAR observer reports of social interactions. Latent within-person correlations based on MSEMs showed that participants and observers agreed moderately on when participants were interacting or not, (r = .39, 95% CI [.35, .42]), and on moment-to-moment fluctuations in conversational depth (r = .31, 95% CI [.25, .37]) and self-disclosure (r = .31, 95% CI [.25, .36]). One reason that agreement was not higher may be that EAR coders only listened to 3 to 3.5 min of each hour that participants reported on.

Latent between-person correlations based on MSEMs also showed that participants and observers agreed moderately on which participants interacted more often (r = .52, 95% CI [.25, .70]), and self-disclosed more on average (r = .51, 95% CI [.12, .80]). However, there was no self–observer agreement on which participants had deeper conversations on average (r = −.33, 95% CI [−.64, −.08]; note that this association was between latent variables and that the observed association was much smaller [−.05], see Table 1).

Quantity of Social Interactions

Within-person effects. Do people feel happier and more socially connected when interacting with others? We found that this was the case for both self-reported and observer-rated social interactions (see Table 2 and Figures 3–4). Indeed, the entirely positive within-person slopes in Figures 3–4 show that every

Table 2
Predicting Happiness and Social Connectedness From Social Interactions

	Happiness				Social connectedness			
	Self-reported (ESM) interactions		Observed (EAR) interactions		Self-reported (ESM) interactions		Observed (EAR) interactions	
Predictor	β	R^2	β	R^2	β	R^2	β	R^2
Quantity of interactions								
Binary interactions								
Within	0.59 [0.49, 0.68]	.07	0.45 [0.37, 0.53]	.05	1.08 [0.98, 1.16]	.20	0.69 [0.61, 0.77]	.10
Between	0.32 [0.12, 0.49]	.10	0.21 [0.01, 0.42]	.05	0.52 [0.37, 0.65]	.27	0.38 [0.18, 0.55]	.14
Continuous interactions								
Within			0.79 [0.68, 0.90]	.08			1.08 [0.97, 1.17]	.13
Between			0.16 [−0.02, 0.33]	.03			0.46 [0.24, 0.63]	.21
Quality of interactions								
Conversational depth								
Within	0.12 [0.08, 0.17]	.07	0.04 [−0.03, 0.10]	.04	0.19 [0.14, 0.22]	.11	0.15 [0.08, 0.21]	.10
Between	0.37 [0.16, 0.55]	.14	−0.24 [−0.57, 0.06]	.06	0.44 [0.29, 0.61]	.20	−0.08 [−0.32, 0.18]	.01
Self-disclosure								
Within	0.21 [0.16, 0.27]	.08	0.14 [0.08, 0.20]	.04	0.27 [0.22, 0.33]	.12	0.19 [0.13, 0.25]	.06
Between	0.38 [0.19, 0.56]	.14	0.05 [−0.20, 0.34]	.01	0.45 [0.24, 0.59]	.20	0.16 [−0.13, 0.47]	.03
Knowing								
Within	0.27 [0.21, 0.31]	.08			0.31 [0.26, 0.36]	.15		
Between	0.29 [0.08, 0.51]	.09			0.56 [0.41, 0.78]	.31		
Liking								
Within	0.36 [0.32, 0.41]	.14			0.42 [0.38, 0.46]	.19		
Between	0.47 [0.30, 0.59]	.22			0.68 [0.54, 0.82]	.46		

Note. ESM = experience sampling method; EAR = Electronically Activated Recorder. The within-person quantity of interactions βs are only standardized with respect to the well-being outcome. All other coefficients are standardized with respect to both the predictor and outcome. R^2 = proportion of variance explained at each level. 95% credibility intervals are shown in brackets.

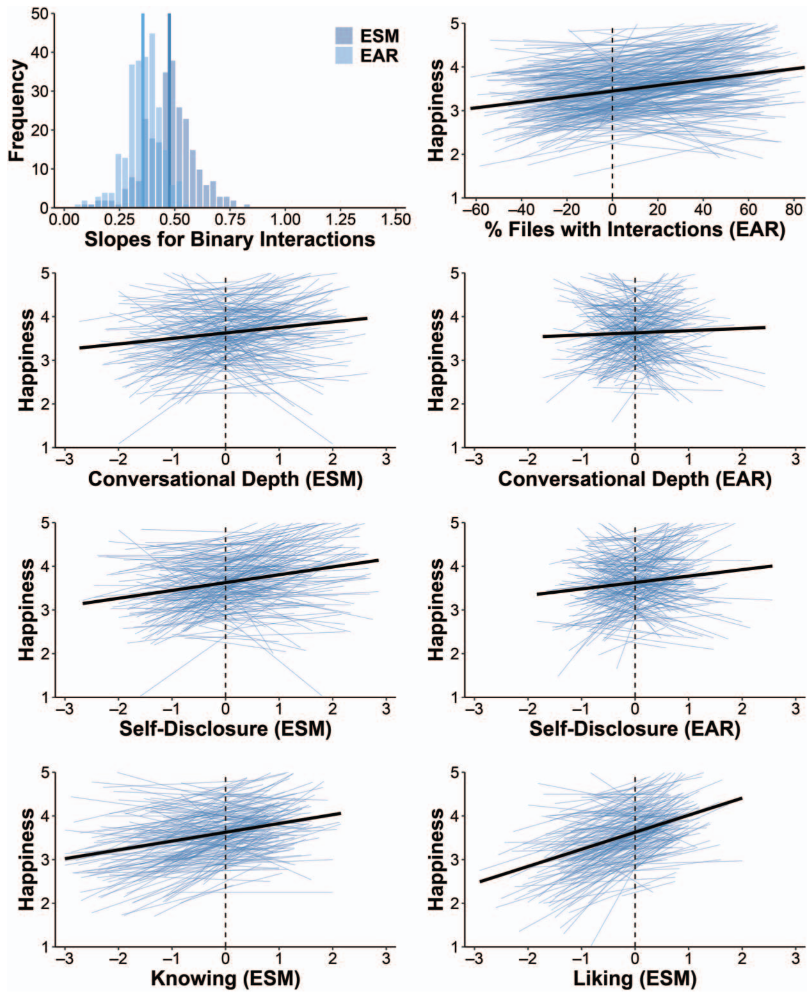

Figure 3. Within-person associations between aspects of social interactions and momentary happiness. The top-left panel shows the histograms for the unstandardized within-person associations between momentary happiness (outcome) and whether or not participants interacted with someone in the past hour (predictor) as rated by the self (experience sampling method [ESM]) or observers (Electronically Activated Recorder [EAR]; estimated in two separate models). The solid vertical lines show the mean slopes. For the remaining panels, each thin line represents the within-person association between each social interaction variable and momentary happiness for each person, and the thick line shows the average within-person association. The *x*-axis shows raw deviations from each person's mean social interaction state, whereas the *y*-axis shows the uncentered 1–5 score on momentary happiness. See the online article for the color version of this figure.

single participant tended to feel happier and more socially connected when they interacted in the past hour, compared to when they did not. Specifically, when participants self-reported interacting (vs. not) in the past hour, their momentary happiness was on average 0.59 *SD* higher, and their momentary social connectedness was on average 1.08 *SD* higher. The effects were slightly smaller, but still substantial, for observer-rated interactions: When participants were observed interacting (vs. not) in the past hour, their momentary happiness was on average 0.45 *SD* higher, and their momentary social connectedness was on average 0.69 *SD* higher.

Does the amount of social interaction within an hour also matter? The more fine-grained continuous measure based on observers' codings showed that participants generally reported greater momentary happiness and feelings of social connectedness when they were observed interacting during a greater proportion of 30 s recordings in a given hour (see Table 2 and Figures 3–4). The effect sizes showed that participants were on average 0.79 *SD* higher in happiness and 1.08 *SD* higher in social connectedness when they were observed to be interacting in all recordings in a given hour (vs. none of them).

Between-person effects. Do people who interact more with others on average also feel happier and more socially connected on average? Participants who had a greater proportion of hours in which they self-reported or were observed interacting with others tended to report greater average feelings of happiness and social connectedness (see Table 2). For the continuous measure of social interactions, participants who were observed interacting in a greater percentage of files on average reported greater average

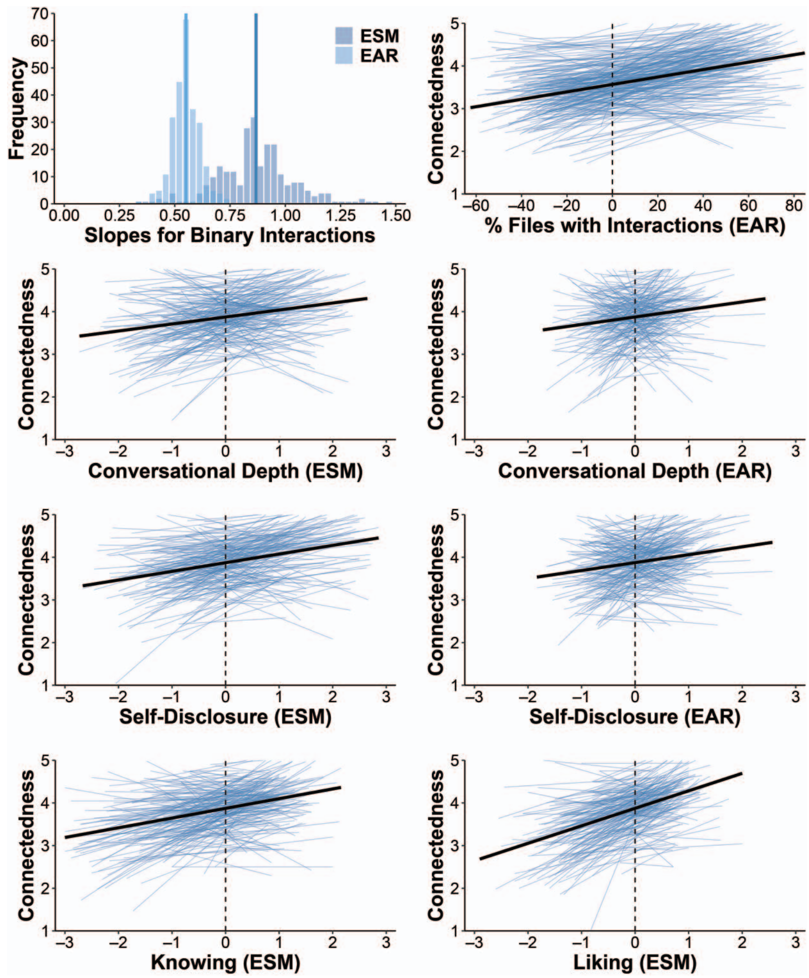

Figure 4. Within-person associations between aspects of social interactions and momentary social connectedness. The top-left panel shows the histograms for the unstandardized within-person associations between momentary social connectedness (outcome) and whether or not participants interacted with someone in the past hour (predictor) as rated by the self (experience sampling method [ESM]) or observers (Electronically Activated Recorder [EAR]; estimated in two separate models). The solid vertical lines show the mean slopes. For the remaining panels, each thin line represents the within-person association between each social interaction variable and momentary social connectedness for each person, and the thick line shows the average within-person association. The *x*-axis shows raw deviations from each person's mean social interaction state, whereas the *y*-axis shows the uncentered 1–5 score on momentary social connectedness. See the online article for the color version of this figure.

feelings of social connectedness, but the association with average happiness was weaker, with a 95% CI that captured zero.

Moderation by trait extraversion. Do the associations between the quantity of interactions and well-being differ for extraverts and introverts? For the six cross-level interaction effects (three quantity variables predicting two well-being outcomes), all point estimates were quite close to zero, and the 95% CIs excluded medium and large effects (see Table 3). This suggests that introverts and extraverts had similarly strong positive within-person associations between the quantity of social interactions and well-being.

We tested the same six interaction effects at the between-person level. Four point estimates were close to zero, though the 95% CIs included medium-sized effects, so we cannot confidently rule out practically meaningful effects (see Table 3). Two interaction effects were moderate in size and had 95% CIs that did not include zero (but did include trivially small effect sizes). Given that these effects did not hold for self-reported social interactions, we are less confident about these effects and will refrain from interpreting them here (but a full description is available in the online supplemental materials). Thus, overall, the quantity of social interaction was similarly related to well-being for introverts and extraverts, at both the within- and between-person levels.

Quality of Social Interactions

Next, we examined whether conversational and relational dimensions of social interaction quality were associated with feelings of happiness and social connectedness.

Within-person effects. The previous results showed that people tend to feel happier and more socially connected when they are

Table 3
Predicting Happiness and Social Connectedness From Social Interactions: The Moderating Effects of Trait Extraversion

Predictor	Happiness: Self-reported (ESM) interactions	Happiness: Observed (EAR) interactions	Social connectedness: Self-reported (ESM) interactions	Social connectedness: Observed (EAR) interactions
Quantity of interactions				
Binary interactions				
Within	0.60 [0.50, 0.69]	0.43 [0.34, 0.50]	1.10 [0.98, 1.20]	0.70 [0.62, 0.79]
Between	0.19 [−0.01, 0.37]	0.08 [−0.14, 0.26]	0.48 [0.30, 0.62]	0.27 [0.06, 0.47]
Trait E	0.30 [0.16, 0.44]	0.34 [0.16, 0.49]	0.23 [0.08, 0.38]	0.31 [0.15, 0.45]
Within × Trait E	0.01 [−0.09, 0.12]	−0.03 [−0.12, 0.06]	0.04 [−0.07, 0.15]	0.01 [−0.09, 0.09]
Between × Trait E	−0.07 [−0.26, 0.12]	**−0.25 [−0.46, −0.05]**	−0.08 [−0.26, 0.08]	−0.06 [−0.26, 0.12]
Continuous interactions				
Within		0.82 [0.66, 0.93]		1.08 [0.95, 1.19]
Between		0.05 [−0.17, 0.20]		0.39 [0.21, 0.54]
Trait E		0.36 [0.22, 0.52]		0.29 [0.15, 0.43]
Within × Trait E		−0.07 [−0.15, 0.03]		−0.11 [−0.23, 0.04]
Between × Trait E		**−0.20 [−0.40, −0.06]**		−0.06 [−0.28, 0.13]
Quality of interactions				
Conversational depth				
Within	0.13 [0.07, 0.18]	0.04 [−0.03, 0.10]	0.19 [0.14, 0.24]	0.14 [0.08, 0.21]
Between	0.32 [0.14, 0.48]	−0.06 [−0.64, 0.26]	0.40 [0.25, 0.55]	−0.04 [−0.42, 0.28]
Trait E	0.20 [0.06, 0.34]	0.25 [0.00, 0.40]	0.23 [0.09, 0.36]	0.33 [0.15, 0.45]
Within × Trait E	−0.16 [−0.37, 0.09]	−0.24 [−0.53, 0.10]	**−0.27 [−0.46, −0.04]**	**−0.26 [−0.50, −0.00]**
Between × Trait E	−0.02 [−0.18, 0.13]	0.18 [−0.06, 0.40]	−0.04 [−0.18, 0.12]	0.16 [−0.15, 0.49]
Self-disclosure				
Within	0.22 [0.16, 0.27]	0.14 [0.08, 0.20]	0.28 [0.22, 0.32]	0.19 [0.14, 0.26]
Between	0.25 [0.10, 0.40]	−0.12 [−0.48, 0.20]	0.34 [0.19, 0.47]	0.08 [−0.29, 0.39]
Trait E	0.22 [0.08, 0.36]	0.32 [0.15, 0.55]	0.26 [0.13, 0.40]	0.31 [0.12, 0.49]
Within × Trait E	0.15 [−0.10, 0.48]	0.01 [−0.41, 0.62]	0.00 [−0.24, 0.24]	0.00 [−0.52, 0.55]
Between × Trait E	0.00 [−0.15, 0.18]	−0.09 [−0.32, 0.22]	0.12 [−0.03, 0.28]	−0.13 [−0.38, 0.19]
Knowing				
Within	0.28 [0.22, 0.31]		0.32 [0.24, 0.36]	
Between	0.26 [0.04, 0.47]		0.55 [0.34, 0.70]	
Trait E	0.22 [0.07, 0.36]		0.21 [0.06, 0.34]	
Within × Trait E	0.07 [−0.27, 0.34]		0.20 [−0.02, 0.41]	
Between × Trait E	−0.02 [−0.26, 0.19]		−0.02 [−0.16, 0.14]	
Liking				
Within	0.38 [0.33, 0.42]		0.43 [0.37, 0.47]	
Between	0.39 [0.23, 0.53]		0.63 [0.49, 0.73]	
Trait E	0.17 [0.03, 0.31]		0.16 [0.03, 0.29]	
Within × Trait E	0.11 [−0.43, 0.81]		0.07 [−0.35, 0.39]	
Between × Trait E	−0.02 [−0.18, 0.13]		−0.02 [−0.14, 0.11]	

Note. ESM = experience sampling method; EAR = Electronically Activated Recorder. The within-person quantity of interactions coefficients are only standardized with respect to the well-being outcome. All other coefficients are standardized with respect to both the predictor and outcome. R^2 = proportion of variance explained at each level. 95% credibility intervals are shown in brackets. Coefficients in bold highlight interaction effects with 95% credibility intervals that do not capture zero.

interacting with others (compared to when they are not). By definition, conversational features (conversational depth and self-disclosure) and relational features (knowing and liking) only apply to time points in which people are interacting with others. Therefore, the following within-person analyses ask whether the quality of social interactions predicts any remaining within-person variability across a relatively restricted range of momentary well-being states.

Conversational features. Participants reported feeling happier and more socially connected when they self-reported having deeper conversations and self-disclosing more during their social interactions in the past hour (see Table 2 and Figures 3–4). For example, each 1 *SD* increase in momentary self-disclosure (relative to participants' average levels of self-disclosure) predicted an average 0.21 *SD* increase in momentary happiness and an average 0.27 *SD* increase in momentary social connectedness (relative to participants' average levels of happiness or social connectedness across all social interactions).

For observer-rated conversational features, participants also reported greater momentary feelings of happiness and social connectedness when observers rated them as being more self-disclosing than usual during their social interactions in the past hour. Observer-rated conversational depth was also associated with feeling more socially connected, but was not detectably associated with momentary happiness.

Relational features. Participants reported feeling happier and more socially connected during interactions in which they reported knowing or liking their interaction partners more, compared to interactions in which they reported knowing or liking their interaction partners less (see Table 2 and Figures 3–4). As explained above, we did not examine these effects using observer ratings of whether participants knew and liked their interaction partners.

Between-person effects. The within-person results suggest that some social interactions feel more rewarding than others, at least in the moment. Is it also the case that people who consistently have higher-quality interactions feel happier and more socially connected in general?

Conversational features. Participants who reported greater average levels of conversational depth and self-disclosure (during their social interactions) also tended to report feeling happier and more socially connected on average (across all time points, including those in which they did not interact with anyone; see Table 2). However, we found no evidence that observer ratings of conversational depth and self-disclosure were associated with overall happiness or social connectedness.

Relational features. Participants who self-reported knowing and liking their interaction partners more on average tended to report feeling happier and more socially connected on average (see Table 2). Again, we did not examine these effects using observer ratings of whether participants knew and liked their interaction partners.

Moderation by trait extraversion. Do the associations between the quality of interactions and well-being differ for extraverts and introverts? The majority of the 12 cross-level interaction effects (six quality variables predicting two well-being outcomes) had 95% CIs that captured zero (see Table 3). However, these effects were imprecisely estimated, with wide credibility intervals that contained small to moderate effect sizes in either direction. This means that there is quite a lot of uncertainty about whether the within-person associations between social interaction quality variables and well-being are stronger for extraverts or for introverts, as well as how large these differences are. For example, a 95% CI ranging from −0.53 to 0.10 indicates that much more positive within-person effects for introverts (vs. extraverts), no differences between extraverts and introverts, and slightly more positive within-person effects for extraverts (vs. introverts) are all plausible values for the true interaction effect.

However, two cross-level interaction effects, for extraversion moderating the associations between self- and observer-reports of conversational depth and social connectedness (but not happiness), emerged as statistically notable (i.e., had 95% CIs that did not include zero). This intriguing (but entirely exploratory) pattern suggests that relatively introverted participants experienced relatively greater increases in momentary feelings of social connectedness during hours in which they had deeper conversations, compared to relatively extraverted participants (see Figure 5). Specifically, the Johnson and Neyman (1936) technique (see Figure 5) suggests that the within-person association between conversational depth and momentary social connectedness was detectably positive for participants with extraversion z-scores lower than 1.22 (for self-reported conversational depth) and 0.70 (for observer-rated conversational depth). These model-predicted values imply that, for relatively extraverted participants, fluctuations in how socially connected they felt would be relatively unrelated to fluctuations in the depth of their conversations. Because this was the only moderation effect that held for both self- and observer-reports of the predictor variable, we are slightly more confident about this effect than the other moderation effects in this study, but consider it to be a new hypothesis to be tested in future research.

We tested the same 12 interaction effects at the between-person level. All of the between-person interaction effects had 95% CIs that captured zero as well as small to moderate effects in both directions (see Table 3). Thus, we did not find much evidence that the quality of social interactions was differentially associated with overall well-being for introverts compared to extraverts.

Summary

To summarize (see Table 4), we found different patterns of results for the quantity and quality of social interactions. The quantity of interactions was robustly associated with well-being: people felt happier and more socially connected while they were interacting with others, and people who more frequently interacted with others also felt happier and more socially connected on average. These effects held whether the occurrence of social interactions was measured using self- or observer-reports.

Self- and observer-reports yielded slightly different answers about the associations between the quality of social interactions

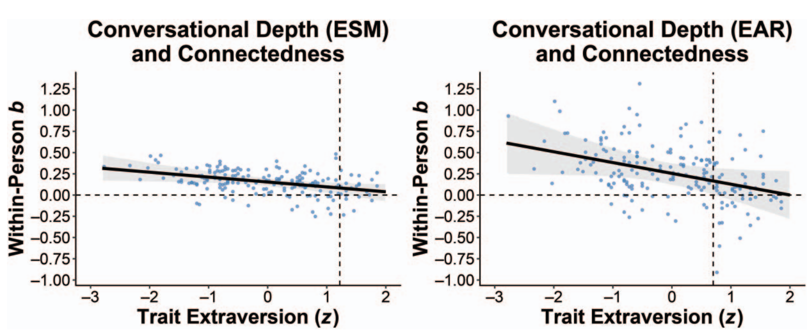

Figure 5. Predicted unstandardized within-person associations between conversational depth and social connectedness (solid black line) at different levels of trait extraversion (z-scored). Gray ribbons show 95% credibility intervals. Each point represents the within-person association for each person (extracted from multilevel structural equation model estimates). The dotted vertical lines show the levels of trait extraversion above which the association between the two variables could plausibly be in either direction. Out of the 36 interaction effects we explored, this pattern seemed to have the most potential as a new hypothesis to be tested in future research. ESM = experience sampling method; EAR = Electronically Activated Recorder. See the online article for the color version of this figure.

Table 4
Summary of Associations Between Social Interactions and Well-Being

	Main effects				Interactions with trait extraversion			
	Happiness		Social connectedness		Happiness		Social connectedness	
Predictor	ESM	EAR	ESM	EAR	ESM	EAR	ESM	EAR
Quantity of interactions								
Binary interactions								
Within	+	+	+	+	?	?	?	?
Between	+	+	+	+	?	–	?	?
Continuous interactions								
Within		+		+		?		?
Between		?		+		–		?
Quality of interactions								
Conversational depth								
Within	+	?	+	+	?	?	–	–
Between	+	?	+	?	?	?	?	?
Self-disclosure								
Within	+	+	+	+	?	?	?	?
Between	+	?	+	?	?	?	?	?
Knowing								
Within	+		+		?		?	
Between	+		+		?		?	
Liking								
Within	+		+		?		?	
Between	+		+		?		?	

Note. ESM = experience sampling method; EAR = Electronically Activated Recorder. Positive and negative effects with 95% credibility intervals that did not capture zero are denoted by + and −, respectively. ? = effects with 95% credibility intervals that captured zero as well as effect sizes that could be practically meaningful (in most cases). Blank cells indicate that analyses were not conducted.

and well-being. Across both self- and observer-reports of social interaction quality, the within-person results generally converged on the conclusion that some social interactions are associated with greater well-being than others: people tended to feel happier and more socially connected during social interactions in which they had deeper conversations, self-disclosed more, and knew and liked their interaction partners more (with the exception that observer-reported conversational depth was not associated with momentary happiness). However, average well-being was only associated with self-reports, but not observer-reports, of high-quality social interactions. These mixed between-person findings are more difficult to interpret because of the low reliability of the observer ratings of conversational depth and self-disclosure (an issue we will consider in the *Discussion*).

Finally, most (32 out of 36) of the effects did not appreciably depend on how extraverted the participant was (but note that the relatively imprecise estimates mean that we cannot rule out practically meaningful interaction effects). One noteworthy exception—which converged across both self- and observer-reports—suggested that people who were more introverted had a stronger positive within-person association between conversational depth and momentary feelings of social connectedness (but not momentary happiness). Given that we did not predict this effect and we conducted many analyses, we consider this to be a new hypothesis that is worth testing in future research.

Discussion

Theory and intuition both suggest that the quality of social interactions—not just their mere presence—should be associated with well-being. To provide a strong, multimethod test of this idea, we obtained both self- and observer-reports of the quantity and quality of social interactions in everyday life. Both methods showed that people report feeling happier and more socially connected when they spend more time interacting with others. Conversational and relational features of social interactions (conversational depth, self-disclosure, and knowing or liking one's interaction partners) were also generally associated with greater well-being, but the effects were larger and more consistent for self-reported (vs. observer-reported) measures of social interaction quality, and for feelings of social connectedness (vs. happiness). Finally, there was generally little evidence that extraverts and introverts showed different associations between aspects of social interactions and well-being, though these estimates were not precise enough to rule out effects that could be practically meaningful.

Stronger Evidence From Multi-Method Assessment

Self- and observer-reports of social interactions each capture different perspectives. Because each method has its unique strengths and limitations, multimethod assessment provides stronger evidence than using either method alone. For assessing the quantity of social interactions, our results suggest that self-reports probably capture social interactions that the EAR misses, but that EAR-based observer-reports allow for more fine-grained estimates of social time.

Whereas EAR observers only had access to brief snippets of audible everyday behavior (i.e., 3–3.5 min of each hour), participants had access to their social interactions across the entire hour, including inaudible interactions (e.g., some kinds of computer-mediated communications). Indeed, for the binary measure of whether or not the participant interacted with someone in the past hour, observers reported slightly fewer social interactions than participants. Thus, although both methods showed a positive association between the quantity of social interactions and well-being, the larger effects for self-reported social interactions may more accurately reflect the true size of the association between the presence of social interactions and well-being (compared to the observer-based measure).

However, by capturing behavior without requiring participants to actively respond, the EAR allows for more fine-grained estimates of social time compared to ESM self-reports (Mehl, 2017). It would be too burdensome to ask people to self-report whether they interacted with someone every 10 min. Moreover, whereas it is straightforward to remember whether or not you engaged in a social interaction in the past hour, it is much more difficult to estimate the amount of time you spent interacting with others. By obtaining observer reports of whether participants interacted in each of the six or seven files in the hour, we found that people felt happier and more socially connected in hours when they spent a greater amount of time in social interactions, and that effect sizes for the continuous measure were stronger than for the relatively crude EAR-based measure of whether or not the participant had interacted at all in the past hour. Thus, the EAR can provide more fine-grained information about the dose-dependent association between the quantity of social interactions and momentary well-being.

Participants and observers also have different perspectives on the quality of social interactions. Sometimes, self-report can be the only valid way to assess relatively subjective, less observable aspects of social interaction quality, such as the extent to which participants knew and liked the people they were interacting with. For relatively observable aspects of social interaction quality, however, a multimethod approach can provide a stronger test of the extent to which well-being is related to the quality of social interactions, observed from a third-person perspective. At the within-person level, both self- and observer-reports suggest that self-disclosure was associated with both indicators of greater momentary well-being, and that conversational depth was associated with greater feelings of social connectedness. Although the effect sizes for the observer-based measures were smaller than for the self-report-based measures, this convergence across methods provides stronger evidence that there is a true association between the quality of social interactions and momentary well-being that is not simply due to common method biases.

However, the between-person results showed that the EAR is not a panacea. The between-person reliabilities were fairly low, suggesting that EAR codings made on an hour-to-hour basis could not be combined to reliably distinguish *which* participants generally had deeper or more self-disclosing conversations (even though observers could tell *when* each participant had deeper or more self-disclosing conversations than they usually did). Thus, the null associations between well-being and observer-rated conversational depth and self-disclosure could either imply that people with higher well-being do not actually have deeper or more self-disclosing conversations (even though they think they do), or that our EAR coding procedures could not reliably detect between-person differences in conversational depth and self-disclosure. This latter possibility seems less likely for self-disclosure than for conversational depth, because there was a moderate amount of self–observer agreement on which participants tended to be more self-disclosing on average (whereas observers and participants did not agree at all about which participants tended to have deeper conversations on average). The strengths and limitations of observer-based methods need to be considered on a case-by-case basis, and may vary depending on the construct being assessed, the observational tool being used, the resources at hand, and the validity of alternative (e.g., self-report) methods.

Further Insights From Convergent and Discriminant Validity

Many researchers rely on ESM self-report measures of social interactions and well-being, but relatively little research has tested the validity of fluctuations in these measures (cf. Choi, Catapano, & Choi, 2017; Sun & Vazire, 2019; Wilson et al., 2017). Multimethod assessment provides information on convergent validity (the extent to which different measures of the same construct agree), whereas assessment of multiple constructs provides information on discriminant validity (the extent to which more conceptually related constructs are more strongly correlated across methods than are less conceptually related constructs; Campbell & Fiske, 1959).

For convergent validity, we tested the extent to which self- and observer-reports of fluctuations in momentary conversational depth and self-disclosure agreed. Participants and observers showed a moderate amount of agreement on within-person fluctuations in conversational depth and self-disclosure. This suggests that people have some self-knowledge of when their conversations are deep or shallow, and more or less self-disclosing. Considering the resource-intensive nature of observer-based measures such as the EAR, it is reassuring to know that ESM self-reports of conversational depth and self-disclosure contain at least some valid within-person variance and can be used as an informative (though of course imperfect) indicator of fluctuations in these aspects of social experience.

For discriminant validity, we asked whether ESM measures of social interactions, social connectedness, and happiness capture distinct experiences. If happiness is influenced by many other aspects of everyday experience besides social interactions, whereas feelings of closeness versus loneliness are conceptually more related to the quantity and quality of one's social interactions, then social interaction measures should be more strongly associated with feelings of social connectedness than with happiness. We found that this was the case across both self-report and observer-based measures of social interactions. These discriminant associations suggest that people do not indiscriminately report greater social connectedness and deeper, more intimate social interactions when they are in a good mood. Instead, measures of social interaction quality, feelings of social connectedness, and happiness each appear to capture distinct experiences.

Searching for a Moderating Role of Trait Extraversion

Are certain popular portrayals correct in claiming that introverts prefer fewer but more intimate social interactions, whereas extraverts enjoy any social interaction (e.g., Cain, 2012)? Or, consistent with reward-sensitivity theories of extraversion, might extraverts get a bigger boost than introverts from deeper interactions (Smillie, 2013)? Overall, our results suggest that any differences between extraverts and introverts in their associations between social interactions and well-being are probably not large enough to be consistently detected with a minimum of five observations from 256 or 192 college students (for the quantity and quality analyses, respectively), at least for the quantity, conversational, and relational features we examined. One intriguing exception was that fluctuations in self- and observer-reported conversational depth were more strongly associated with greater feelings of social connectedness (but not happiness) for those who were more introverted, compared to those who were more extraverted. Considering the number of interaction effects we tested, this finding should be interpreted with caution and treated as an interesting hypothesis to be tested in future studies. Experimental tests would shed more light on the causal explanation for this effect, if it is robust.

Furthermore, extraversion is a heterogeneous construct; whereas its affiliative aspect involves gregariousness and enjoyment of close interpersonal bonds, its agentic aspect involves a more general motivational disposition characterized by assertiveness and social dominance (Depue & Collins, 1999; DeYoung, Quilty, & Peterson, 2007). Thus, theoretically, the affiliative aspect of extraversion should predict greater enjoyment of warm, affectionate social interactions, whereas the agentic aspect may predict positive affect in social situations where goal pursuit and reward are especially salient. Future studies could investigate the extent to which specific aspects of extraversion—and other personality traits (e.g., neuroticism; Mueller et al., 2019; Shackman et al., 2018)—moderate the association between different aspects of social interactions and well-being.

Limitations and Future Directions

The main limitation of the current study is that our naturalistic design—which involved capturing naturally occurring fluctuations in social experiences and well-being in everyday life—means that we cannot draw any conclusions about the causal explanation that underlies the association between social experiences and well-being. Although experimental manipulations of the quantity and quality of social interactions have provided causal evidence that social interactions influence well-being (e.g., Epley & Schroeder, 2014; Jacques-Hamilton, Sun, & Smillie, 2019; Sandstrom & Dunn, 2014a), experimental manipulations of mood have also shown that positive mood can lead people to act more extraverted and become more self-disclosing (Cunningham, 1988; Whelan & Zelenski, 2012). For many aspects of social interactions, it seems likely that the effects are bidirectional. Moreover, it seems likely that third variables also contribute to the associations we observed. For example, receiving good news likely increases well-being and also causes people to seek out others to share the good news with.

As noted throughout, EAR observer-based measures have many important limitations. Because of ethical and feasibility considerations (see Robbins, 2017), our EAR observers only had access to relatively brief snippets of audible behaviors (thereby missing social interactions that were inaudible or that occurred when the device was not recording, as well as nonverbal aspects of social interaction quality), and only rated the participants' own behaviors (rather than the behaviors of the people they were interacting with). In addition, even with six observers per participant, our EAR coding procedures could not reliably distinguish which participants had deeper conversations on average.

Alternative methods for capturing everyday social interactions exist but have different tradeoffs. For example, mobile sensing methods excel at measuring objective social behaviors (e.g., number and length of calls and text messages, number of copresent others; Harari et al., 2019) but provide less information on the quality of social interactions, which currently requires human judgment. At the other extreme, following people around with a professional video-recording team (Craik, 2000) would provide comprehensive information on all observable features of their social interactions, but at the cost of high invasiveness (the presence of the video-recording team could change the behavior of the participants and their interaction partners) and lower sample sizes (as it would unfeasible to capture and code a large sample of people and days using such a method).

Future research should also harness new study designs to investigate how the quality of one's relationship with specific interaction partners makes some partners consistently more or less rewarding to interact with. Asking people to provide in-the-moment ratings of how much they like, know, or are close to their current interaction partner is susceptible to halo and other shared method biases. In contrast, measuring relationship type (e.g., romantic partner, friend, family, colleague, stranger; Mueller et al., 2019; Venaglia & Lemay, 2017) is more objective but less psychologically informative, and blurs distinctions between different interaction partners of the same "type." Future research could overcome these limitations by asking participants to rate several dimensions (e.g., closeness, liking, relationship satisfaction, relationship importance) of their relationship with 10–20 frequent interaction partners in a baseline survey. After every social interaction in the subsequent two weeks (i.e., event-contingent sampling), participants could complete a very brief ESM survey to report who they interacted with (from a list of the interaction partners they rated in the baseline survey, plus general categories for nonlisted individuals), and their well-being during the interaction. Such a design would provide a strong test of how one's overall relationship with specific interaction partners translates into more or less rewarding social interactions.

Ultimately, because different methods have complementary strengths and weaknesses, future research should continue to examine the association between social relationships and well-being using a broad range of methods. Eventually, this will allow us to draw stronger conclusions as a field by triangulating across methodologically diverse studies.

Constraints on Generality

We believe that our findings are likely to generalize to alternative self-report measures of happiness and feelings of social connectedness, as well as alternative measures of the social interaction variables we assessed in this study. However, our sample of young adults at a North American university limits our ability to generalize these effects to other age groups and to non-Western cultures. For example, socioemotional selectivity theory predicts that as people approach the end of life, they pay more attention to the emotional quality of their social relationships, and choose to narrow their social networks to focus on emotionally meaningful relationships (Carstensen, Isaacowitz, & Charles, 1999). This implies that the association between the quality of social interactions and well-being should be stronger for older adults (compared to younger adults), and that the same might be true for the quantity of interactions (assuming that older adults do indeed engage in more emotionally meaningful interactions on average, compared to younger adults).

Conclusion

Do people feel happier and more socially connected when they interact more with others? Is well-being more strongly related to some kinds of interactions? Both self- and observer-reports of the quantity of social interactions were robustly associated with greater well-being, at least among college students in North America. Having deeper, more intimate interactions was also consistently associated with feeling more socially connected in the moment. These convergent findings for self- and observer-reports suggest that the associations between well-being and the quantity and quality of social interactions are not just in people's heads. This provides a foundation for future studies to examine the generality of these associations across age groups and cultures, and, ultimately, to uncover the causal explanations for these associations.

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(*Appendix follows*)

Appendix

Table A1
Demographic Characteristics of Included and Excluded Participants

Variable	Included: Quantity analyses (n = 256)	Included: Quality analyses (n = 192)	Excluded (n = 161)
Gender (%)			
Female	69.53	70.31	62.11
Male	30.08	29.17	37.27
Not reported	0.39	0.52	0.62
Age in years, M (SD)	19.17 (1.78)	19.04 (1.64)	19.88 (2.96)
Ethnicity (%)			
White	56.25	58.85	49.69
Asian or Asian American	23.83	22.4	23.6
Black or African American	9.77	8.33	11.8
Other or multiple	7.03	6.25	11.8
Not reported	2.73	3.65	1.86
American Indian or Alaska Native	0.39	0.52	0.62
Native Hawaiian or Other Pacific Islander	0	0	0.62

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EAR Exclusions and Additional Coding Details

This description has been copied (with minor modifications) from a previous manuscript that used different variables from the same dataset (Sun & Vazire, 2019).

EAR Coder Response Options

In the first version of the hour-level coding survey, research assistants had the option of selecting “Not applicable”. In the second version, we changed this response option to “No way to tell”, and asked coders to try their best to make a judgment on the 1–5 scale, and to only select the “No way to tell” option if there was no information that could be used to make a judgment on a given item (e.g., if the sound quality of the files provided insufficient information). In addition, we slightly modified the wording of the items from how the participant “acted” or how they “were”, to how they “seemed” during the hour, to remind coders that we were interested in their holistic impressions.

Informativeness Ratings

In the first version of the hour-level coding survey (i.e., roughly the first three coders per participant), coders had five options for judging how informative the hour was, with instructions for each scale point (1 = no noise, 2 = there is noise but not sure what they’re doing, 3 = there is noise and you can tell what they’re doing, but not what they’re saying, 4 or 5 = talking; we asked coders to make a judgment about how informative the hour was between 4 and 5). We instructed coders to only complete the survey if the hour block was at least “3” on informativeness. However, several coders completed surveys for hours that they rated as being uninformative (i.e., rated as 1 or 2). As these hours seemed to contain information on participants’ behavior (based on the coders’ open-ended descriptions of what the participant was doing), we recoded surveys with at least some completed ratings as being informative.

To prevent confusion, in the second version of the survey (i.e., roughly the last three coders per participant), we simplified the response options to three options ((1) No noise, white noise, or sleeping in all files; (2) Uninformative noise in all files; (3) Information on participants' behaviors or situation in at least one file), and recoded the first two options as "Uninformative" and the third option as "Informative".

Number of Coders

If a coder did not finish coding all hours for a participant during their time as a research assistant, the participant was reassigned to a new coder, who coded that participant from the beginning. This meant that some hour blocks were coded by up to 14 coders. In addition, due to human error, some hour blocks were coded by fewer than 6 coders. For the current analyses, we decided to include a maximum of 6 coders as indicators for the conversational depth and self-disclosure latent variables, to reduce model complexity and convergence issues. To decide which coders to retain (out of the possible 14 coders), for each participant, we rank-ordered coders by the number of hours they had coded for that participant, then kept the 6 coders who had coded the most hours for each participant.

Analyses for Social Connectedness Items

For the main analyses, for conceptual reasons, we combined the close/connected and loneliness (reversed) items into a social connectedness composite. As the within-person reliability of this composite was lower than expected, we subsequently re-ran the analyses using the individual items as separate outcomes. These results suggest that, overall, the main effects were larger for the close/connected item than for the loneliness item (see Table S1). In addition, the moderating effect of trait extraversion found in the main analyses (a cross-level interaction for conversational depth; see Table 3) appeared to be driven by the close/connected item; this interaction effect was not detectable for the loneliness item (see Table S2). Finally, three additional between-person interactions emerged, but seem unlikely to be robust as they did not generalize across self- and observer-report methods, or across the two social connectedness items (see Table S2).

Table S1

Predicting Closeness/Connectedness and Loneliness from Social Interactions

	Close, connected				Lonely			
	Self-Reported (ESM) Interactions		Observed (EAR) Interactions		Self-Reported (ESM) Interactions		Observed (EAR) Interactions	
	β	R^2	β	R^2	β	R^2	β	R^2
Quantity of interactions								
Binary interactions								
Within	1.23 [1.14, 1.31]	.24	0.78 [0.70, 0.86]	.12	–0.47 [–0.59, –0.36]	.09	–0.33 [–0.43, –0.22]	.05
Between	0.56 [0.40, 0.69]	.31	0.40 [0.21, 0.58]	.16	–0.27 [–0.44, –0.06]	.07	*–0.16 [–0.36, 0.00]*	.03
Continuous interactions								
Within			1.21 [1.10, 1.30]	.15			–0.49 [–0.58, –0.40]	.05
Between			0.49 [0.32, 0.65]	.24			–0.27 [–0.47, –0.08]	.07
Quality of interactions								
Conversational depth								
Within	0.24 [0.19, 0.29]	.12	0.16 [0.10, 0.22]	.08	–0.06 [–0.10, –0.01]	.06	–0.08 [–0.14, –0.02]	.11
Between	0.46 [0.27, 0.61]	.21	–0.12 [–0.44, 0.19]	.02	–0.24 [–0.44, –0.04]	.06	0.18 [–0.39, 0.82]	.06
Self-disclosure								
Within	0.33 [0.28, 0.39]	.15	0.24 [0.18, 0.30]	.09	–0.10 [–0.15, –0.04]	.05	*–0.06 [–0.12, 0.00]*	.03
Between	0.54 [0.36, 0.66]	.30	0.19 [–0.12, 0.47]	.04	*–0.12 [–0.25, 0.06]*	.01	–0.05 [–0.31, 0.26]	.01
Knowing								
Within	0.37 [0.32, 0.42]	.18			–0.12 [–0.18, –0.07]	.07		
Between	0.63 [0.47, 0.79]	.40			–0.28 [–0.42, –0.10]	.08		
Liking								
Within	0.47 [0.37, 0.50]	.24			–0.19 [–0.24, –0.14]	.07		
Between	0.65 [0.50, 0.81]	.42			–0.44 [–0.60, –0.31]	.19		

Note. ESM = Experience Sampling Method, EAR = Electronically Activated Recorder. The within-person quantity of interactions βs are only standardized with respect to the well-being outcome. All other coefficients are standardized with respect to both the predictor and outcome. R^2 = proportion of variance explained at each level. 95% credibility intervals are shown in brackets. *Italicized* coefficients denote item-level effects where the 95% CIs suggest a different conclusion than the effects for the composite measure (reported in Table 2).

Table S2
Predicting Closeness/Connectedness and Loneliness from Social Interactions: The Moderating Effects of Trait Extraversion

	Close, connected		Lonely	
	Self-Reported (ESM) Interactions	Observed (EAR) Interactions	Self-Reported (ESM) Interactions	Observed (EAR) Interactions
Quantity of interactions				
Binary interactions				
Within	1.24 [1.14, 1.33]	0.77 [0.68, 0.84]	–0.47 [–0.60, –0.34]	–0.33 [–0.41, –0.24]
Between	0.53 [0.34, 0.70]	0.34 [0.14, 0.54]	–0.22 [–0.39, –0.02]	–0.12 [–0.37, 0.12]
Trait E	0.20 [0.05, 0.35]	0.27 [0.12, 0.40]	–0.17 [–0.31, –0.01]	–0.20 [–0.36, –0.03]
Within × Trait E	0.08 [–0.01, 0.16]	0.03 [–0.06, 0.12]	0.03 [–0.11, 0.16]	0.02 [–0.08, 0.11]
Between × Trait E	0.09 [–0.09, 0.25]	0.02 [–0.15, 0.18]	***0.24 [0.04, 0.46]***	0.11 [–0.10, 0.32]
Continuous interactions				
Within		1.19 [1.06, 1.29]		–0.50 [–0.64, –0.39]
Between		0.46 [0.28, 0.60]		–0.20 [–0.38, 0.04]
Trait E		0.26 [0.14, 0.39]		–0.18 [–0.34, –0.04]
Within × Trait E		–0.11 [–0.21, 0.01]		0.11 [–0.01, 0.22]
Between × Trait E		0.01 [–0.14, 0.17]		0.03 [–0.21, 0.24]
Quality of interactions				
Conversational depth				
Within	0.24 [0.18, 0.29]	0.15 [0.09, 0.22]	–0.05 [–0.11, 0.01]	–0.08 [–0.14, –0.02]
Between	0.42 [0.27, 0.54]	0.06 [–0.35, 0.43]	–0.21 [–0.37, –0.05]	0.20 [–0.08, 0.52]
Trait E	0.26 [0.13, 0.37]	0.33 [0.16, 0.46]	–0.16 [–0.30, –0.02]	–0.18 [–0.32, 0.01]
Within × Trait E	**–0.29 [–0.49, –0.05]**	**–0.29 [–0.55, –0.02]**	*0.22 [–0.04, 0.43]*	*0.18 [–0.05, 0.39]*
Between × Trait E	0.04 [–0.10, 0.19]	0.02 [–0.22, 0.30]	0.02 [–0.15, 0.20]	***–0.39 [–0.64, –0.12]***
Self-disclosure				
Within	0.33 [0.28, 0.38]	0.24 [0.17, 0.29]	–0.09 [–0.14, –0.04]	–0.06 [–0.11, 0.00]
Between	0.47 [0.34, 0.60]	0.08 [–0.39, 0.60]	–0.06 [–0.23, 0.12]	–0.13 [–0.42, 0.18]
Trait E	0.22 [0.09, 0.35]	0.31 [0.04, 0.50]	–0.22 [–0.35, –0.07]	–0.18 [–0.34, –0.02]
Within × Trait E	–0.08 [–0.32, 0.25]	–0.11 [–0.43, 0.20]	–0.07 [–0.34, 0.30]	–0.11 [–0.60, 0.44]
Between × Trait E	***0.14 [0.02, 0.29]***	–0.01 [–0.27, 0.23]	–0.08 [–0.23, 0.09]	0.25 [–0.10, 0.56]
Knowing				
Within	0.38 [0.30, 0.42]		–0.10 [–0.15, –0.06]	
Between	0.58 [0.39, 0.74]		–0.30 [–0.49, –0.08]	
Trait E	0.20 [0.06, 0.34]		–0.14 [–0.28, 0.01]	
Within × Trait E	0.20 [–0.04, 0.42]		–0.05 [–0.31, 0.19]	
Between × Trait E	0.13 [–0.01, 0.27]		0.19 [–0.01, 0.37]	
Liking				
Within	0.48 [0.42, 0.52]		–0.18 [–0.23, –0.13]	
Between	0.62 [0.48, 0.72]		–0.40 [–0.54, –0.25]	
Trait E	0.16 [0.02, 0.29]		–0.10 [–0.25, 0.04]	
Within × Trait E	0.08 [–0.31, 0.36]		–0.06 [–0.32, 0.28]	
Between × Trait E	0.10 [–0.02, 0.23]		0.14 [–0.01, 0.29]	

Note. ESM = Experience Sampling Method, EAR = Electronically Activated Recorder. The within-person quantity of interactions coefficients are only standardized with respect to the well-being outcome. All other coefficients are standardized with respect to both the predictor and outcome. R^2 = proportion of variance explained at each level. 95% credibility intervals are shown in brackets. Coefficients in **bold** highlight interaction effects with 95% credibility intervals that do not capture zero. *Italicized* coefficients denote item-level interaction effects where the 95% CIs suggest a different conclusion than the interaction effects for the composite measure (reported in Table 3).

Additional Moderation Effects

Figure S3 illustrates the additional moderation effects from the main analyses that had 95% credibility intervals that did not capture zero (see Table 3). We chose not to elaborate on these effects in the main text, as they did not hold for self-reported social interactions (see Figure S1), and therefore seemed less robust. However, for transparency, we offer a brief interpretation here.

These effects imply that the positive association between the observer-based binary or continuous measure of the quantity of social interactions and average self-reported happiness was stronger for those who were more introverted, than for those who were more extraverted (see Table 3 and Figure S1). Model-predicted values derived from the Johnson-Neyman (1936) technique (see Figure S1) suggest that there was no detectable between-person association between observer-rated quantity of social interactions and average happiness for participants who had extraversion *z*-scores higher than –0.64 (for the binary measure) or –1.14 (for the continuous measure).

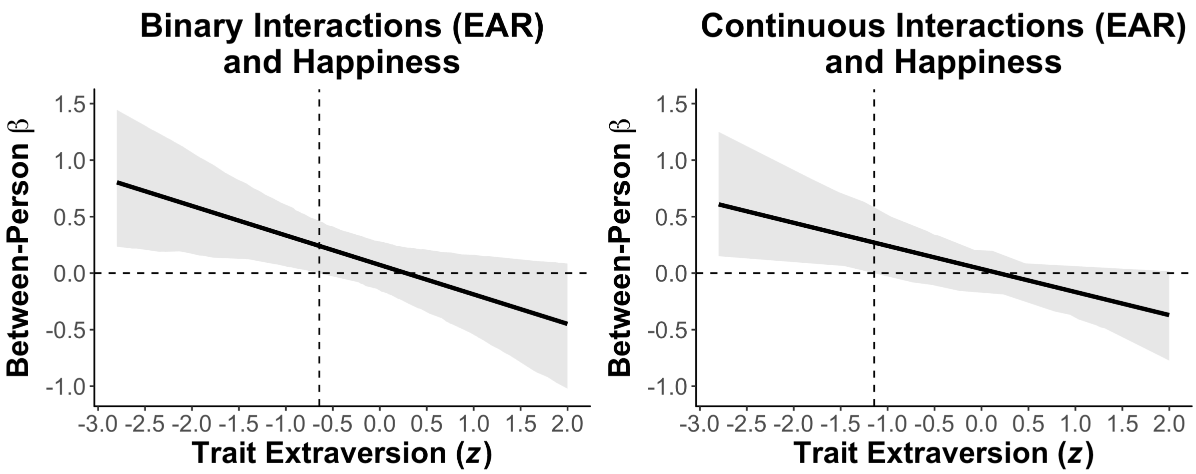

Figure S1. Predicted standardized between-person associations between the EAR binary and continuous quantity of social interaction variables and happiness (solid black line) at different levels of trait extraversion (*z*-scored). Gray ribbons show 95% credibility intervals. The dotted vertical line shows the level of trait extraversion above which the association between the two variables could plausibly be in either direction. ESM = Experience Sampling Method, EAR = Electronically Activated Recorder.