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Happiness and the Propensity to Interact With Other People: Reply to Elmer (2021)

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In 2019, we reported the results of a large experience-sampling study in which we sought to reconcile two literatures (Quoidbach et al., 2019). The first showed that *happiness* was associated with more social interaction, and the second showed that *unhappiness* was associated with more social interaction. We found that average happiness predicted more social interaction, whereas momentary unhappiness predicted subsequent pleasant (but not unpleasant) categories of social interaction. To distinguish the effect of momentary fluctuations in a person's happiness from the longer-term trends (e.g., happy people are more socially engaged, happy days are often socially active ones), we argued it was essential to control for participants' daily happiness levels.

In his insightful Commentary, Elmer (2021) pointed out that our decision to control for daily happiness (H_{day}) was problematic for two reasons. First, for 34% of observations, H_{day} included information about future states of happiness that should have no bearing on people's propensity to socialize at a previous point in time. Second, for 49% of observations, H_{day} was equal to current happiness (H_{t+1}), that is, happiness recorded at the same time as the social interaction we sought to predict. Given the overrepresentation of H_{t+1} in H_{day}, and informed by an empirical model in which the change in happiness between t and $t + 1$ was used as a covariate, Elmer suggested our negative association between happiness and subsequent social interaction might be "driven by observations of individuals who were happy before (at t) and were not interacting at the subsequent time point ($t + 1$) because they had become less happy by the subsequent time point" (p. 958).

To avoid these difficulties—while still attempting to disentangle short- versus long-term effects of happiness on social interaction—Elmer used our original data (https://osf.io/bxgn4) to compute several alternative models, including models that controlled for average happiness over the last 24 hr ($H_{pastday}$) and average happiness over the past week ($H_{pastweek}$). Using these alternative specifications, he found that people were *more* likely to report interacting with others when they were happy a few hours before.

We thank Elmer for pointing out that the effects we reported depend on the specific covariate that is used. To better understand this intriguing dependency, we performed a series of follow-up analyses to pinpoint which component of the H_{day} covariate is critical to the results and to assess how viable different covariates are from a statistical standpoint. We then attempted to shed light on why controlling for H_{day} (or H_{t+1}) instead of $H_{pastday}$, $H_{pastweek}$, or an unadjusted model leads to radically different inferences. One explanation is Elmer's *reduced-happiness account*: When the model includes the H_{day} (or H_{t+1}) covariate, happiness at t captures the change in happiness between t and $t + 1$. A second explanation—also inspired by Elmer's observation but not foregrounded by him—is a *temporal-proximity account*. Because several hours typically separated reports at t and $t + 1$ in our data set, changes in happiness are likely to have occurred between successive assessments. With such noisy data, it is difficult to isolate the short-term signal (i.e., momentary shift) part

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of happiness at t from the longer-term signal (i.e., enduring circumstances, dispositions). If this is the case, controlling for concurrent happiness (alone or through H_{day}) might have provided an imperfect proxy for these unobserved factors and helped isolate the effect of momentary fluctuations in happiness. We examined these accounts in our original data and the publicly available data set from the World Health Organization (WHO) Study on Global AGEing and Adult Health (SAGE), in which representative samples of people in six countries provided temporally finer-grained affect and social-interaction data. These analyses suggest that the temporal proximity between affect and behavior measurements might be a critical factor in determining the effect of happiness on social behavior.

Method

The role of average happiness

To assess the importance of the inclusion of concurrent happiness (H_{t+1}) in the daily-average-happiness covariate, we compared three models including different covariates: (a) mean daily happiness excluding happiness at time t (the original covariate), (b) mean daily happiness excluding both happiness at time t and time $t + 1$, and (c) mean daily happiness excluding happiness at time t and either happiness at time $t - 1$ or happiness at time $t + 2$ (in the case of the first pair of observations for the day). To enable valid comparisons among models and to ensure that averages were based on at least two measures, we restricted all our analyses to the same subsample of 5,422 individuals who had four or more complete observations (i.e., at least three pairs) for at least 1 day (total $N = 45{,}866$ pairs of observations). Binomial-family generalized linear mixed models with log-link functions and individual-level random intercepts and slopes were then run using the *lme4* package (Version 1.1-26; Bates et al., 2015) in R (Version 4.0.2; R Core Team, 2020). These models related the binary outcome (being alone at time $t + 1$) to happiness at t, adjusting for time of day (12 dummy variables for each of the 2-hr time bins from 12:00 a.m. to 11:59 p.m.), day of the week (weekday, Saturday, or Sunday), and each average-happiness covariate in turn. The results of these analyses were then compared with each other and with the results of a model not adjusting for daily average happiness. Data and the accompanying R script to reproduce all analyses can be found on OSF (https://osf.io/a4w63).

Statistically comparing models

To assess whether our original choice of covariate (daily average happiness excluding happiness at t) was statistically reasonable compared with Elmer's qualitatively reasonable alternative suggestions (i.e., average happiness over the previous 24 hr and average happiness over the previous 7 days; $H_{pastday}$ and $H_{pastweek}$), we compared models including each of these covariates using two standard model-fit metrics: Akaike information criterion (AIC; Akaike, 1973) and Bayesian information criterion (BIC; Schwarz, 1978; see also Vrieze, 2012). As Elmer acknowledges, the previous day's average that he used suffers from the same limitation as our daily average: In 47% of the cases, it was based on only one observation. Therefore, we report results of a subsample of 10,204 individuals who had five or more complete observations over 48 hr (three or more that day, plus two or more in the previous 24-hr period; total $N = 64{,}644$ pairs of observations). This allows us to compute meaningful measures of average happiness both daily and over the previous 24 hr. Keeping the sample size constant also allowed direct comparison of the fit indices of the different models. For completeness, results from models using all available observations are presented in Section S1 in the Supplemental Material.

Explaining the effects of controlling for happiness

Elmer proposed an explanation for why controlling for happiness at $t + 1$ might lead to the observation that people who are currently feeling unhappy are more likely to later engage in social interactions. When this covariate is included in the model, it is possible that happiness at t actually captures the change in happiness between t and $t + 1$. As Elmer puts it, "the residual negative effect of H_t on P_{t+1} that emerged in the original analysis was likely driven by observations of individuals who were happy before (at t) and were not interacting at the subsequent time point ($t + 1$) because they had become less happy by the subsequent time point" (p. 958). A testable prediction of this reduced-happiness account is that the negative association between momentary happiness and the propensity to later engage in social interactions should disappear if we restrict the analysis to observations in which happiness *increased* between t and $t + 1$. We tested this prediction by examining our original model on the subsample of observations for which happiness at $t + 1$ was higher than happiness at t ($n = 107{,}411$ observations from 25,377 participants).

Elmer's observation that participants may have gotten more or less happy between two consecutive measurements suggests another potential explanation, which might be called the temporal-proximity account. In our original data set, the average gap between episodes at times t and $t + 1$ was 4.5 hr. Given our experience-sampling design, we do not know how long each of these episodes lasted, nor do we know how many emotional and social episodes happened in between. Some participants might have already engaged in multiple social activities, others might have gone through significant emotional changes. We postulate that controlling for concurrent happiness (H_{t+1}) essentially (albeit imperfectly) captures these unobserved factors, thereby considerably reducing their influence and helping to isolate the associations between momentary fluctuations in happiness and social interactions. If this explanation accounts for the discrepancy between Elmer's findings and ours, then unhappiness at time t should predict a higher propensity to engage socially at time $t + 1$ even when models do not control for H_{t+1} (or any covariate derived from it) if the precise durations of the two episodes are known and no other emotional and social episodes happened in between. In contrast, unhappiness at t should not predict social interactions at $t + 2$ or $t + 3$ (because many things might have happened in between) unless the model approximates these unobserved variables using concurrent happiness at $t + 2$ or $t + 3$, respectively, as a proxy.

Although the temporal resolution of our original data set does not allow us to test this alternative explanation, the publicly available WHO SAGE (Wave 1) data set does (see Fig. S1 in the Supplemental Material available online). In this study, nationally representative samples of people in China, Ghana, India, Mexico, Russia, and South Africa completed a modified version of the day-reconstruction method, providing high-temporal-resolution data about affect and social-interaction dynamics (for detailed descriptions of the study, see Ayuso-Mateos et al., 2013; Kowal et al., 2012). Participants were asked to report, in chronological order and across different episodes of their previous day, how they felt and whom they were with. In this data, episodes were measured back to back, such that successive happiness and social-interaction records follow one another with no time gap (e.g., "What did you do and how did you feel when you woke up? What did you do and how did you feel next?"). For the purposes of this Reply, we focus on the binary variable that encoded whether or not they were alone (1 = alone). Participants were also asked to report the positive and negative emotions they felt at the time of each episode, with each emotion encoded as not at all (1), a little (2), or very much (3). We then calculated a total composite happiness score by subtracting the mean of the negative emotions (worried, rushed, irritated or angry, depressed, tense or stressed) from the mean of the positive emotions (calm or relaxed, enjoying), which resulted in a continuous score from −2 to 2 (for a similar approach, see Taquet et al., 2020).

To assess whether the low temporal resolution of our original data set explains why adjusting for happiness at time $t + 1$ is necessary, we compared results from models relating happiness at time t (H_t) to being alone one, two, and three time points later (A_{t+1}, A_{t+2}, and A_{t+3}), both with and without controlling for concurrent happiness (H_{t+1}, H_{t+2}, and H_{t+3}, respectively) or average daily happiness (excluding happiness at time t). For instance, in the model with A_{t+3} as the dependent variable, the association was estimated between happiness at the time of the first observation of the day (H_t) and being alone at the time of the fourth observation of the day, between happiness at the time of the second observation and being alone at the time of the fifth observation, and so on. The mean activity duration in the sample was 76.6 min (SD = 92.0 min, interquartile range = 30–90 min). The model with A_{t+3} as the dependent variable thus creates pairs of activities approximately 4 hr apart (which mimics our original data set), whereas the model with A_{t+2} and A_{t+1} as dependent variables assesses associations between happiness and social interactions that are temporally closer.

Because our analysis required at least four observations per day, we focused on a sample of 19,384 participants providing a total of 43,059 observations. Note that the date was not recorded in these data, so these models did not adjust for the day of the week. In addition, only the start time for the first activity of the day was recorded, as well as the duration of that and each subsequent activity. Thus, the end time of the previous activity was taken as a proxy for the start time of the next activity for the time-of-day covariate.

Results

The role of average happiness

In our original article, in which analyses were based on the whole sample, daily average happiness was exclusively derived from happiness at $t + 1$ for 49% of observations. Here, by focusing on subsamples of the data for which there were at least four observations per day, we were able to compute a series of daily averages that were different from happiness at $t + 1$. Our analyses (detailed in Section S1) confirm and further sharpen Elmer's observation: The inclusion of information about happiness at $t + 1$ turns out to be critical to the direction of the effect. As can be seen in Tables S1, S2, and S3 in the Supplemental Material, the model in which H_{t+1} was excluded from the daily average shows that current happiness is associated with an increased propensity to later engage socially (this model is similar to the model without a daily-average covariate, and these results are consistent with those of Elmer's

Table 1. Relation Between Momentary Happiness (H_t) and Subsequent Propensity to Be Alone at Three Subsequent Time Points (A_{t+1}, A_{t+2}, and A_{t+3}) in the Study on Global AGEing and Adult Health (SAGE) Data Set

	Not controlling for concurrent happiness		Controlling for concurrent happiness		Controlling for daily average happiness	
Relation	*OR*	95% CI	*OR*	95% CI	*OR*	95% CI
$H_t \rightarrow A_{t+1}$	1.036*	[1.008, 1.064]	1.173***	[1.133, 1.215]	1.100***	[1.057, 1.144]
$H_t \rightarrow A_{t+2}$	1.028*	[1.000, 1.057]	1.141***	[1.103, 1.181]	1.082***	[1.039, 1.126]
$H_t \rightarrow A_{t+3}$	1.026	[0.998, 1.055]	1.120***	[1.084, 1.158]	1.056**	[1.015, 1.098]

Note: n = 43,059 observations from 19,384 individuals. The odds ratio (*OR*) refers to the likelihood of being alone given a 1-point increase in happiness at time t, which was reported on a scale from −2 to 2. CI = confidence interval.
*$p < .05$. **$p < .01$. ***$p < .001$.

models). In contrast, models that controlled for H_{t+1}, either directly or as part of the computation of the daily average, show that current happiness is associated with a decreased propensity to later engage socially (consistent with our original findings). Note that results using the whole sample—including participants for whom daily averages were based on one observation—were identical (see Section S1).

Statistically comparing models

Table S4 in the Supplemental Material reports the model-fit indices for our original specification (controlling for H_{day}), for Elmer's alternative specifications (controlling for $H_{pastday}$ and $H_{pastweek}$), and for a model that controls simply for H_{t+1}. Although model-selection techniques do not provide information about the theoretical soundness of the different models, a comparison of the AIC and BIC suggests that our original specification (H_{day}) and its streamlined version (H_{t+1}) are both viable statistical models. In fact, comparing the AIC and BIC of each of the models suggests a marginal improvement in fit when the H_{day} or H_{t+1} covariate is included, compared with the average of the past 24 hr or 7 days, as well as when no adjustment is made for daily mean happiness. Note that results using the whole sample—including participants for whom average covariates were based on one observation—were similar (see Section S2 in the Supplemental Material).

Explaining the effects of controlling for happiness

With regard to Elmer's reduced-happiness account, strong statistical evidence remains for a positive relationship between H_t and A_{t+1} in the subsample of observations for which happiness increased between t and t + 1 (odds ratio = 1.002, 95% confidence interval = [1.001, 1.003], p = .0004). This result would seem to rule out the possibility that the association we found was driven by observations of people who were initially happy and have subsequently become less happy.

With regard to the temporal-proximity account that Elmer's observation inspired, results in Table 1 show that in the WHO data, in which affect and activities were measured back to back, unhappiness at time t significantly relates to a higher propensity to engage socially at time t + 1 when models do not control for concurrent happiness. Consistent with the temporal proximity account, the statistical evidence for a positive relationship between unhappiness at t and social interactions at t + 2 was weaker (but still significant at the 5% level), and it was weaker still when predicting social interactions at t + 3, with the 95% confidence interval for this relationship including zero. However, when the model controlled for concurrent happiness, potentially approximating unobserved changes, there was strong statistical evidence for a positive relationship between unhappiness at t and social interactions at t + 1, t + 2, and t + 3. Including time elapsed between the different episodes as a covariate and controlling for a mean daily-happiness covariate computed using only measures that had occurred earlier in the day led to virtually identical results (see Sections S3 and S4 in the Supplemental Material).

Discussion

Current happiness reflects both momentary and longer-term factors. Because many self-regulation and balancing processes happen within the scope of a day (e.g., Khare & Inman, 2009), we initially believed that the key to isolating the signal of momentary affective fluctuations was to control for overall happiness at the day level.

Inspired by Elmer's critique, the current analyses suggest that another element might be essential to capture momentary-level relationships between affect and behavior: temporal proximity. When measures of happiness and subsequent interactions are relatively distant from each other (as in our original data set), any model that does not account for concurrent happiness seems to capture the longer-term links between happiness and social behavior. In line with decades of cross-sectional studies and as Elmer empirically demonstrated, results show that happy people are more socially engaged (e.g., Diener & Seligman, 2002; Mehl et al., 2010). However, when happiness and subsequent interactions are measured back to back (as in the analysis of the WHO data set) or when concurrent happiness is accounted for (potentially capturing unobserved changes between observations), the sign of the relationship flips. In line with decades of research on coping and attachment, results show that people seem particularly prone to seek social relationships when they have experienced a recent decrease in happiness (e.g., Thayer et al., 1994).

We believe that our interchange with Elmer points to exciting directions for future work concerned with the links between affect dynamics and everyday behavior. It also highlights the value of open-science practices, including sharing data and code related to scientific reports.

One puzzle is why none of the analyses of the WHO data set, including models that examined the relationship between affect and temporally distant social interactions, revealed a positive relationship between happiness and social engagement. One possibility is that when reconstructing their day, participants might have somehow already "scaled" their emotions at the level of the day—in line with research showing that participants provide lower affect ratings using the day-reconstruction method than they do during experience sampling (Lucas et al., 2021). Examining this possibility—and further testing the temporal-proximity account—are key future directions.

When making our raw data publicly available, one of our goals was to generate scientific discussions of the type Elmer instigated. Our productive interchange reminds us that seemingly straightforward choices about design, sampling, and statistical controls profoundly shape the answers researchers get. Thoroughly assessing the impact of these decisions promises to move the field beyond questions about the simple direction of effects to more nuanced consideration of the drivers of these effects, their time scale, and their magnitude under different circumstances.

Transparency

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Author Contributions

Q. Dercon analyzed the data and prepared the tables. M. Desseilles and Y.-A. de Montjoye helped with the data collection. J. Quoidbach, J. J. Gross, and M. Taquet wrote the manuscript. All the authors approved the final manuscript for submission.

Declaration of Conflicting Interests

The author(s) declared that there were no conflicts of interest with respect to the authorship or the publication of this article.

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Open Practices

Analysis code for the present study has been made publicly available on OSF at https://osf.io/a4w63. Data used in the present study are available from the World Health Organization at https://apps.who.int/healthinfo/systems/surveydata/index.php/catalog/sage. Data for the original study (Quoidbach et al., 2019) are available at https://osf.io/bxgn4. This article has received the badges for Open Data and Open Materials. More information about the Open Practices badges can be found at http://www.psychologicalscience.org/publications/badges.

Supplemental Material

Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/09567976211012673

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