In Which Direction Does Happiness Predict Subsequent Social Interactions? A Commentary on Quoidbach et al. (2019)
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Published in:
Psychological Science

DOI:
10.1177/0956797620956981

IMPORTANT NOTE: You are advised to consult the publisher's version (publisher's PDF) if you wish to cite from it. Please check the document version below.

Document Version
Publisher's PDF, also known as Version of record

Publication date:
2021

Link to publication in University of Groningen/UMCG research database

Citation for published version (APA):
https://doi.org/10.1177/0956797620956981

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Quoidbach and colleagues (2019) investigated the bidirectional relationship between happiness and social behavior. For this, they used experience-sampling data from 30,793 individuals who reported on their daily happiness and social-interaction partners. In line with the hedonic-flexibility principle, results showed that happier individuals were less likely to interact with other people at the next measurement time point than less happy individuals (see Quoidbach et al., Fig. 2). Furthermore, they reported evidence that individuals seek different interaction partners depending on their happiness and that certain interaction partners are more likely to increase individuals’ happiness.

Laudably, Quoidbach and colleagues followed good open-science practice and published their data online. Furthermore, their research is highly important for advancing knowledge on the interplay between the social environment and emotional experiences.

However, a methodological issue jeopardizes one of their main findings, namely the finding that happiness ($H_t$) is associated with a decreased probability of future interactions ($P_{t+1}$; see Quoidbach et al., Fig. 2). I will show that (a) when the raw data are investigated and (b) when the multilevel analyses are conducted excluding a particular covariate or with a set of more justifiable ones, the aforementioned association reverses in direction and is estimated to be positive (i.e., that happier individuals are more likely to interact subsequently than less happy individuals).

The data used by Quoidbach and colleagues are very rich in terms of participating individuals ($N = 30,793$); however, the data are often very sparse on an individual’s daily level: Participants on average had 1.49 ($SD = 0.85$) consecutive data points per analyzed day (computed using the publicly available data from the original study at https://osf.io/bxgn4). This is problematic because Quoidbach and colleagues controlled for the variable $H_{day}$, which represents an individual’s average happiness on a given calendar date (excluding happiness at the previous time point, $H_t$). The $H_{day}$ variable suffers from two measurement-related limitations. First, on 66% of the observed days, there was only one observation per individual from which this “average” was calculated. Second, when the focus is on a given time point, the variable $H_{day}$ contains information from observations of future happiness. In fact, in 49% of the data points, the $H_{day}$ value is identical to happiness at the subsequent time point ($H_{t+1}$), and in the remaining cases, $H_{t+1}$ is part of the $H_{day}$ average calculation. Hence, the $H_{day}$ variable might not be a valid control for a daily average but often represents happiness at the next time point ($H_{t+1}$). If the aim was “to assess whether people’s current happiness significantly predicts their future social interactions” (Quoidbach et al., p. 1114), future happiness ($H_{t+1}$) should not be included as part of the variable that is controlled for—or at the very least the overrepresentation of $H_{t+1}$ in $H_{day}$ should be highlighted and the model results should be interpreted with that in mind.

Quoidbach and colleagues argued for the presence of the variable $H_{day}$ in the following way:

Because our goal was to capture the high-frequency dynamics in happiness (e.g., hourly changes in happiness) while controlling for the low-frequency dynamics (e.g., daily or weekly changes in happiness), we included daily average happiness as a covariate in the regression models. (p. 1113)
According to this reasoning, controlling for alternative variables, such as the average of the past 24 hr (H\textsubscript{pastday}) or the past week’s average (H\textsubscript{pastweek}), should reveal similar results. To overcome the limitations of this H\textsubscript{day} variable, I conducted additional robustness analyses on the publicly available data set with alternative model specifications.

### Method

The analysis reported by Quoidbach and colleagues was reproduced as closely as possible using the publicly available data from their study (see https://osf.io/bxgn4 for data from the original study). For this reanalysis, the following multilevel time-lagged logistic regression model was estimated by Quoidbach and colleagues (Equation 1, p. 1114):

\[
\logit(P(P_i^{t+1}) = \beta_0 + \beta_1 H_t + \beta_{day} H_{day} + \beta_d D + \beta_T T + \beta_p P_i^t,
\]

with \(\beta_0 = \gamma_0 + u_0\) and \(\beta_1 = \gamma_1 + u_1\).

\(P_i^{t+1}\) represents individuals’ reports of being in a social interaction at the next measurement time point and is the dependent variable in this analysis (1 = in interaction, 0 = alone). The \(H_t\) variable entails the previous measure of happiness (reported on a scale from 0 to 100), of which the fixed effect \(\gamma_1\), representing the effect of happiness on subsequent interactions, is the coefficient of interest in this analysis. The \(H_{day}\) variable represents an individual’s average happiness on a given day, excluding the individual’s happiness at \(H_t\). If there is one data point on a given day (66% of the data points), the \(H_{day}\) variable is identical to the happiness of the time point to be predicted (\(t + 1\)). On days when there are two observations (24% of the data points), \(H_{day}\) is computed using the average of \(H_{t+1}\) and the other measure of that day. Also see Table S3 in the Supplemental Material available online for a data excerpt and example calculation of \(H_{day}\). The variables \(D, T\), and \(P_i^t\) control for the day of the week (weekday, Saturday, Sunday), time of day (in 2-hr bins starting at midnight), and whether the person was in a social interaction at the previous time point. The reference categories were specified as Saturday between 12:00 p.m. and 2:00 p.m.

The model is specified with random intercepts \(u_0\) and random slopes \(u_1\), accounting for individual differences in social-interaction tendencies and individual differences in the effects of previous happiness measures (\(H_t\)) on social interactions. All \(\beta\)s and \(\gamma\)s are subject to the estimation. The estimation was carried out with the glmer function of the lme4 package (Version 1.1-19; Bates et al., 2015) in R (Version 3.5.2; R Core Team, 2018). Data-preparation procedures and model estimation are documented in the R script available at https://osf.io/zk98q.

To better account for “low-frequency dynamics” of happiness that do not include future happiness values, I further included an \(H_{pastweek}\) Variable and an \(H_{pastday}\) variable in the model, capturing the effects of the average happiness of an individual reported in the past week (excluding the current day) and the past 24 hr (excluding the measurements \(H_t\)), respectively. The calculation of \(H_{pastweek}\) and \(H_{pastday}\) was documented in the R script available at https://osf.io/zk98q. It is important to note that the variables \(H_{pastweek}\) and \(H_{pastday}\) were also calculated on the basis of only a few observations (\(M = 3.02, SD = 3.56\), and \(M = 0.86, SD = 1.23\), respectively). Moreover, they were computed using the publicly available data set, which was subdivided to contain only consecutive reports within a 12-hr time window. The nonsubdivided data might provide a more reliable estimate of the past week’s and past day’s average happiness.

Overall, this analysis focused on the comparison between model results based on different specifications (i.e., with and without the \(H_{day}\) variable and the alternative measures \(H_{pastweek}\) and \(H_{pastday}\)).

### Results

Figure 1 shows the results of the reanalysis and the additional analyses conducted. The full model results are reported in Table S1 in the Supplemental Material. The red squares and error bars in Figure 1 represent the predicted values and 95% confidence intervals (CIs), respectively, of the odds ratios (ORs) of participants’ interacting with other people at time \(t + 1\) depending on their level of happiness at time \(t\). These values closely resemble the results reported by Quoidbach and colleagues, log OR = -0.003, 95% CI = [-0.003, -0.002], OR = 0.997, \(p < .001\). The green triangles in Figure 1 represent predicted odds ratios of a model in which the \(H_{day}\) variable was removed. When the \(H_{day}\) variable was removed from the analyses, the association changed direction, log OR = 0.006, 95% CI = [0.005, 0.006], OR = 1.006, \(p < .001\). Also, the raw data (i.e., means; gray dots in Fig. 1), which are not based on predicted values of a statistical model, suggest a positive association between happiness and the probability of being in a social interaction at the next time point.

Instead of controlling for an individual’s daily happiness average, I created a further model that controlled for the individual’s average happiness over the past week. The predicted ORs based on the model including \(H_{pastweek}\) are reported as blue asterisks in Figure 1, log OR = 0.004, 95% CI = [0.003, 0.005], OR = 1.004,
The predicted ORs of a model containing the $H_{\text{pastday}}$ variable are represented as blue squares in Figure 1, log OR = 0.003, 95% CI = [0.002, 0.004], $OR = 1.003, p < .001$. The models including $H_{\text{pastweek}}$ or $H_{\text{pastday}}$ suggest a positive association between happiness and subsequent social interactions. Further models using other alternative measures (e.g., past happiness measures of the current day, $H_{\text{earlier_in_day}}$, person-mean-centered happiness, $H_{\text{PMC}}$) can be found in Table S2 in the Supplemental Material and the accompanying R script (https://osf.io/zk98q).

So why does only the $H_{\text{day}}$ model reveal a negative association between happiness and subsequent social interactions? One reason might be the overrepresentation of $H_{r+1}$ in $H_{\text{day}}$, because a model with $H_{r+1}$ instead of $H_{\text{day}}$ suggests almost identical results (see Table S2). After the model adjusted for the positive cross-sectional association (effect of $H_{r+1}$), log OR = 0.015, 95% CI = [0.014, 0.015], $OR = 1.015, p < .001$, previous happiness at time $t$ was negatively associated with being in an interaction at $t + 1$, log OR = −0.003, 95% CI = [−0.004, −0.003], $OR = 0.997, p < .001$. In this case, the effect of $H_{r}$ cannot be interpreted independently of the $H_{r+1}$ effect, as they are highly correlated, $r(220292) = .70, p < .001$, and part of the same model. Note that the $H_{r+1}$ effect is about 5 times larger than the effect of $H_{r}$. Hence, in order for the total contribution of happiness to be negative, $H_{r}$ must be about 5 times larger than $H_{r+1}$, which is rarely the case in the observed data (2.5% of cases).

The nature of the interplay between $H_{r}$ and $H_{r+1}$ can best be understood when looking at the change in happiness between $t$ and $t + 1$ (i.e., using $\Delta H = H_{r+1} - H_{r}$). A model with $\Delta H$ instead of $H_{r+1}$ was estimated (see
Table S2). This model essentially contains identical information to the $H_{t+1}$ model, but interpreting it is more straightforward. The results of that model suggest that if there is no happiness change between $t$ and $t + 1$, the level of happiness at $t$ predicts interactions at $t + 1$ positively, log $OR = 0.012$, 95% CI $= [0.011, 0.012]$, $OR = 1.012$, $p < .001$. With each positive change in happiness, the likelihood of interactions increases, log $OR = 0.015$, 95% CI $= [0.014, 0.015]$, $OR = 1.015$, $p < .001$. In the other direction, this also means that if someone becomes unhappy between $t$ and $t + 1$, interactions become less likely. Hence, 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. The aspect of how future happiness ($H_{t+1}$) as part of $H_{day}$ plays a role in the claimed association is not discussed in the original article.

**Discussion**

The results reported in this Commentary suggest that one of the main findings claimed by Quoidbach and colleagues is not robust. Quoidbach and colleagues reported a negative association between individual’s happiness ($H_t$) and the likelihood of future interactions ($P_{t+1}$). However, in my reanalysis, I found that the raw data and statistical models, in which the control variable $H_{day}$ was removed, suggest that the association between happiness and the likelihood of future interactions is positive. Also, in models with alternative specifications with average happiness in the past week ($H_{pastweek}$) or the past 24 hr ($H_{pastday}$) or $H_{pastweek and pastday}$, the stated association was estimated to be positive.

The proclaimed negative effect of happiness on subsequent social interactions seems to be biased by the presence of unreported $H_{day}$ information in the model. The overrepresentation of $H_{day}$ in $H_{day}$ is neither discussed nor considered in Quoidbach et al.’s interpretation of effects. This reanalysis suggests that if individuals were happy before and they were not interacting at the subsequent time point (the proclaimed negative effect of $H_t$), it is likely that they became unhappy between the two measurement time points. Although dynamic investigations of happiness and social interactions are novel, the finding that less happy individuals are less likely to socially interact has been frequently demonstrated (e.g., Elmer & Stadtfeld, 2020; Pavot et al., 1990; Sandstrom & Dunn, 2014). This reanalysis is in line with that literature.

A limitation of this reanalysis is that the alternative covariates ($H_{pastweek}$ and $H_{pastday}$) were not computed on the complete data set, that is, before the data were reduced to only subsequent reports within 12 hr. The calculation of the alternative covariates was based on the reduced data used for the present reanalysis (see https://osf.io/bxgn4 for data). The findings regarding the probability of participants’ interacting with certain interaction partners (e.g., best friends) when they were previously unhappy (see Quoidbach et al., Fig. 3a) was also affected by the $H_{day}$ variable. See the Supplemental Material for additional analyses of these findings.

It is important to note that the intent of this Commentary is not to undermine the work of Quoidbach and colleagues. The importance and novelty of their research is without question. Nevertheless, the findings related to the prediction of social behavior (see Quoidbach et al., Figs. 2 and 3a) are not robust. Fortunately, Quoidbach and colleagues published their data online, which made this reanalysis possible. Beyond further encouraging open-science practices, I suggest that raw data and results of stepwise models should be more frequently reported in the psychological sciences.

**Transparency**

*Action Editor:* D. Stephen Lindsay  
*Editor:* D. Stephen Lindsay  
*Author Contributions*  
T. Elmer is the sole author of this article and is responsible for its content.

*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.

*Funding*  
This research was supported by the Swiss National Science Foundation (Grant Nos. P2EZP1_188022 and 10001A_169965).

*Open Practices*  
Scripts for the present analyses have been made publicly available via OSF and can be accessed at https://osf.io/zk98q. 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.

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Acknowledgments
I thank Kieran Mepham, Laura Bringmann, Markus Eronen, Alvaro Uzaheta, and Christoph Stadtfeld for providing valuable feedback on this manuscript.

Supplemental Material
Additional supporting information can be found at http://journals.sagepub.com/doi/suppl/10.1177/0956797620956981

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