In Which Direction Does Happiness Predict Subsequent Social Interactions?

A Commentary on Quoidbach et al. (2019)

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Introduction

Quoidbach and colleagues (2019) investigated the bidirectional relationship between happiness and social behavior. For this, they used experience sampling data of 30,793 individuals reporting happiness and social interaction partners in their daily lives. In line with the ‘hedonic-flexibility principle’, they showed that happier individuals are *less* likely to interact with others at the next measurement timepoint than less happy individuals (see Figure 2 in Quoidbach et al. 2019). Furthermore, they reported evidence that individuals seek different interaction partners depending on their happiness and that certain interaction partners are more likely to increase individual’s happiness.

Laudably, Quoidbach and colleagues (2019) followed an 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 Figure 2 in Quoidbach et al. 2019). I will subsequently show that (1) when investigating the raw data and (2) 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 (2019) are very rich in terms of participating individuals ($N = 30,793$), however, the data is often very sparse on an individual’s daily level: Participants on average had 1.49 ($SD = 0.85$) consecutive data points per analyzed day¹. This is

¹ Computed based on the openly available data (osf.io/bxgn4).

problematic, because Quoidbach and colleagues (2019) controlled for a variable H_{day} , which represents an individual’s average happiness on a given calendar date (excluding happiness at the previous timepoint; H_t). The H_{day} variable suffers from two measurement-related limitations: First, in 66% of the observed days there is only one observation per individual based on which this “average” is calculated¹. Second, when focusing on a given timepoint, the variable H_{day} contains information from future happiness observations. In fact, in 49% of the datapoints, the H_{day} value is identical to the happiness at the subsequent timepoint (H_{t+1}), 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 timepoint (H_{t+1}). If the aim was to “assess whether people’s current happiness significantly predicts their future social interactions” (Quoidbach et al., 2019; p. 4), 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 (2019) 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. 3). According to this reasoning, controlling for alternative variables, such as the average of the past 24 hours $H_{pastDay}$ or the past week’s average $H_{pastWeek}$, should reveal similar results. To overcome the limitations of this H_{day} variable, I conducted additional robustness analyses on the publicly available dataset with alternative model specifications.

Methods

The analysis reported by Quoidbach and colleagues (2019) is reproduced as closely as possible based on openly available data of this study (osf.io/bxgn4). For this reanalysis, a multilevel time-lagged logistic regression model was estimated as reported in Eq. 1 (p. 4) in Quoidbach and colleagues (2019):

$$\text{logit}P(P_{t+1}^j) = \beta_{0i}^j + \beta_{ci}^j H_t + \beta_{day}^j H_{day} + \beta_d D + \beta_T T + \beta_p P_t^j$$

$$\text{With } \beta_{0i}^j = \gamma_0^j + u_{0i}^j \text{ and } \beta_{ci}^j = \gamma_c^j + u_{ci}^j$$

P_{t+1}^j represents individuals' reports of being in a social interaction at the next measurement timepoint and is the dependent variable of this analysis (1 = in interaction; 0 = alone). The H_t variable entails the previous measure of happiness (reported on a 0 to 100 scale), of which the fixed effect γ_c^j , 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 datapoint on a given day (66% of the datapoints), the H_{day} variable is identical to the happiness of the timepoint to be predicted ($t+1$). On days where there are two observations (24% of the datapoints), H_{day} is computed based on the average of H_{t+1} and the other measure of that day. Also see the Supplementary Material Table 3 for a data excerpt and example calculation of H_{day} . The variables D, T, P_t^j control for the day of the week (Weekday, Saturday, Sunday), time of the day (in 2-hour bins starting at midnight), and whether the person was in a social interaction at the previous timepoint. The reference categories were specified as Saturday between 12.00-14.00h.

The model is specified with random intercepts u_{0i}^j and random slopes u_{ci}^j , accounting for individual differences in social interaction tendencies and individual differences in the effects

of previous happiness measures (H_t) on social interactions. All β s and γ s are subject to the estimation. The estimation was carried out with the *glmr* function of the *lme4* R-package (*lme4* version 1.1-19; Bates, Mächler, Bolker, & Walker, 2015; R version 3.5.2). The data preparation and model estimation are documented in the R-script available in the Supplementary Materials.

To better account for “low-frequency dynamics” of happiness that do not include future happiness values, I further included a $H_{pastWeek}$ variable and a $H_{pastDay}$ 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 hours (excluding the measurements H_t), respectively. The calculation of $H_{pastWeek}$ and $H_{pastDay}$ is documented in the R-script available in the Supplementary Material. It is important to note that the variables $H_{pastWeek}$ and $H_{pastDay}$ also suffer from few observations on which the average is calculated on, $M = 3.02$ ($SD = 3.56$) and $M = 0.86$ ($SD = 1.23$), respectively. Moreover, they are computed based on the openly available dataset, which was subdivided to only contain consecutive reports within a 12-hour time window. The non-subdivided data might provide a more reliable estimate of the past week’s and past day’s average happiness.

Overall, the focus of this analysis lies in 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 additional analyses conducted. The full model results are reported in the Supplementary Materials Table 1. The red squares in Figure 1 represent the predicted values and 95% Confidence Intervals of the odds ratios to subsequently interact at time $t+1$ depending on the level of happiness at time t , closely resembling the results reported by Quoidbach and colleagues (2019), $\log OR = -0.003$, 95% CI = $[-0.003, -0.002]$, $OR = 0.997$, $p < .001$. The green triangles in Figure 1 represent predicted odds ratios of a model where the H_{day} variable was removed from the model. When removing the H_{day} variable from the analyses, the said association changes direction, $\log OR = 0.006$, 95% CI = $[0.005, 0.006]$, $OR = 1.006$, $p < .001$. Also, the raw data (i.e., mean values; gray points in Figure 1), that are not based on predicted values of a statistical model, suggest a positive association between happiness and the odds ratio of being in a social interaction at the next timepoint.

Instead of controlling for an individual’s daily happiness average, in a further model I controlled for the individual’s average happiness over the past week $H_{pastWeek}$. The predicted odds ratios based on the model including $H_{pastWeek}$ are reported as dark blue asterisks in Figure 1, $\log OR = 0.004$, 95% CI = $[0.003, 0.005]$, $OR = 1.004$, $p < .001$. The predicted odds ratios of a model containing the $H_{pastDay}$ variable are represented as light blue squares in Figure 1, $\log OR = 0.003$, 95% CI = $[0.002, 0.004]$, $OR = 1.003$, $p < .001$. The models including $H_{pastWeek}$ or $H_{pastDay}$ suggest a positive association between happiness and subsequent social interactions. Further models using other alternative measures (e.g., passed happiness measures of the current day $H_{earlierInDay}$, person-mean centered happiness $H_{t_{pmc}}$) can be found in the Supplementary Materials Table 2 and the accompanying R-Script (osf.io/zk98q).

Figure 1. Raw values (i.e., mean values) and predicted values of the Odds Ratios (incl. 95% confidence interval) of being with other people at time $t + 1$ depending on previous happiness at time t . The raw data represents the mean (and 95% confidence interval) Odds Ratio of being in a social interaction per happiness level and is shown with gray circles. The predicted values including the daily average covariate H_{day} are shown in red squares and closely resemble the ones reported in Quoidbach and colleagues (2019). The green triangles show the predicted values without the daily average variable. Dark blue asterisks represent the predicted values from a model where the daily average was replaced by the average happiness of the past week $H_{pastWeek}$. Light blue squares show the predicted values controlling for the average happiness of the past 24 hours $H_{pastDay}$. Full model results are reported in the Supplementary Material Table 1.

So why does only the H_{day} model reveal a negative association between happiness and subsequent social interactions? One reason might be the overrepresentation of H_{t+1} in H_{day} , as a model with H_{t+1} instead of H_{day} suggests almost identical results (see Supplementary Materials Table 2). *Net of* the cross-sectional association that is positive (effect of H_{t+1} , log OR = 0.015, 95% CI = [0.014, 0.015], OR = 1.015, $p < .001$), the previous happiness at time t is 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_t cannot be interpreted independently of the H_{t+1} effect, as they are highly correlated ($r(220292) = .70$, $p < .001$) and part of the same model. Note that the H_{t+1} effect is about five times larger than the effect of H_t . Hence, H_t must be about five times larger than H_{t+1} for the total contribution of happiness for the interaction likelihood to be negative, which is rarely the case in the observed data (2.5% of cases).

The nature of the interplay between H_t and H_{t+1} can best be understood when looking at the change in happiness between t and $t+1$ (i.e., using $H\Delta = H_{t+1} - H_t$). A model with $H\Delta$ instead of H_{t+1} was estimated (see Supplementary Material Table 2). This model essentially contains identical information to the H_{t+1} model, but the interpretation 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 is likely driven by observations of individuals who were happy before (at t) and are not interacting at the subsequent timepoint ($t+1$) because they have become less happy by the subsequent

timepoint ($t+1$). The aspect of how future happiness (H_{t+1})— as part of H_{day} — plays a role in the proclaimed association is not discussed in the original article.

Discussion

The results reported in this commentary suggest that one of the main findings proclaimed by Quoidbach and colleagues (2019) is not robust. Quoidbach and colleagues (2019) reported a *negative* association between individual’s happiness (H_t) and the likelihood of future interactions (P_{t+1}). However, in my reanalysis I find that the raw data and statistical models, in which the control variable (H_{day}) is removed, suggest that the association between happiness and the likelihood of future interactions is *positive*. Also in models with alternative model specifications with a happiness average of the past week ($H_{pastWeek}$) or the past 24 hours ($H_{pastDay}$), the said association is estimated to be positive.

The proclaimed negative effect of happiness on subsequent social interactions seems to be biased by the presence of (unreported) H_{t+1} information in the model. The overrepresentation of H_{t+1} in H_{day} is neither discussed nor considered in the effect interpretation by Quoidbach et al. (2019). This reanalysis suggests that if individuals were happy before and they are not interacting at the subsequent timepoint (the proclaimed negative effect of H_t), it is likely that they became unhappy between the two measurement timepoints. While dynamic investigations of happiness and social interactions are novel, the finding that less happy individuals are less likely to socially interact has been demonstrated numerously (e.g., Elmer & Stadtfeld, 2020; Pavot, Diener, & Fujita, 1990; Sandstrom & Dunn, 2014). This reanalysis is in line with this literature.

A limitation of this reanalysis is that the alternative covariates ($H_{pastWeek}$ and $H_{pastDay}$) were not computed on the complete dataset, i.e., before the data was reduced to only subsequent

reports within 12 hours. The calculation of the alternative covariates was based on the reduced data made available online (osf.io/bxgn4).

The findings regarding the probability of interacting with certain interaction partners (e.g., best friend) when being unhappy before (reported in Figure 3a of Quoidbach et al., 2019) are also affected by the H_{day} variable. See the Supplementary Materials for additional analyses on these findings.

It is important to note that this commentary does not aim at undermining the work of Quoidbach and colleagues (2019). The importance and novelty of their research is without question. Nevertheless, the findings related to the prediction of social behavior (Figure 2 and 3a of the original article) are not robust. Fortunately, Quoidbach and colleagues (2019) followed an open science practice and published their data online, which made this reanalysis possible. Beyond further encouraging open science practices, I suggest that reports of raw data and stepwise model results should be more frequently reported in psychological sciences.

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