** All data and materials reported for this manuscript are publicly available online and can be accessed at https://osf.io/hg9f2/

Supplementary Materials for

Why Being Social and Active Boosts Wellbeing: A Mediating Role of Positive Emotions

Power Analysis

To decide whether our sample size would be well-powered to detect our findings, we followed the recommendations of using the *simr* package (Green & MacLeod, 2016) in Arend & Schäfer (2019). To account for the maximum complexity of our multilevel models, we ran the power analyses on our most elaborate model. This model will include three level 1 predictors (person-mean centered technology-mediated interaction, face-to-face interaction, and positive emotion intensity) and three level 2 predictors (participants' mean levels of technology-mediated interaction, face-to-face interaction, and positive emotion intensity). As model complexity decreases power, our more parsimonious models including fewer predictors will likely be better powered. Following Arend & Schäfer (2019), we can estimate the required sample size to detect effects with the following parameters: fixed effects (i.e., a standardized indicator for the strength of the association between a predictor variable and an outcome variable), the intraclass correlation coefficient (ICC) of the outcome variable, correlation coefficient between the random intercept and random slope, level of significance, and target level of power. Importantly, as these power analyses are used to test if our sample size would be well-powered to detect the effects we sought to investigate, the required input for these power analyses is based on previous literature, not on the current study's data.

First, Arend & Schäfer (2019) recommend assuming small-to-medium fixed effects in case a suited informant from previous literature is lacking. In correspondence with conventional effect sizes (based on Cohen, 1988), we set the standardized effect sizes for fixed effects to .2. We also tried a more conservative approach by setting it to .1, thereby assuming small effects. This did not affect the conclusions, hence below we merely report the results of the power analysis assuming small-to-medium effects. Then, Arend & Schäfer (2019) performed a literature review and report that within samples with repeated measurements at level 1 a mean ICC of .42 was found. In a previous diary study in which the same outcome variable was used as in the current study (Sun et al., 2022), the wellbeing outcome variable had an ICC of .83. Therefore, we decided to set the ICC parameter value to a slightly higher value of .5. Thirdly, we set the correlation between the random intercept and random slope to 0, following Arend & Schäfer's recommendation (2019) to generate a more conservative estimate of power. Lastly, level of significance was set to .05, and target level of power to .8.

We ran the power analysis of two-level models with the before-mentioned parameters. The power analysis suggested that our study would be well-powered to detect within-person effects (1.00, 95% CI [0.996, 1.00]) and underpowered to detect between-person effects (0.49,

95% CI [0.46, 0.52]). This suggests that our selected sample size was appropriate for testing the key predictions which concern within-person mediation effects. The code for power analysis can be found at
https://osf.io/hg9f2/?view_only=afced5f164a6434eb93b6abb165b9aff

Assessment of Engagement in Activities

To assess what type of activity participants were engaged in, they were asked select one or multiple activities from this list (A denotes active activities and P denotes passive activities): waiting (P), praying (A), eating (A), hobbies/leisure time activities (A), household chores (e.g., washing, cleaning) (A), intimate relations (A), watching children (A), cooking (A), being on the way (e.g., in the train, bus, tram, metro, car, by foot in the city) (A), communicating online (e-mail, social networking like Twitter, Facebook, Instagram, texting, WhatsApp) (A), relaxing and doing nothing (P), personal hygiene (A), socializing with people (A), exercising (A), watching TV/ Netflix / Youtube, etc. (P), resting (P), volunteering/ helping people/ donating, etc. (A), working/ studying (A), shopping (online or offline) (A), video call/ phone call (A). The activities were presented in random order and participants were unaware of any distinction being made between passive and active activities.

Assessment of Wellbeing

We assessed participants' wellbeing using ten items. Subjective Health was measured from 0 (Strongly disagree) to 100 (Strongly agree) using four questions: "I feel physically healthy", "I feel mentally healthy", "I feel stressed", and "I'm tired". Eudaimonic wellbeing was adapted from Rosenberg Self-Esteem Scale (Rosenberg, 2015) and Questionnaire for Eudaimonic wellbeing , with two questions measured from 1 (Totally disagree) to 7 (Totally agree): "At this moment, I feel good about myself" and "At this moment, I have the feeling that I lead a purposeful and meaningful life". Resilience questions were adapted from the Ego resilience and Resiliency Scale (Hou & Ng, 2014) and consisted of three items: "I would describe myself as a pretty strong person", "I have a high capacity to overcome setbacks", and "I feel that in very difficult situations I am able to respond in positive ways", which participants answered on a scale from 1 (Totally disagree) to 7 (Totally agree). One item, taken from Lucas & Donnellan (2012), measured life satisfaction: "All in all, how satisfied are you with your life?" with responses ranging from 0 (Completely dissatisfied) to 10 (Completely satisfied).

From the items above, we then created a composite wellbeing score by averaging the items (after reverse coding as needed). To assess the coherence of the ten wellbeing items, we used data from days 2, 5, 8, 11, and 14 to calculate Cronbach's alpha. To additionally check for stability of the wellbeing outcome over different timepoints during the day, we selectively included the data of timepoint 1 for day 2, timepoint 2 for day 5, timepoint 3 for day 8, timepoint 4 for day 11, and timepoint 5 for day 14. The results (α = 0.84; 0.87; 0.86; 0.87; 0.88) demonstrate excellent internal consistency, justifying the use of a composite wellbeing score in the subsequent analyses.

Assessment of SES

The subjective socioeconomic status is measured by the MacArthur Scale of Subjective Social Status ladder question (Adler et al., 1994). In this measure, participants rate their overall standing relative to others in their self-defined community on a scale of 1-10.

Mediation Analyses: A Step-by-Step Approach

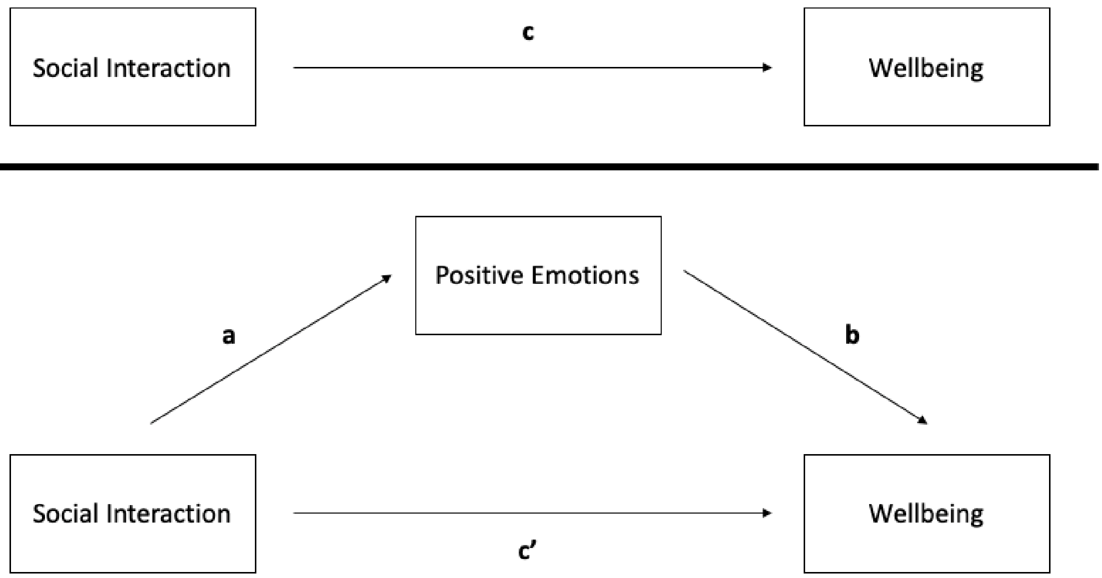
To investigate if the effect of social interaction (H1) and active activities (H2) on wellbeing is mediated by momentary positive emotional experiences, we analyzed whether wellbeing would be predicted by social interaction and active activities, whether momentary positive emotional experiences would be predicted by social interaction and active activity, and whether wellbeing would be predicted by momentary positive emotional experiences. We also tested whether the relationships between wellbeing and social interaction and active activity would be nullified when controlling for momentary positive emotional experiences.

In accordance with (Baron & Kenny, 1986; Judd & Kenny, 1981), we undertook 4 steps to establish mediation. First, we examined the effects of the predictors (X; social interaction (H1) and Active activity (H2)) on the outcome variable (Y; wellbeing) [1], referred to as the c-path, see Figure 1. Then, we tested the effects between the predictor and the mediator (M; Momentary Positive Emotion Experience), which relates to the a-paths in Figure 1. For the third and fourth steps, we regressed wellbeing on the predictor and the mediator, which provides the b- and c'-path (see Figure 1). If c' is reduced to 0, this means the effect of the predictor (Social Interaction (H1) and Active activity (H2)) on wellbeing is completely mediated by positive emotions. If c' is reduced but not to zero, this indicates a partial mediation effect.

[1] All analyses for H1 and H2 were performed separately.

Figure 1

Visual Representation of the Mediation Model for H1



Note. In mediation models, the a-path stands for the effect of the predictor (X) on the mediator (M), the b-path for the effect of the mediator (M) on the outcome variable (Y), the c-path for the effect of the predictor (X) on the outcome variable (Y), and the c'-path for the effect of the predictor (X) on the outcome variable (Y) after controlling for the effect of M on Y.

Statistical Procedure and Used Packages

The statistical analyses were conducted with R (R Core Team, 2020) and Mplus Version 8 (Muthén et al., 2017). In R, we conducted multilevel regressions using Maximum Likelihood (ML) estimation with the *nlme* package (Pinheiro et al., 2022). To compare different predictors, we used Wald tests using the *multcomp* package (Hothorn et al., 2008). We used likelihood ratio tests to compare different models (Hoffman, 2015) and R^2_{GLMM} (Nakagawa et al., 2017; Nakagawa & Schielzeth, 2013) from the *MuMIn* package (Barton, 2020) to calculate the variance explained, which provides two values: the variance explained by fixed effects alone (marginal R^2 or $R^2_{\text{GLMM(M)}}$) and the variance explained by fixed and random effects overall (conditional R^2 or $R^2_{\text{GLMM(C)}}$). We used Mplus for the multilevel mediation analysis when estimating the whole model.

Linear Trends of Wellbeing Over Time and Alternative Error Covariance Structures

First, we tested which unconditional model (i.e., model without predictors) would best reflect the observed (co-)variation patterns over time in order to appropriately test the effects of the predictors on the outcome (Hoffman, 2015). To establish whether we needed to include time as a predictor in the models, we investigated overall linear trends of wellbeing over the 75 observations of the entire data collection period. We first fit random-intercept models with time as a fixed factor to test if time affects wellbeing (in general across all participants), while accounting for baseline differences in participants' wellbeing. We opted to include observation to control for time for all subsequent models as it is more specific than merely including day (comparison of models including day vs observation yielded no statistical difference). As can be seen in Table 1, wellbeing showed a slight positive linear trend over time; adding the fixed effect of time improved model fit significantly compared to a random-intercept-only model, $-2\Delta LL(1) = 24.07$, $p < .0001$. This indicates that we need to take observation into account to control for the effect of time. To investigate if the effect of time on wellbeing varied between participants, we then added observation as a random slope to the model. Compared to the model with observation as a fixed factor only, adding random slopes for observation improved the model's fit significantly, $-2\Delta LL(\sim 2) = 264.25$, $p < .0001$. This shows that there were individual differences in how participants' wellbeing fluctuated over the course of the data collection period.

We visually inspected the autocorrelation function (ACF) of within-person residuals of the model including a fixed effect of observation, a random intercept, and random slopes for observation. The ACF plot showed that the wellbeing outcome still had remaining autocorrelation, indicating that the wellbeing outcome scores were not independent, which aligned with our expectation that wellbeing scores that were measured closer in time (e.g., day 1, timepoint 1 and 2), correlate more strongly than wellbeing scores measured further apart (e.g., day 1, timepoint 1 and day 15, timepoint 5). Therefore, we needed to evaluate alternative covariance structures to establish which past wellbeing outcome scores to control for.

Based on the ACF plot, we fit a model with an autoregressive (AR) structure of the first order. Models with an autoregressive structure of the p^{th} order, AR(p), predict wellbeing while taking the wellbeing value of the p past observations into account. An AR(1) structure fit significantly better than the random linear time model without autocorrelation specified, $-2\Delta LL(\sim 1) = 610.65$, $p < .0001$. This implies that the wellbeing value of the previous observation needs to be considered when predicting wellbeing. Subsequently, we again inspected the ACF of the normalized residuals of this AR(1) model to see if there was any remaining autocorrelation that needed to be addressed (Pinheiro & Bates, 2000). There was still some remaining autocorrelation, so we fit a model with an AR(2) structure. The AR(2) model fit significantly better than the AR(1) model, $-2\Delta LL(\sim 1) = 45.33$, $p < .0001$, which indicates that we needed to take the wellbeing value of the past two observations into account when predicting wellbeing. However, the ACF plot of the normalized residuals still indicated significant autocorrelation, leading us to try an ARMA structure instead. Moving-average models of the p^{th} and q^{th} other, ARMA(p, q), take the error term of the q previous observations into account when predicting wellbeing, and thereby, control for autocorrelation in wellbeing (Field et al., 2012).

An ARMA(1,1) model had a significantly better fit than the AR(1) model, $-2\Delta LL(\sim 1) = 83.38$, $p < .0001$, but there was no statistical difference between the ARMA(1,1) model and the AR(2) model. The ACF plot of the normalized residuals still indicated significant autocorrelation, so we tried an ARMA(2,1) structure, which significantly fit better than both the ARMA(1,1) model, $-2\Delta LL(\sim 1) = 36.45$, $p < .0001$, and the AR(2) model, $-2\Delta LL(\sim 1) = 74.50$, $p < .0001$. This indicates that participants' wellbeing of a specific timepoint is affected by their wellbeing of the previous two timepoints. Moreover, this shows that the error terms of a wellbeing value at a specific timepoint are not independent from the error terms of their wellbeing of the previous timepoint. Thus, we needed to take the wellbeing values of the past two timepoints and the error term of the previous observation into account when predicting wellbeing. To see if we could further improve the model, we tried ARMA(2,2) and ARMA(3,1) models, but neither provided a better fit. Additionally, the ARMA(2,1) model's ACF plot of the normalized residuals indicated that the autocorrelation was sufficiently addressed. Thus, we maintained a second-order autoregressive first-order moving-average structure, ARMA(2,1), for all subsequent analyses, meaning that we take the previous two measurement's wellbeing value and the previous measurement's error term into account. The corresponding parameter estimates for the autocorrelation of wellbeing values were significantly different from zero, $\varphi_1 = 1.12$, 95% CI [1.10, 1.10] for the previous wellbeing value, $\varphi_2 = -0.19$, 95% CI [-0.24, -0.13] for the wellbeing value two timepoints before the current timepoint, and $\theta_1 = -0.77$, 95% CI [-0.83, -0.69] for the error terms of the previous wellbeing value.

Table 1

Unconditional Models of Wellbeing

Model	Linear fixed effect of time	Linear random effect of time	AR(1)	AR(2)	ARMA(1,1)	ARMA(2,1)
Intercept	4.422*** (0.059)	4.422*** (0.060)	4.410*** (0.060)	4.408*** (0.060)	4.404*** (0.060)	4.396*** (0.059)
Observation	0.001*** (0.0003)	0.001* (0.001)	0.001* (0.001)	0.001** (0.001)	0.001** (0.001)	0.002** (0.001)
Observations	5,961	5,961	5,961	5,961	5,961	5,961
Log Likelihood	-3,686.20	-3,554.07	- 3,248.75	- 3,226.08	-3,207.06	-3,188.83
AIC	7,380.40	7,120.14	6,511.50	6,468.16	6,430.12	6,395.67
BIC	7,407.17	7,160.30	6,558.35	6,521.71	6,483.66	6,455.90

Note. * p < .05; ** p < .01; *** p < .001; AIC/BIC = Akaike/Bayesian Information Criterion.

Linear Trends of Positive Emotions Over Time and Alternative Error Covariance Structures

As we later included positive emotions as a mediator in models, we also needed to establish which model best reflected the observed (co-)variation patterns over time of positive emotions and specify an appropriate error covariance structure to take the autocorrelation of the momentary positive emotional experiences variable into account. Again, we first fit random intercept models with observation as a fixed factor, which test if time related to positive emotions (in general across all participants), while accounting for baseline differences in participants' positive emotions by allowing intercepts to vary between participants. As can be seen in Table 2, the positive emotions variable showed a slight negative linear trend over time, indicating that the intensity of momentary positive emotions reported by participants decreased over the course of the data collection period. Adding the fixed effect of observation improved model fit significantly compared to a random-intercept-only model, $-2\Delta LL(1) = 5.47$, $p = .019$. Then, we investigated if the effect of time on positive emotions varied between participants by adding observation as a random factor to the model. Adding random slopes for observation improved the model's fit significantly compared to the model with observation as a fixed factor only, $-2\Delta LL(\sim 2) = 288.71$, $p < .0001$. This shows that there were considerable differences between participants in how the intensity of their momentary emotional experiences fluctuated over the course of the data collection period. However, the ACF plot of the residuals indicated remaining autocorrelation, indicating that observations closer in time correlated more strongly than observations further apart. Consequently, we then fit a model with an AR(1) structure, taking the positive emotions variable's value of the previous observation into account. The AR(1) model fit significantly better than the random intercept, random slopes model of time with no autocorrelation specified, $-2\Delta LL(\sim 1) = 82.90$, $p < .0001$. However, the ACF plots still showed some remaining autocorrelation, so we fit a model with an AR(2) structure, which fit significantly better than the model with an AR(1) structure, $-2\Delta LL(\sim 1) = 7.30$, $p = .007$. This indicates that taking the past two observations' values of the positive emotions variable into account fits the data better than only taking the positive emotions variable's value of the previous observation into account. However, the ACF plot of the normalized residuals still indicated significant autocorrelation. Hence, we fit a model with an ARMA(1,1) structure, which not only takes the previous positive emotions variable's value into account but also the error terms of the previous value of the positive emotions variable. The ARMA(1,1) model fit significantly better than the AR(1) model, $-2\Delta LL(\sim 1) = 53.17$, $p < .0001$, but did not differ from the AR(2) model. Again, the ACF plot of the normalized residuals indicated that the autocorrelation was not sufficiently addressed, so we fit a model with an ARMA(2,1) structure. The ARMA(2,1) model provided a significantly better fit than the ARMA(1,1) model, $-2\Delta LL(\sim 1) = 7.74$, $p = .005$. The ARMA(2,1) model also outperformed the AR(2) model, $-2\Delta LL(\sim 1) = 53.61$, $p < .0001$. We then tried to improve the model by testing an ARMA(3,1) and an ARMA(2,2) structure. The ARMA(3,1) model fit significantly better than the ARMA(2,1) model, $-2\Delta LL(\sim 1) = 4.10$, $p = .043$. The ARMA(2,2) model also provided a better fit than the ARMA(2,1) model, $-2\Delta LL(\sim 1) = 5.50$, $p = .019$. The ARMA(3,1) model and the ARMA(2,2) did not statistically differ, but ARMA(2,2) showed slightly better AIC and BIC values. Therefore, we concluded that a second-order autoregressive second-order moving-average structure, ARMA(2,2), provided the best fit for subsequent analyses with positive emotions as the outcome variable. This analysis thus takes the previous two measurement's value of the positive emotions variable and error terms into account. The corresponding parameter estimates for the autocorrelation within the positive emotions variable measures were significantly different from zero, $\varphi_1 = 0.31$, 95% CI [0.14, 0.19] for the previous value of the positive emotions variable, $\varphi_2 = 0.56$, 95% CI [0.20, 0.79] for the positive emotions variable's value two timepoints before the current timepoint, θ_1 = -0.16, 95% CI [-0.19, 0.20] for the error terms of the previous value of the positive emotions variable, and θ_2 = -0.54, 95% CI [-0.75, -0.25] for the error terms of the positive emotions variable value two timepoints before the current timepoint.

Table 2

Unconditional Models of Positive Emotions

Model	Linear fixed effect of time	Linear random effect of time	AR(1)	AR(2)	ARMA(1,1)	ARMA(2,1)	ARMA(3,1)	ARMA(2,2)
Intercept	68.312***	68.406***	68.372***	68.369***	68.344***	68.326***	68.337***	68.333***
	(1.312)	(1.314)	(1.313)	(1.313)	(1.306)	(1.305)	(1.306)	(1.305)
Observation	-0.015*	-0.019	-0.018	-0.018	-0.016	-0.015	-0.016	-0.016
		(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)	(0.015)
Observations	5,992	5,992	5,992	5,992	5,992	5,992	5,992	5,992
Log Likelihood	-23,155.46	-23,011.10	-22,969.65	-22,966.00	-22,943.07	-22,939.20	-22,937.15	-22,936.45
AIC	46,318.92	46,034.21	45,953.30	45,948.01	45,902.14	45,896.40	45,894.29	45,892.90
BIC	46,345.71	46,074.40	46,000.19	46,001.59	45,955.72	45,956.68	45,961.28	45,959.88

Note. * $p < .05$; ** $p < .01$; *** $p < .001$; AIC/BIC = Akaike/Bayesian Information Criterion.

Lagged Effects

For exploratory purposes, we analyzed if there were any lagged effects of face-to-face interactions, technology-mediated interactions, or active activities on wellbeing. This tests if, for example, face-to-face interactions increase not only concurrent wellbeing, but also subsequent wellbeing. We first created variables of the previous two timepoints' face-to-face interaction, technology-mediated interaction, and active activities and added these variables to the existing models as predictors, and the current timepoint's wellbeing as the outcome variable. We also added a variable of the previous timepoints' positive emotions variable to the model as a predictor.

In the social interactions model, on top of concurrent social interactions, there were no significant effects of the previous time point's face-to-face interactions or technology-mediated interactions on subsequent wellbeing. The previous time point's positive emotion intensity did significantly predict subsequent wellbeing, b =.001, $t(5840) = 2.37$, $p = .018$. We also tested if positive emotions would carry over two time points, but found no such effect. In the active activities model, active activities of previous time points did not predict wellbeing; only positive emotions of the previous time point – on top of concurrent positive emotions – had a significant positive effect on wellbeing, $b = 0.002$, $t(5266) = 2.87$, $p = .004$. We then tested if positive emotions of two time points earlier predicted current wellbeing, and found no significant effect. These findings suggest that there is no direct effect of social interactions or active activities on wellbeing outside of the current moment, but the effect of positive emotions on wellbeing lasts longer and benefits wellbeing up until a few hours after.

Long-term Effects

Six months after the 15-day ESM period, participants were asked to fill in one more questionnaire. This post-ESM questionnaire assessed life satisfaction using 5 items (Diener et al., 1985) and wellbeing using 6 items (Riverside Wellbeing, Margolis et al., 2022). We used this post-ESM questionnaire to exploratory probe the long-term effects of social interactions and active activities on wellbeing. We calculated the percentage of participants' reported observations participants that involved face-to-face interactions, technology-mediated interactions, or active activities. We also calculated the average intensity of the most intensely experienced positive emotions during the 15-day ESM-period. We then analyzed if the number of face-to-face interactions, technology-mediated interactions, active activities, or positive emotions during the ESM period predicted life satisfaction or Riverside wellbeing 6 months after the ESM period.

The number of face-to-face interactions a person had during the ESM-period significantly predicted post-ESM life satisfaction ($b = 1.17$, $t(105) = 2.13$, $p = .035$), which turned non-significant when we added the average positive emotion intensity as a predictor. The number of face-to-face interactions a person had during the ESM-period also significantly predicted post-ESM wellbeing ($b = 1.56$, $t(105) = 2.71$, $p = .008$), which was still significant after we added the average positive emotion intensity as a predictor. When we then controlled for pre-ESM levels of life satisfaction and wellbeing, this effect also turned non-significant.

The number of technology-mediated interactions, active activities, and average positive emotion intensity during the ESM-period did not have any significant effects on post-ESM life satisfaction or post-ESM wellbeing.

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