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Social Psychology

Connected Despite Lockdown: The Role of Social Interactions and Social Media Use in Wellbeing

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Humans are social beings, but during the COVID-19 pandemic, people around the world were periodically in lockdown and were required to try to physically distance themselves from others. The resultant limitation of face-to-face interactions presented a challenge to wellbeing. During periods of lockdown, people could, however, still connect to others via technology, but it is unknown whether such interactions offer benefits comparable to face-to-face interactions. In the present study, we examined how different ways of interacting with others impacted wellbeing during a period of lockdown in the United Kingdom. In a 30-day diary study conducted in April-June 2020, 110 adults reported the time they spent daily on face-to-face interactions and technology-mediated communication (video, phone, text) with different interaction partners. They also indicated the time they spent on active and passive social media use and their end-of-day wellbeing. Multilevel regressions indicated that more face-to-face interactions both within and outside of one's household positively predicted wellbeing, while technology-mediated communication had less consistent positive effects. Additionally, more active and less passive social media use predicted better wellbeing. These results highlight the complexity of benefits of different kinds of social interactions during lockdowns in the COVID-19 pandemic and point to the importance of taking into account communication channels, interaction partners, and how people use social media when studying the effects of connecting to others.

Introduction

Humans are a profoundly social species, yet in response to the COVID-19 pandemic, governments around the world have required citizens to behave in ways that go against their inherent social inclinations: People were asked to stay at home as much as possible and to physically distance themselves from others when going out (known as lockdown). Distancing measures are crucial to slow the spread of COVID-19 (Tian et al., 2020), but their implementation gave rise to concerns about wellbeing because social isolation and feelings of loneliness impact wellbeing negatively (Brooks et al., 2020; Holt-Lunstad et al., 2015). In response to these challenges, the World Health Organisation recommended that people use technology-mediated communication (video calls, phone calls, text-based) and social media in order to stay socially connected (World Health Organization, 2020a). The present study tests these recommendations empirically and longitudinally. Utilising a 30-day daily diary study, we directly tested to what extent interactions, including via technology, relate to wellbeing during a period of lockdown.

Face-to-Face Interactions

For most of human history, essentially all interactions happened face-to-face. However, physical interactions have been limited during the COVID-19 pandemic, and especially in periods of lockdown (please see Supplementary Materials "Information on the Physical Distancing Measures in the United Kingdom" for details on lockdown rules during the present study data collection period). Previous research has consistently found positive associations between the quantity of face-to-face interactions and wellbeing. For example, having more face-to-face interactions is associated with greater life satisfaction (Mehl et al., 2010; Milek et al., 2018), self-reported health (Fiorillo & Sabatini, 2011), happiness (Diener & Seligman, 2002), improved mood (Watanabe et al., 2016), and positive affect (Watson et al., 1988, 1992).

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Pre-pandemic research suggests that under normal circumstances, both interacting with close others (such as family) and less-close others (such as acquaintances) can promote wellbeing (Sandstrom & Dunn, 2014). However, it is unclear whether in-person interactions still consistently predict wellbeing during periods of lockdown, given that both the frequency and characteristics of face-to-face interactions have changed. While interactions within one's household (usually close others) are generally unconstrained, face-to-face interactions outside of one's household are limited dramatically. Interactions outside of one's household can involve contact with both close and less close others, but during periods of lockdown, interactions can only take place under physical distancing conditions and increase one's risk of infection. In the current work, we test the relationship between face-to-face interactions and wellbeing during a period of lockdown. We differentiated between face-to-face interaction within and outside one's household in order to directly compare their effects. Drawing on past literature, we predicted that face-to-face interactions both within and outside of one's household would be positively associated with wellbeing (H1).

Technology-Mediated Communication

In recent decades, social life includes technology-mediated communication, which allows people to maintain and expand their social networks despite physical distance (Lieberman & Schroeder, 2020). Pre-pandemic research suggests that communication via video, phone, and text is associated with better wellbeing, including reduced risk of loneliness (Teo et al., 2019), increased subjective wellbeing (Ahn & Shin, 2013), and reduced negative mood (Sacco & Ismail, 2014). Given the advantages of connecting to others online, the WHO suggested at the outbreak of the COVID-19 pandemic that people should use technology-mediated communication to connect to others (World Health Organization, 2020b). But how helpful is technology-mediated communication, especially compared to face-to-face interactions? In normal circumstances, technology-mediated communication has been found to be less effective in eliciting feelings of connectedness and less beneficial in terms of wellbeing than face-to-face interactions (Holtzman et al., 2017; Sacco & Ismail, 2014; Sherman et al., 2013; Wohn et al., 2017). However, it is unclear how beneficial technology-mediated communication is for wellbeing during periods of lockdown when face-to-face interactions are limited.

Here, we tested the relationship between technology-mediated communication and wellbeing during a period of lockdown and compared it directly to the benefits of face-to-face interactions. We compared the effects of video calls, phone calls, and text-based communication in order to capture potential differential effects across different channels of communication. Based on pre-pandemic findings, we predicted that more technology-mediated communication (video, phone, text) would be associated with improved wellbeing, but less so than face-to-face interactions (H2).

Social Media Use

Besides video, phone calls, and texting, many social interactions take place on social media (e.g., Facebook, Twitter). On these platforms, users can post their own content, engage with others, and browse content (Escobar-Viera et al., 2018). While some studies have suggested a positive link between social media use and wellbeing, others have found social media use to be associated with poorer wellbeing (Kross et al., 2013; Valenzuela et al., 2009), including during the COVID-19 pandemic (Lades et al., 2020; Lisitsa et al., 2020). However, these studies have not distinguished between different ways of using social media. Recent theorising suggests that previous contradictory findings may be reconciled by differentiating between active and passive social media use (Verduyn et al., 2017). Active social media use involves sharing content with which others can engage, as well as interacting with others and their content (e.g., posting, commenting). In contrast, passive social media use refers to consuming content without engaging with it, such as passive browsing (Escobar-Viera et al., 2018). Thus, while active social media use constitutes a form of social interaction, passive social media excludes interactions and may even hamper wellbeing (Krasnova et al., 2013; Verduyn et al., 2015). Given the empirical support for differential wellbeing effects of active versus passive social media use (Burke et al., 2010; Deters & Mehl, 2013; Escobar-Viera et al., 2018; Kim et al., 2014; Tandoc et al., 2015), we therefore predicted that more active social media use would be associated with enhanced wellbeing, while more passive social media would be linked to worse wellbeing (H3).

It is worth noting that, while measuring social media use time via self-report method is common, a recent meta-analysis suggested that people tend to overestimate social media use (Parry et al., 2021). Furthermore, Sewall and colleagues found that correlations between estimated social media use and wellbeing were consistently stronger than the correlations between actual use and wellbeing variables (Sewall et al., 2020). Therefore, in the present study, we heed calls to Sewall et al (2020) and consider retrospective estimates as perceived, rather than actual, social media use.

Quantity versus Quality of Interactions

Past work has consistently found that the *quantity* of social interactions one has is associated with greater wellbeing. This has been shown by research using a wide range of methods, including retrospective and momentary self-reports (Kushlev et al., 2018; Lucas et al., 2008; Rohrer et al., 2018; Srivastava et al., 2008), as well as mechanical clickers for counting social interactions as they occur (Sandstrom & Dunn, 2014), and observer ratings based on unobtrusive audio recordings of everyday behaviour (Mehl et al., 2010; Milek et al., 2018). Less is known about how much the *quality* of social interactions—including what happens during a social interaction and who one is interacting with—matters for wellbeing. One recent study using the Electronically Activated Recorder (EAR) in combination with experience sampling examined the role of conversational depth, amount of self-disclosure, and relational factors including knowing and liking one's interaction partners in relation to wellbeing. They found that both conversational and relational aspects of social interaction quality were associated with wellbeing, but the effects were larger and more consistent for self-reported versus observer-reported quality variables, within-person versus between-person associations, and for predicting social connectedness versus happiness (J. Sun et al., 2019). In the present study, we focus on comparing different channels of communication on wellbeing, limiting our research questions to the quantity (time) of different types of interactions on wellbeing; our data are openly shared in the hope that they may provide a useful resource for researchers interested in related research questions, including the role of interaction partners.

The Present Study

Here, we sought to empirically compare the wellbeing benefits of staying connected in different ways in a period of lockdown during the COVID-19 pandemic. We examined this research question longitudinally with a 30-day daily diary approach. Specifically, we investigated to which extent different ways of interacting with others (face-to-face interactions, technology-mediated communication, and social media use) would relate to enhanced end-of-day wellbeing during a period of strict lockdown measures in the United Kingdom (UK). In follow-up analyses, we explored whether interacting with different categories of interaction partners (e.g., friends, colleagues) would affect wellbeing differentially for different interaction channels. We want to note that our hypotheses and analyses were not pre-registered.

Using a longitudinal, rather than cross-sectional, approach to study this research question has two important benefits. Firstly, the diary method provides granular, rich data of participants' daily lives (Fu, 2007) while reducing recall biases that are prevalent in cross-sectional studies (Reis et al., 2014). Secondly, daily diary data provide information about between-person effects on wellbeing (as is also possible with cross-sectional approaches), but also within individuals. Thus, the diary approach allowed us to investigate whether people who report having more interactions on average also tend to report higher wellbeing on average, that is, between-person effect. Additionally, it enabled us to examine whether participants reported higher wellbeing on days on which they spent more time interacting with others through certain channels of communication, that is, within-person effect (Ohly et al., 2010).

Methods

Participants and Procedure

Participants were recruited via personal networks and targeted group adverts on Facebook. In diary studies, at least 100 participants are recommended for predictors at the person level (Maas & Hox, 2005; Ohly et al., 2010). We therefore recruited 140 participants to take into account potential dropouts. The final sample consisted of 110 participants (55 women, 53 men, 2 other) between 18 and 71 years old (M = 37.98, SD = 12.83). All participants resided in the United Kingdom during the study period. Detailed information about the sample and data exclusion procedures can be found in the Supplementary Materials "Detailed Information on Participants, Data Exclusion and Reimbursement" section.

The study was approved by the University of Amsterdam Department of Psychology Ethics Committee. Participation was voluntary and all participants provided digital informed consent. Before the diary period, participants answered demographic questions and reported their wellbeing during the past week.[1] For the subsequent 30 days, participants answered a brief (~10 minutes) daily online diary questionnaire each evening shortly before going to bed. Participants reported with whom they had interacted and through which channels of communication, as well as their social media use, and their end-of-day wellbeing. After the 30-day diary period, participants answered a post-diary questionnaire containing the same extended wellbeing-related measures as the pre-diary questionnaire. Data collection took place between 10 April 2020 and 9 June 2020; the UK government enforced a strict lockdown throughout this period (see Supplementary Materials "Information on the Physical Distancing Measures in the United Kingdom" section for details). Participants completed between 19 and 30 daily diaries (M = 27.92, SD = 3.25) and received proportionate monetary reimbursement (see Supplementary Materials "Detailed Information on Participants, Data Exclusion and Reimbursement" section for details).

Materials

Pre-/Post-Diary Questionnaire

Demographics. Participants reported their gender, age, ethnicity, education level, employment status, relationship status, who they lived with, and where in the UK they lived.

Wellbeing. To establish a baseline of participants' wellbeing, participants answered validated wellbeing measures in the pre- and post-diary questionnaires, including symptoms of depression (PHQ-9; Kroenke et al., 2001), anxiety (GAD-7; Spitzer et al., 2006), and stress (PSS-4; Cohen et al., 1983) in the past week, as well as their global life satisfaction (SWLS; Diener et al., 1985).

Daily Questionnaire

Social Interactions. We asked participants to estimate the time they had spent on various forms of social interactions (face-to-face within their household and outside their household, video calls [e.g., FaceTime, Skype, Zoom], phone calls, and digital written communication [e.g., emails, text messages]) that day in 15-minute increments from 0 to 5+

1 We only report here the measures of interest for the hypotheses addressed in the present study; the full set of measures is available on OSF: https://osf.io/zfe6x/

hours. For each mode of interaction, participants reported how long they had spent interacting with different categories of interaction partners (e.g., family, friends, colleagues). We used the overall amount of time that participants indicated per channel of interaction (summed across all types of interaction partners) as predictors for subsequent analyses investigating the effects of mode of communication (Hypotheses 1-3). We additionally examined the effects of different interaction partners in exploratory follow-up analyses.

Social Media Use. We also asked participants to estimate the time they had spent using social media *actively* (e.g., liking, up-/downvoting, sharing, commenting, posting) and using social media *passively* (e.g., scrolling/browsing social media feeds/pages, reading/watching content) in half-hour increments from 0 to 10+ hours (adapted from past research, Escobar-Viera et al., 2018; Smeets et al., 2019).

Daily Wellbeing. We measured several different facets of wellbeing by adapting or shortening existing questionnaires to minimise participant burden in the daily questionnaires, adapted from past research (Block & Kremen, 1996; Cheung & Lucas, 2014; Kass et al., 1991; Ryff, 1989), see Supplementary Materials "Daily Wellbeing Items" section for details. We measured eudemonic wellbeing (i.e., flourishing) and resilience with two items each, and life satisfaction, physical health, mental health, stress, depression, and tiredness with one item each. We used the mean-score of these items as the wellbeing outcome for all analyses (see Supplementary Materials "Daily Wellbeing Items" section for details).

Statistical Analyses

All analyses were performed in the statistical environment *R* (R Core Team, 2020). We conducted multilevel regressions using Maximum Likelihood (ML) estimation with the *nlme* package (Pinheiro et al., 2021). Repeated daily measures at level 1 (N_1 = 3071 measurement occasions) were nested within persons at level 2 (N_2 = 110 participants).

We first established whether a multilevel approach was justified based on the wellbeing outcome's intraclass correlation (ICC) calculated from the random intercept-only models. The ICC was 0.83 (see Table 1), and thus significantly different from zero, −2ΔLL(1) = 4861.81, p < .001.[2] This indicated that 17% of the outcome's variance could be explained by within-person longitudinal variations, indicating that it was necessary to take the nested data structure into account (Hoffman, 2015). Therefore, we concluded that a multilevel approach was justified and continued with random-intercept models. Allowing intercepts to vary between participants accounts for baseline differences in participants' wellbeing. Next, to ensure appropriate tests of fixed effects, we checked for temporal dependency in wellbeing by including the day of data collection as a predictor, and next specified an appropriate error covariance structure to take wellbeing's autocorrelation into account (Hoffman, 2015), see Supplementary Materials "Linear Trends of Wellbeing Over Time and Alternative Error Covariance Structures" section for details. We then established baseline models by including fixed effects of the level 2 control variables gender[3] and age (grand-mean centred), and the level 1 control variable day of the week.[4] To investigate our research questions, we then regressed wellbeing on social interactions (within one's household, outside one's household, via video, phone, and text) and social media use (active and passive) in hours. Level 1 predictors were person-mean centred, and the grand-mean centred person-means were re-introduced at level 2, allowing us to investigate the contribution of within- and between-person effects separately (Raudenbush & Bryk, 2002). The person-mean-centred predictors can show within-person effects; comparing the daily measurement to the person's mean relates to the question of whether a person's daily wellbeing was higher on days on which they reported more social connections than was typical for them. The re-introduced person-means can indicate effects between persons. This comparison of different individuals' means speaks to the question of whether people who, on average, had more social interactions of a given type also tended to report higher wellbeing on average. When including our predictors, we first fit models with only fixed effects and then added random effects (i.e., allowing the slopes to vary between participants) for all level 1 predictors. By including random slopes, we can account for the fact that our predictors' effects on wellbeing may vary between participants. As the models failed to converge when random effects were allowed to correlate, we made the simplification of including independent random effects.

We used likelihood ratio tests (LRTs) to test whether the addition of a set of fixed or random effects significantly improved the model. We assessed the significance of individual fixed effects with Wald tests. To compare different predictors, we used Wald tests on their regression coefficients using the *multcomp* package (Hothorn et al., 2008). We utilised R^2_{GLMM} (Nakagawa et al., 2017; Nakagawa & Schielzeth, 2013) calculated with the *MuMIn* package Version 1.43.17 (Barton, 2020) to quantify the variance in wellbeing explained by our models. It consists of two values: the variance explained by fixed effects alone (*marginal* R^2 or

2 We use ~*df* to indicate that the *p*-values are calculated based on a chi-square distribution with *df* degrees of freedom. The likelihood ratio statistic −2ΔLL generally follows a chi-square mixture under a null hypothesis that constrains variance components (Self & Liang, 1987). The reported *p*-values under chi-square distributions are more conservative than the correct ones under the suitable chi-square mixtures; it is, therefore, safe to conclude statistical significance of an effect if the *p*-value is less than .05.

3 We entered two dummy variables, female (0 = male, 1 = female), and other gender (0 = male, 1 = other).

4 We coded 0 = weekday, 1 = weekend

$R^2_{GLMM(m)}$) and the variance explained by fixed and random effects overall (*conditional* R^2 or $R^2_{GLMM(c)}$).

Results

Descriptive Results

Wellbeing During the Pandemic

When comparing the sample's average scores on the wellbeing measures in the pre- and post-diary questionnaires (PHQ-9, GAD-7, PSS-4, SWL) to general population values before the COVID-19 pandemic, we find more severe symptoms of depression and anxiety and lower life satisfaction, but similar stress levels (see Supplementary Materials "Details Wellbeing at Pre- and Post-Questionnaire" section for details). To test whether wellbeing changed significantly from the pre- to the post-diary questionnaire, we computed paired Student's t-tests. We found no statistically significant changes in depression,[5] $t(109) = 0.80$, $p = .427$, stress, $t(109) = 0.79$, $p = .431$, or life satisfaction, $t(109) = -0.06$, $p = .949$, but a significant decrease in anxiety, $t(109) = 3.08$, $p = .003$. After applying the Benjamini-Hochberg procedure to control the false discovery rate (Benjamini & Hochberg, 1995), anxiety was still significant with adjusted p value = .010.

Time Spent on Social Interactions and Wellbeing

See Table 1 for the means, standard deviations, and intercorrelations of all variables of interest. Participants, on average, spent around three and a half hours per day interacting face-to-face with household members, and around 40 minutes a day interacting face-to-face with people who were not members of their own household. In terms of technology-mediated communication, they spent almost an hour on video calls, around 30 minutes on phone calls, and around 80 minutes on digital written communication per day on average. Finally, participants reported using social media actively for around 40 minutes, and passively for around 75 minutes per day.

Multilevel Analyses

We included day of data collection in the model to account for trends over time and identified the best fitting alternative error covariance structure to address remaining autocorrelation (see Supplementary Materials "Linear Trends of Wellbeing Over Time and Alternative Error Covariance Structures" section for details). We retained a first-order autoregressive, first-order moving-average structure, ARMA(1,1) for all subsequent analyses, thereby taking the previous day's wellbeing value and error term into account. Adding the control variables significantly improved model fit compared to the random linear time model with an ARMA(1,1) error covariance structure, $-2\Delta LL(4) = 29.32$, $p < .001$. Participants reported significantly higher wellbeing on the weekend, and on average, women reported significantly lower wellbeing than men (see Table 2).

Hypothesis Tests

To investigate whether more face-to-face interactions and technology-mediated communication were associated with enhanced wellbeing (H1 and H2), we examined the amount of time spent interacting through different modes of communication (face-to-face with people within one's household, face-to-face outside one's household, video calls, phone calls, and written communication) and social media use (active and passive). Figure 1 illustrates the relationship between wellbeing and these different ways of connecting to others. Table 2 displays the results of the control models, fixed effects only models, and random-effects models.

Before testing our hypotheses, we assessed whether including the set of predictors improved overall model fit. An LRT indicated significantly better model fit compared to the model with control variables only, $-2\Delta LL(14) = 61.22$, $p < .001$. Including random variation around the fixed effects of the predictors again improved model fit significantly, $-2\Delta LL(\text{~}6) = 112.66$, $p < .001$.[6] The final random-effects model primarily yielded significant within-person effects, meaning that daily fluctuations in people's social interactions and social media use affected their daily wellbeing. In contrast, between-person differences in social connections generally did not correspond to differences in wellbeing. Overall, the fixed effects explained a small amount of variance (.116) in wellbeing in the final model.

Face-to-Face Interactions (H1). As hypothesised, face-to-face interactions positively predicted wellbeing, yielding support for H1. On days on which participants reported spending more time interacting face-to-face within or outside their household than usual, they reported significantly higher end-of-day wellbeing. We found no difference between the effects of face-to-face interactions within and outside the household, $\Delta\beta = 0.02$, $SE = 0.02$, $z = 1.01$, $p = .312$.

Technology-Mediated Communication (H2). We hypothesised that technology-mediated communication would also positively predict wellbeing, albeit less strongly than face-to-face interactions (H2). The results did not yield consistent positive effects for technology-mediated communication. While we found a significant positive within-person effect of written digital communication, neither video calls nor phone calls significantly predicted well-

5 Utilising the *rstatix* package (Kassambara, 2021), we identified two extreme outliers for the difference in PHQ-9 score from pre- to post-diary questionnaire (more than three times the interquartile range over/under the third and first quartile, respectively). Excluding these two outliers for the comparison of the PHQ-9 scores did not change the pattern of results, $t(107) = 1.56$, $p = .241$.

6 The model does not contain a random effect of active social media use. Fitting the model with random effects for all predictors resulted in a non-negative-definite Hessian matrix. As there was virtually no variance around the fixed effect of active social media use, we excluded this random effect, which allowed convergence.

Table 1. Means, Medians, Standard Deviations (SD), Intraclass Correlation (ICC), and Intercorrelations of the Variables of Interest

Variable		*Mean*	*Median*	*SD*	*ICC*	*1*	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*
1	Gender (% female)	50.00%		-	-										
2	Gender (% other)	1.82%		-	-	-0.14									
3	Age	37.98		12.83	-	-.30*	0.02								
4	Wellbeing	3.8		1.15	0.83	-0.23	-0.05	0.09							
5	Interaction in household	194	180	156	0.83	0.01	-0.18	0	0.09						
6	Interactions outside household	37	0	77	0.38	-0.05	-0.09	-0.01	0.15	0.06					
7	Video calls	54	0	80	0.39	0.24	0.15	-.31**	0.08	0.01	0.11				
8	Phone calls	29	0	51	0.51	-0.05	-0.1	-0.03	0.05	0.04	.33**	.41***			
9	Digital written communication	80	60	77	0.57	0.24	-0.09	-.27*	-0.09	-0.06	0.15	.36**	.49***		
10	Active social media use	41	30	50	0.6	-0.07	0.13	0.1	-0.15	-0.09	-0.13	-0.09	-0.05	0.11	
11	Passive social media use	76	60	71	0.57	0.22	-0.17	-0.1	-0.13	-0.01	-0.18	-0.11	-0.12	0.17	.45***

Note. * $p < .05$. ** $p < .01$, *** $p < .001$. The p-values have been corrected for multiple comparisons using the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). The wellbeing outcomes have a range of zero to six; the time variables are indicated in minutes. The zero-order Pearson correlations between day-level variables are based on person-averages (N = 110 participants) across the diary measurement points. Of note, only two participants indicated their gender as 'other'.

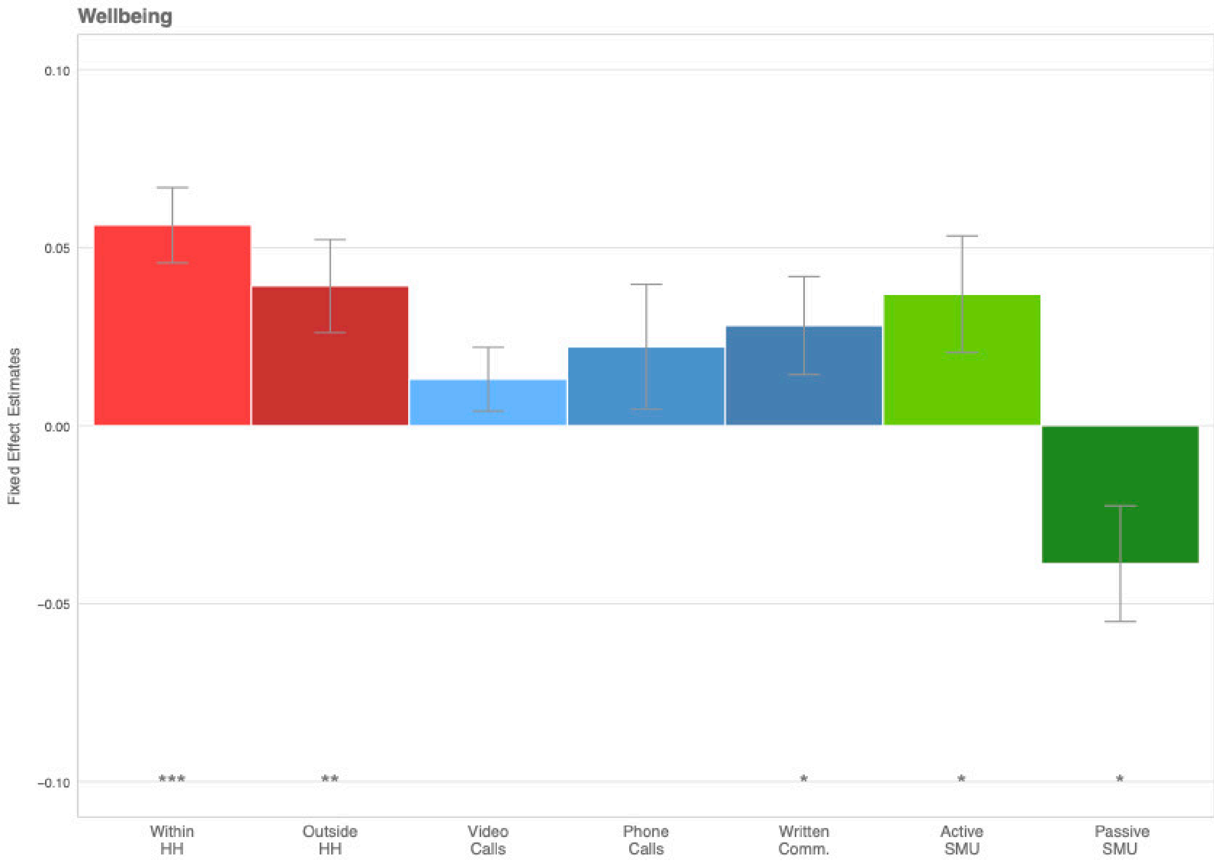

Figure 1. Within-Person Effects of Social Interaction and Social Media Use on Wellbeing

Note. These fixed effect estimates are based on the models including random effects.
Error bars indicate the standard errors. * p < .05; ** p < .01; *** p < .001.
HH = household; SM = social media use.

being. We next tested whether the effects of technology-mediated communication were weaker than those of face-to-face interactions with Wald Tests on the within-person regression coefficients, controlling the false discovery rate by applying the Benjamini-Hochberg procedure (Benjamini & Hochberg, 1995). In contrast to our predictions, these tests indicated that the differences between the within-person effects of face-to-face interactions (both within and outside the household) and technology-mediated communication (video, phone, text) were mostly not significantly different (see Supplementary Materials "Additional Information on the Main Analyses" section). The only statistically significant difference was that face-to-face interactions in the household had a significantly stronger effect on wellbeing than video calls, $\Delta\beta = 0.04$, $SE = 0.01$, $z = 3.19$, $p = .001$ (Benjamini-Hochberg adjusted p value = .008). Furthermore, we found one between-person effect: Participants who, on average, reported more video calls over the entire diary period tended to report significantly higher wellbeing.

Social Media Use (H3). Finally, we found evidence supporting H3: While active social media use positively predicted wellbeing, passive social media use predicted wellbeing negatively. On days on which participants reported spending more time on active social media use, they reported significantly higher end-of-day wellbeing. In contrast, spending more time using social media passively related to significantly lower daily wellbeing.

Post-hoc Power Analysis for Hypothesis Testing

We conducted a post-hoc power analysis to evaluate the power of detecting between-person and within-person effects in our study, given the data of 110 participants and 28 diary entries. We used the Monte Carlo simulation using the shiny app PowerAnalysisIL (Lafit et al., 2021). Given the limitations of the shiny app, we simplified our model's error structure: the results reported in Table 2 were based on ARMA(1,1), for the power analysis we ran the model with the autocorrelation structure AR(1).

We first did the simulation for the effect of a Level 2 continuous predictor on the mean level outcome (Model 2 in the PowerAnalysisIL app). As person-level video communication was the only variable significantly predicting wellbeing in the model, we used the parameters related to this variable to conduct the power analysis. Results suggested that there was a power of .72 to detect this effect given our sample size and repeated measures.

We then simulated the effect of a Level 1 continuous predictor on the outcome with random slope (Model 3 in the PowerAnalysisIL app). We first used the largest effect, face-to-face interactions within household, to examine the power of detecting this effect. Results suggested that there

Table 2. Multilevel Regression Analyses Predicting Wellbeing from Social Interactions in Hours

Model	(C)	(F)	(R)
Intercept	3.939*** (0.139)	3.995*** (0.139)	3.990*** (0.140)
Day	0.003 (0.002)	0.002 (0.002)	0.002 (0.002)
Age	0.001 (0.008)	0.006 (0.008)	0.006 (0.008)
Gender = Female	-0.443* (0.195)	-0.534** (0.201)	-0.528* (0.204)
Gender = Other	-0.514 (0.695)	-0.500 (0.730)	-0.505 (0.738)
Weekend	0.085*** (0.018)	0.074*** (0.018)	0.067*** (0.018)
In HH (Daily)		0.047*** (0.008)	0.056*** (0.011)
Out HH (Daily)		0.012 (0.008)	0.039** (0.013)
Video (Daily)		0.006 (0.008)	0.013 (0.009)
Phone (Daily)		-0.001 (0.014)	0.022 (0.018)
Written (Daily)		0.009 (0.010)	0.028* (0.014)
Active SMU (Daily)		0.032* (0.016)	0.037* (0.016)
Passive SMU (Daily)		-0.043*** (0.012)	-0.039* (0.016)
In HH (Mean)		0.024 (0.038)	0.025 (0.039)
Out HH (Mean)		0.180 (0.116)	0.188 (0.117)
Video (Mean)		0.261* (0.127)	0.258* (0.129)
Phone (Mean)		0.141 (0.187)	0.118 (0.189)
Written (Mean)		-0.080 (0.113)	-0.092 (0.115)
Active SMU (Mean)		-0.245 (0.156)	-0.229 (0.158)
Passive SMU (Mean)		0.090 (0.121)	0.086 (0.122)
Observations	3,071	3,071	3,071
LogLikelihood	-2,164.227	-2,133.617	-2,077.290
AIC	4,350.454	4,317.234	4,216.579
BIC	4,416.781	4,467.978	4,403.502
$R^2_{GLMM(m)}$	0.046	0.114	0.116
$R^2_{GLMM(c)}$	0.823	0.824	0.839

Note. Per outcome, we display the model with only control variables (C), with only fixed effects of the predictors (F), and the model with the predictors' random effects included (R). * p < .05; ** p < .01; *** p < .001. Numbers in parentheses are standard errors. HH = Household; SMU = Social Media Use; AIC/BIC = Akaike/Bayesian Information Criterion; $R^2_{GLMM(m)}$ and $R^2_{GLMM(c)}$ refer to the variance explained by fixed and total effects, respectively.

was a power of 1.00 to detect this effect size. We then used the smallest significant effect, written communication, to test the power of detecting this effect. Results suggested that there was a power of .99 to detect this smallest effect size. In sum, there is a power between .99 and 1.00 to detect the Level 1 significant effects in our main hypothesis testing model.

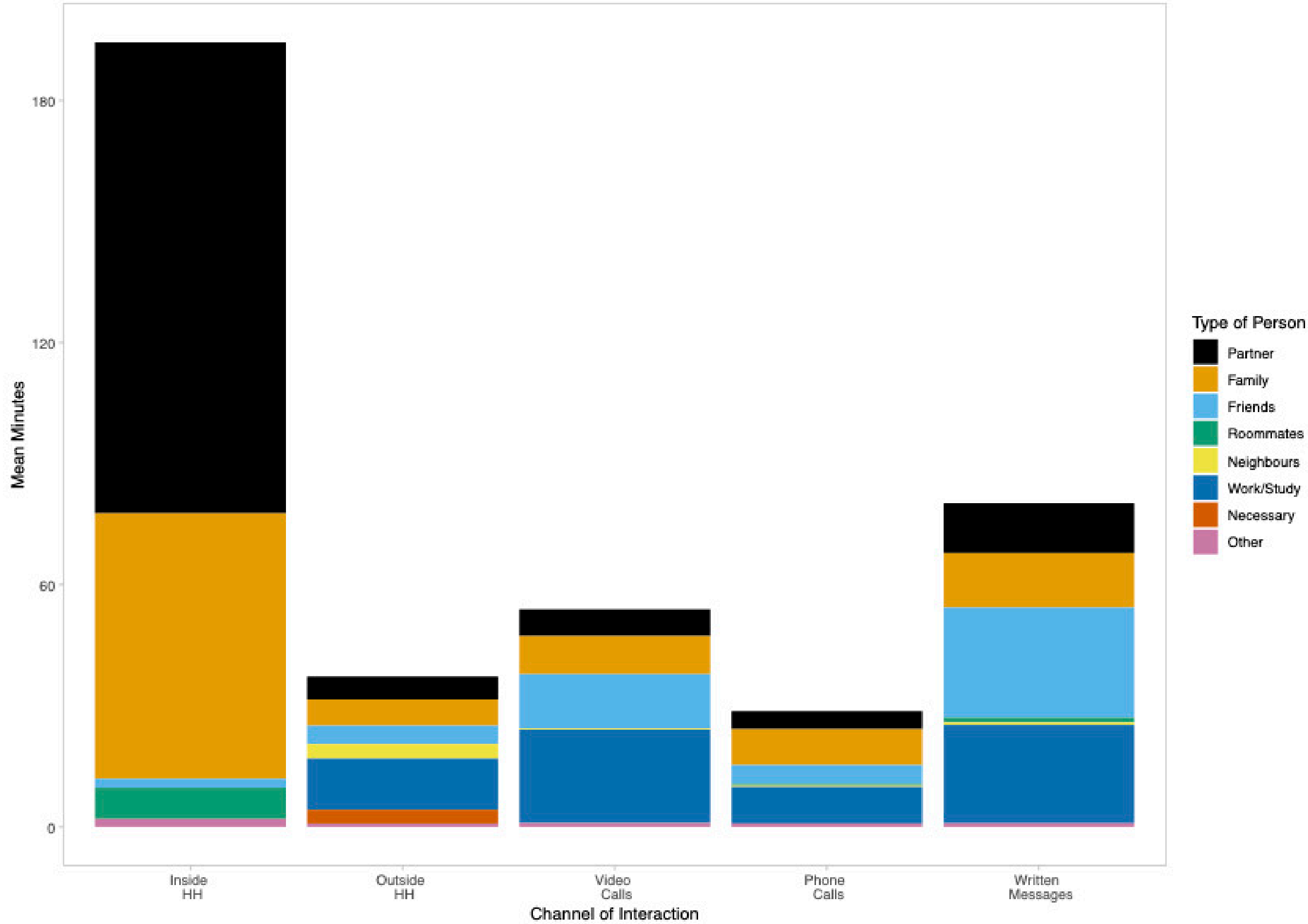

Figure 2. Average Time Spent Interacting with Different Categories of People Through

Note. HH = household. "Necessary contacts" refer to contacts involving necessary chores (e.g., grocery store staff, doctor)

Exploratory Follow-Up Analyses of Interaction Partners

Figure 2 displays how long participants spent interacting with different categories of interaction partners per mode of communication, averaged across participants and days. We explored whether the wellbeing effects of social interactions differed depending on the category of interaction partner. To this end, we ran separate multilevel models for each mode of communication, with repeated measures of interactions nested in participants, following the same steps as for the main analyses. Participants interacted very rarely with some categories of interaction partners in certain modes of communication, resulting in many '0 minutes' responses; we only included predictors if they had at least 500 nonzero responses (see Supplementary Materials "Additional Information on the Exploratory Analyses" section for details).

As can be seen in Table 3, the final random-effects models yielded several significant within-person effects (see also Supplementary Materials "Additional Information on the Exploratory Analyses" section for details). Face-to-face interactions with a cohabiting partner had a positive effect on daily wellbeing. More video calls and written digital communication with one's friends also increased end-of-day wellbeing. On days on which participants spent more time on the phone with their family than usual, they reported significantly higher end-of-day wellbeing. More surprisingly, on days on which participants spent more time on face-to-face interactions outside their household involving essential daily life chores (e.g., grocery shopping), they reported significantly higher end-of-day wellbeing. We did not find any significant within-person effects of interactions with work-/study-related contacts, but we did find a positive between-persons effect for video calls: Participants who, on average, reported more video calls with work-/study-related contacts over the entire diary period tended to report significantly higher wellbeing. Due to too few responses, we could not examine the effects of interactions with neighbours or roommates.

Figure 3 displays the time participants spent on interactions with different interaction partners, aggregating communication channels, averaged across participants and days. Participants spent the most time interacting with their partner and other family members during our data collection period. We examined the relationship between interaction partners and wellbeing using multilevel models. Similar to the analyses reported in Table 3, we ran one model without random slope (F), and a second model with random slopes (R), allowing the relationships between in-

Table 3. Multilevel Regression Analyses Predicting Wellbeing from Social Interactions With Different Categories of People Through Different Modes of Communication in Hours

Mode	Face-to-face within HH		Face-to-face outside HH		Video Calls		Phone Calls		Written Digital Communication	
Model	(F)	(R)	(F)	(R)	(F)	(R)	(F)	(R)	(F)	(R)
Intercept	3.941*** (0.139)	3.943*** (0.139)	3.936*** (0.139)	3.936*** (0.139)	3.983*** (0.134)	3.983*** (0.134)	3.933*** (0.139)	3.932*** (0.139)	3.938*** (0.144)	3.935*** (0.145)
Age	0.002 (0.002)	0.002 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)	0.003 (0.002)
Gender = Female	-0.421* (0.196)	-0.419* (0.196)	-0.444* (0.195)	-0.444* (0.195)	-0.513** (0.190)	-0.514** (0.190)	-0.437* (0.195)	-0.436* (0.195)	-0.457* (0.212)	-0.447* (0.213)
Gender = Other	-0.401 (0.700)	-0.402 (0.700)	-0.528 (0.698)	-0.530 (0.698)	-1.167 (0.695)	-1.168 (0.696)	-0.523 (0.696)	-0.523 (0.697)	-0.466 (0.688)	-0.470 (0.691)
Weekend	0.066*** (0.018)	0.062*** (0.018)	0.085*** (0.018)	0.085*** (0.018)	0.074*** (0.018)	0.074*** (0.018)	0.086*** (0.018)	0.086*** (0.018)	0.070*** (0.019)	0.071*** (0.019)
Partner (Daily)	0.073*** (0.012)	0.075*** (0.016)	-	-	-	-	-	-	0.026 (0.030)	0.002 (0.047)
Family (Daily)	0.018 (0.014)	0.027 (0.016)	-	-	0.007 (0.024)	0.007 (0.024)	0.086** (0.032)	0.088** (0.034)	0.020 (0.036)	0.026 (0.037)
Friends (Daily)	-	-	-	-	0.062*** (0.015)	0.061*** (0.015)	-	-	0.092*** (0.023)	0.104*** (0.031)
Work/Study (Daily)	-	-	-	-	-0.020 (0.011)	-0.018 (0.012)	-	-	-0.043** (0.015)	-0.012 (0.024)
Necessary (Daily)	-	-	0.220*** (0.056)	0.207*** (0.062)	-	-	-	-	-	-
Partner (Mean)	0.056 (0.049)	0.057 (0.049)	-	-	-	-	-	-	-0.082 (0.243)	-0.083 (0.244)
Family (Mean)	-0.004 (0.060)	-0.004 (0.060)	-	-	0.717 (0.410)	0.718 (0.410)	-0.114 (0.465)	-0.115 (0.465)	0.168 (0.489)	0.155 (0.491)
Friends (Mean)	-	-	-	-	-0.578 (0.314)	-0.578 (0.315)	-	-	-0.344 (0.217)	-0.335 (0.218)
Work/Study (Mean)	-	-	-	-	0.481** (0.168)	0.482** (0.168)	-	-	0.159 (0.183)	0.160 (0.184)
Necessary (Mean)	-	-	-0.343 (1.265)	-0.375 (1.265)	-	-	-	-	-	-
Observations	3,071	3,071	3,071	3,071	3,071	3,071	3,071	3,071	3,071	3,071
LogLikelihood	-2,143.254	-2,137.053	-2,156.257	-2,155.391	-2,147.232	-2,146.530	-2,160.357	-2,160.237	-2,149.242	-2,129.552

AIC	4,316.507	4,308.106	4,338.514	4,338.783	4,328.464	4,331.059	4,346.714	4,348.473	4,336.485	4,305.104
BIC	4,406.954	4,410.612	4,416.901	4,423.199	4,430.970	4,445.624	4,425.100	4,432.890	4,451.050	4,443.788
$R^2_{GLMM(m)}$	0.057	0.057	0.047	0.047	0.131	0.131	0.046	0.046	0.073	0.070
$R^2_{GLMM(c)}$	0.823	0.825	0.823	0.824	0.823	0.823	0.823	0.824	0.824	0.830

Note. Per outcome, we display the model with only fixed effects of the predictors (F) and the model with the predictors' random effects included (R). * p < .05; ** p < .01; *** p < .001. Numbers in parentheses are standard errors. AIC/BIC = Akaike/Bayesian Information Criterion; $R^2_{GLMM(m)}$ and $R^2_{GLMM(c)}$ refer to the variance explained by fixed and total effects, respectively. HH = Household. Necessary refers to necessary interactions outside one's household, e.g., when grocery shopping. If an effect is not included ('-'), we did not include the predictor in the analyses; since we did not have enough responses to investigate interactions with neighbours or roommates in any mode of communication, these were left out of the table for brevity.

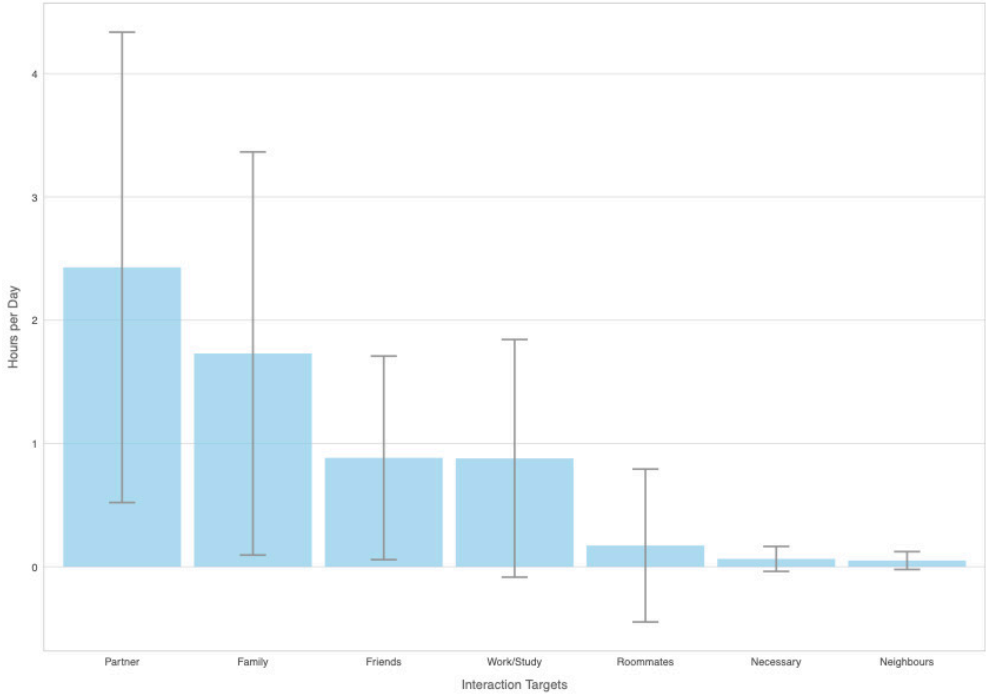

Figure 3. Average Time Spent Interacting with Different Categories of People Aggregating

teraction partners and wellbeing to differ between participants. The results are reported in Table 4. In the random-effects model, we found a significant positive relationship between interacting with friends (within-person effect) and end-of-day wellbeing. Note that the results on the interactions with roommates, individuals involving necessity, and neighbours should be interpreted with caution, as there were many zeros in those categories.

Exploratory Reverse Relationship between Wellbeing and Social Interactions

We also conducted another follow-up exploratory analysis to test a relevant theoretical question: does psychological wellbeing relate to subsequent increased social interactions? However, inspection of the data suggested that the distribution of social interactions was largely right-skewed. This is not a problem when these variables were treated as predictors, as they were in the analysed reported above; however, it would be a problem if they are used as the outcome. Highly skewed variables being treated as the outcome would violate (multilevel) regression models' assumptions.

Nevertheless, to try it out, we ran multilevel regression analysis, using the face-to-face interactions (both in-household and outside-household), as well as active social media use, passive social media use, as the four outcome variables; momentary wellbeing and wellbeing from yesterday (lagged effect of wellbeing) as predictors with ARMA(1,1) as the correlation structure. We then tested the assumptions of these models. All four models violated two assumptions: homogeneity of variance and the normal distribution of models' residuals. Therefore, the results are not reported in the present manuscript; yet the code for these analyses could be found on the OSF page https://osf.io/zfe6x/.

Discussion

Constraints on physical social interaction presented a challenge to wellbeing (Brooks et al., 2020), raising concerns about the consequences of lockdowns introduced to slow the spread of the COVID-19 pandemic (Holmes et al., 2020). In this study, we empirically tested the effectiveness of WHO's recommendation to use technology-mediated communication and social media during physical distancing periods. In a 30-day daily diary study, we examined whether daily technology-mediated communication (video, phone, text) and active and passive social media use would predict wellbeing similarly to, or differently from face-to-face interactions within and outside one's household. Our findings show that even during strict lockdown measures, face-to-face interactions yield the most consistent positive relationship with wellbeing. Notably, we found that interactions both within and outside one's household were beneficial. In direct comparisons, we did not find significant differences between the effects of face-to-face interactions and technology-mediated communication. However, the effects of technology-mediated communication on wellbeing were inconsistent, with only written digital communication significantly predicting enhanced wellbeing across interaction partners. Social media use consistently predicted wellbeing, but the effects were dependent on how social media was used: while active social media use positively influenced wellbeing, passive social media use affected wellbeing negatively. Exploratory follow-up analyses indicated that interactions with both close and less close interaction partners generally had positive relationships with wellbe-

Table 4. Multilevel Regression Analyses Predicting Wellbeing from Social Interactions with Different Targets Across All Modes of Communication in Hours

	wellbeing	
	(F)	(R)
Intercept	3.281***	3.466***
	(0.750)	(0.766)
day56	-0.004	-0.0003
	(0.008)	(0.008)
Age	-0.011	-0.011
	(0.025)	(0.025)
Gender = Female	0.216	0.002
	(0.621)	(0.635)
Gender = Other	-0.002	-0.002
	(0.003)	(0.003)
Weekend	-0.232	-0.244
	(0.14)	(0.129)
Partner (Daily)	0.019	0.024
	(0.107)	(0.157)
Family (Daily)	0.066	0.045
	(0.078)	(0.111)
Friends (Daily)	0.167	0.175*
	(0.085)	(0.083)
Roommates (Daily)	-0.396	-0.087
	(0.407)	(0.402)
Neighbours (Daily)	-0.871	-0.819
	(0.480)	(0.782)
Work/Study (Daily)	-0.01	-0.014
	(0.055)	(0.051)
Necessary (Daily)	0.401	0.4
	(0.581)	(0.568)
Partner (Mean)	0.268	0.175
	(0.166)	(0.177)
Family (Mean)	-0.023	-0.02
	(0.142)	(0.14)
Friends (Mean)	0.284	0.194
	(0.373)	(0.373)
Roommates (Mean)	-0.311	-0.247
	(0.477)	(0.470)
Neighbours (Mean)	3.9	4.258
	(4.439)	(4.43)
Work/Study (Mean)	-0.145	-0.086
	(0.295)	(0.294)
Necessary (Mean)	-1.914	-1.694
	(2.568)	(2.576)
Observations	109	109
LogLikelihood	-88.918	-86.844
AIC	227.836	237.687
BIC	295.12	323.81
$R^2_{GLMM(m)}$	0.153	0.104
$R^2_{GLMM(c)}$	0.881	0.894

Note. We display the model with only fixed effects of the predictors (F) and the model with the predictors' random effects included (R). * p < .05; ** p < .01; *** p < .001. Numbers in parentheses are standard errors. AIC/BIC = Akaike/Bayesian Information Criterion; R_GLMM(m)^2 and R_GLMM(c)^2 refer to the variance explained by fixed and total effects, respectively.

ing. Note that since the hypotheses and data analyses were not pre-registered, our study is exploratory in nature.

Social Interactions and Wellbeing

Face-to-Face Interactions

In line with our predictions (H1) and research conducted before the COVID-19 pandemic (Diener & Seligman, 2002), we found that, during a period of lockdown, face-to-face interactions positively predicted wellbeing. Interestingly, we found comparable effects for face-to-face interactions within (such as family members) and outside the household (such as interactions with neighbours or at the supermarket). Our findings align with those of a previous study conducted during the COVID-19 pandemic, which found that in-person interactions with both close and less close interaction partners benefitted wellbeing (Tibbetts et al., 2021). This indicates that across different interaction partners, face-to-face interactions are consistently beneficial for wellbeing during a lockdown period. This was further corroborated by our follow-up analyses. For face-to-face interactions within the household, we found positive wellbeing effects of interacting with one's partner, and for face-to-face interactions outside of the household, we found that contacts necessary for daily life (e.g., at the supermarket) were also positively associated with daily wellbeing. These results also align with pre-pandemic findings underlining the importance of casual interactions with acquaintances and even strangers (Epley & Schroeder, 2014; Sandstrom & Dunn, 2014). Strikingly, despite carrying an increased risk of infection, such casual interactions appear to remain helpful to people's psychological wellbeing during a lockdown period.

These findings highlight the importance of safe opportunities for face-to-face interactions. For example, during the lockdown period, the UK government allowed single-adult households (and some other people) to form so-called *support bubbles* with one other household, allowing them to interact without having to physically distance (Department of Health and Social Care, 2020). If these bubbles were exclusive and remained the same over time, they enabled non-distanced face-to-face interactions with limited epidemic risk (Leng et al., 2020). Moreover, individuals should not underestimate the benefits of casual face-to-face interactions outside of their household or support bubble.

Technology-Mediated Communication

We also tested the WHO's recommendation to utilise technology-mediated communication during periods of physical distancing, by investigating the extent to which connecting with others via technologically mediated communication would be related to wellbeing. We had hypothesised that video calls, phone calls, and written digital communication would all be associated with improved wellbeing, but less strongly than face-to-face interactions (H2). The results do not provide clear support for this hypothesis. We found only scattered positive effects of technology-mediated communication on wellbeing, yet direct comparisons did not indicate that face-to-face interactions related to wellbeing more than technology-mediated communication consistently.

Our findings do show, however, that technology-mediated communications predict wellbeing less consistently across interaction partners than do face-to-face interactions. Follow-up analyses on interactions with different partners showed that texting and video calls with friends, as well as phone calls with family members, positively predicted daily wellbeing. This aligns with findings by Lades and colleagues (Lades et al., 2020), who found positive wellbeing effects of interacting with friends and family during the pandemic; though in their study, the mode of communication was not differentiated.

Finally, we found that people who, on average, reported more video calls over the diary period also tended to report higher wellbeing. In our follow-up analyses, we found this pattern for video calls specifically with contacts from work/school. These findings likely reflect differences in socioeconomic status between participants, as those who can work from home likely have higher socioeconomic status (Mongey et al., 2020), which in itself has been linked to higher wellbeing during the pandemic (R. Sun et al., 2020). In summary, we found the effects of technology-mediated communications to be less consistent compared to face-to-face interactions, and largely depending on who the interaction partners are.

Social Media Use

We found that active social media use predicted better daily wellbeing, while passive social media use predicted poorer daily wellbeing. This finding is in line with our hypotheses (H3) and consistent with previous research (Liu et al., 2019). While a previous study found that social media use reduced wellbeing during the COVID-19 pandemic (Lades et al., 2020), that study did not differentiate between active and passive social media use. Given that passive use usually outweighs active use (Verduyn et al., 2017), those findings may thus have reflected passive social media use. The pandemic may, in fact, exacerbate the negative effects of passive social media use: When browsing the internet, one is likely to see content about COVID-19, and exposure to COVID-19-related information on social media has been linked to poorer psychological wellbeing (Gao et al., 2020).

In the present study, we gave participants definitions of "active" (e.g., liking, up-/downvoting, sharing, commenting, posting) and "passive" social media use (e.g., scrolling/browsing social media feeds/pages, reading/watching content) based on definitions used in previous research (Verduyn et al., 2017). However, we cannot rule out the possibility that participants may have been influenced by their own idiosyncratic understandings of these concepts. Moreover, these categories somewhat confound different levels of "active" social media use. For example, "liking" a post is less interactive than commenting on a post. Yet, in the present study, both "liking" and "commenting" belong to the same "active use" category. Future research on social media use and wellbeing may benefit from more detailed differentiation between different social media use behaviours (see Valkenburg et al., 2022).

The present findings highlight the importance of differentiating between active and passive social media use, given their opposing relationships with wellbeing. Therefore, recommendations to use social media to keep connected should perhaps be qualified to emphasise that it is important to actively use, rather than just passively browse, social media.

Limitations and Future Directions

It is worth noting several limitations of the present study. First, the sample size of 110 participants precluded meaningful analyses of age and living context (e.g., only 12 participants reported living alone), and may have limited our ability to detect between-person effects of social interactions and wellbeing. While we primarily found within-person effects, our findings are consistent with a large-scale cross-sectional study conducted during the pandemic, which suggests that people who, on average, have more social interactions also report higher levels of wellbeing (Nitschke et al., 2020). Our models also suggested large random effects, that is, large individual differences in the relationships between social interactions, social media use, and wellbeing. A larger sample size would be needed to allow for tests of individual differences, such as whether effects differ between people with differences in personality, attachment style, or relationship status. To fully address the contributions of within- and between-person effects of different kinds of social interactions during lockdown periods, further longitudinal studies with larger samples are needed.

Secondly, both the time that participants spent on each communication channel and end-of-day wellbeing were measured using self-report. Since wellbeing reflects people's overall evaluation of their own life, it is usually assessed via self-report (Diener et al., 2003). Moreover, self-reported wellbeing has been shown to exhibit considerable cross-situational consistency and temporal stability in comparisons of family versus friend informant reports (Sandvik et al., 2009). For face-to-face interactions, there is a substantial correlation between self-reported and objective measurement (Thiele et al., 2014). For social media use, a 15-country study (N = 49,934) suggested that self-reported Facebook use was moderately correlated (r = 0.42 for the best-performing question) with actual Facebook use (Ernala et al., 2020), this study and some other research have suggested that people tend to overestimate the time they spend on social media (Verbeij et al., 2021). Furthermore, participants reported interactions separately for different interaction partners, but our analyses were not able to take into account the fact that interactions may have overlapped (e.g., interacting with both friends and partner at the same time).

Third, the present study followed individuals for 30 days only, precluding conclusions about potential long-term effects. Evidence from a previous epidemic suggests that relying on technology-mediated communication during a period of physical isolation can be a risk factor for worsened mental health several months later (Jeong et al., 2016). Further work will be needed to examine whether the effects we have documented will have long-term effects on our wellbeing.

Finally, we could not rule out the possibility that a third variable could be associated with both wellbeing and social interactions. For example, good weather might encourage people to spend more time outdoor together with household members, to have more face-to-face interactions with non-household members, as well as to use less technology-mediated communication; at the same time, good weather may also relate to people's enhanced wellbeing. We thus cannot draw causal conclusions between social interactions and wellbeing in the current study. Relatedly, due to the extreme right-skewed distribution of social interactions (especially social media use) in the present study, we could not easily test the theoretical question whether higher wellbeing relates to more social interactions.

Conclusion

When many countries introduced strict lockdown and physical distancing measures during the COVID-19 pandemic, the WHO recommended the use of technology-mediated communications and social media in such situations. The present study empirically tested the effects of technology-mediated communications on wellbeing and compared them to face-to-face interactions using a longitudinal method. Our findings have implications both for policymakers who decide on public health measures and for individuals who have to navigate a changed social environment. We find that face-to-face interactions, both within and outside the household, have a consistently positive relationship with daily wellbeing. The findings for technology-mediated communication were less consistent, especially across different interaction partners. Finally, we found that while active social media use is positively linked to daily wellbeing, passive social media use is negatively related to wellbeing. These findings echo Charles Dickens' (1856, p. 10) insight about electronic communication at its dawn nearly a century and a half ago: "I [...] am as thankful to it as any man can be for what it does for us. But it will never be a substitute for [a] face."

Author contributions

Contributed to conception and design: RS, CR, DS
Contributed to acquisition of data: RS, CR
Contributed to analysis of data: RS, CR, YL
Contributed to interpretation of data: RS, CR, YL, DS
Drafted and/or revised the article: RS, CR, YL, DS
Approved the submitted version for publication: RS, DS

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Competing interests

The authors claim no conflict of interests.

Data accessibility statement

The full set of measures, data and code is available on the OSF: https://osf.io/zfe6x/

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