Effects of COVID-19 related social media use on well-being

Abstract

In times of crisis such as the COVID-19 pandemic, citizens need to stay informed about recent political events. To this end, people increasingly use social media. However, because social media are particularly engaging, many find it hard to disconnect, especially during times of crisis. Using data from the Austrian Corona Panel Project consisting of 3,485 participants from 34 waves, controlling for several stable and varying confounders, the results showed that COVID-19 related social media use did not meaningfully reduce well-being. Other factors such as health, income, exercise, or internal locus of control showed larger and meaningful effects.

Keywords: COVID-19, well-being, social media, news use, panel study.

Effects of COVID-19 related social media use on well-being

During the COVID-19 pandemic it was critical to stay informed regarding the latest developments. How dangerous is the virus? In what region is it spreading? How is it transmitted? What are the current safety regulations? To obtain relevant information, many people heavily relied on social media, with use being at an all time high (Statista, 2021). Some actually could not stop using social media to learn about COVID-19 related news. A new phenomenon termed "doomscrolling" emerged (Sharma et al., 2022). Many users were glued to their screens and found it hard to pursue other relevant activities such as working, taking a break, or even looking after their children. In the media it was hence increasingly asked whether using social media for COVID-19 related reasons would, next to all other stressors, create an additional burden on mental health (Sandstrom et al., 2021). Although research has begun addressing this question (e.g., Bendau et al., 2021; Eden et al., 2020; Sewall et al., 2021), it still largely unknown if COVID-19 related social media use during the pandemic has had a meaningful impact on well-being. This study hence aims to 1) reveal the effect of the different types and channels of social media use on individual well-being, 2) provide generalizable and robust results by analyzing a large-scale longitudinal data-set with 34 waves, and 3) determine the within-person causal effects by analyzing how changes in social media use lead to changes in well-being.

Understanding Well-being and Media Use

This study investigates how different *facets* of well-being are affected by different *types* and different *channels* of communication (Meier & Reinecke, 2020). Building on the typology of subjective well-being (Diener et al., 2018), three different well-being facets are analyzed: life satisfaction, positive affect, and negative affect. Because effects of social media depend on how they are used (Verduyn et al., 2015), I further distinguish three types of use and five popular channels. The types of use include reading, liking and sharing, and posting COVID-19 related content. In doing so, this study analyzes social media use focused on COVID-19 related content, which includes posting thoughts about the pandemic, reading posts and comments, or retweeting and liking COVID-19 related news. Liking and sharing are combined as they both represent low-threshold, platform-ingrained, easily quantifiable interactions. The five channels to be investigated are Facebook, Twitter, Instagram, WhatsApp, and YouTube, which at the time ranked among the most popular social media services in Austria.

Social Media Effects on Well-Being

How easily can well-being be affected by external influences? In general, according to the set-point theory, well-being is surprisingly stable (Lykken, 1999). Although specific events such as marriage or salary increase can have significant impacts on well-being, in most cases effects are short-term, with well-being after some time returning to prior levels (Diener et al., 2018). Specific factors such as unemployment, disability, or death, however, can cause long-term changes in well-being (Lucas, 2007). So although well-being can be affected by external events and factors, this does not happen easily.

Can social media use be such a factor? Current literature overviews suggest that social media use on average does seem to decrease well-being (Meier & Reinecke, 2020). However, for most well-being outcomes, such as life satisfaction, general well-being, or loneliness, the effects are small (Meier & Reinecke, 2020). These small findings can be explained with the differential susceptibility of media effects model (Valkenburg & Peter, 2013), which states that there is substantial *variation* of media effects for individual users. Whereas for some users social media are more beneficial, for others they are more harmful. On average, however, and this is central for this study here, effects tend to be small (Valkenburg & Peter, 2013). For example, in one study it was estimated that roughly one quarter of all users experienced negative effects, another quarter positive effects, while for the rest the effects were neutral (Beyens et al., 2021). Whether or not effects are positive or negative depend on (a) dispositional factors (e.g., personality, temperament, gender), (b) developmental factors (e.g., age, developmental tasks), (c) and social factors (e.g., environment, norms, upbringing). Finally, effects depend also on the content that is consumed. If the content is aligned with dispositions, developmental capacities, and converging contexts, effects tend to be stronger (Valkenburg & Peter, 2013).

Why are the effects of social media use on well-being small on average? Two prominent media effect theories argue implicitly against strong average negative effects. First, according to mood management theory (Zillmann, 1988), using media can affect people's moods. Use can be stimulating or overwhelming, relaxing or boring. After some time, users implicitly learn which media help them balance their mood and affect according to their own situational needs (Zillmann, 1988). Those media that eventually become part of one's media repertoire hence, on average, tend to be beneficial for users to regulate their mood (Marciano et al., 2022). In conclusion, if a certain medium is used frequently, mood-management theory argues that it is likely not detrimental for well-being.

Second, while mood management theory considers media use mainly driven by implicit learning experiences, uses and gratifications theory upholds that the process is more explicit and rational (Katz et al., 1973). Users select those media that they expect to have a desired effect, for example on mood, knowledge, or entertainment. If those beneficial media effects are missing, people will spend their time elsewhere. And social media, in general, offer several beneficial effects, explaining why they are used that much. They help find relevant information, maintain and foster relationships, express one's personality, and entertain oneself (Pelletier et al., 2020). In conclusion, because people spend so much time on social media consuming COVID-19 related content, according to both mood management theory and uses and gratifications theory this indirectly suggest that average effects on well-being are likely not particularly negative.

Social Media During COVID-19

If we look at COVID-19 related use more specifically, how could the various types and channels of COVID-19 related social media use affect well-being? Several uses and gratifications exist, which help explain why people used social media frequently during the pandemic. Despite incorrect information, social media provide a vast platform for disseminating *accurate and timely information* about COVID-19 (John Hopkins University, 2023). Access to reliable information can help people make informed decisions, alleviate uncertainties, and feel empowered during the pandemic. Social media platforms enable individuals to *connect with others* who are experiencing similar challenges during the pandemic (Guazzini et al., 2022). Engaging in online communities and support groups can provide emotional support and create a network of like-minded individuals. Many mental health organizations and professionals utilize social media to share tips, strategies, and resources for *maintaining mental well-being* during the pandemic (Twitter, 2020). Engaging with such content might help individuals prioritize their mental health and develop resilience during challenging times. Social media campaigns and initiatives can promote *positive COVID-19 behaviors*, such as mask-wearing, physical distancing, hand hygiene, and vaccination (Athey et al., 2023; Hunt et al., 2022). Public health organizations and influencers leverage the power of social media to spread awareness and encourage responsible actions, contributing to public health efforts and fostering a sense of collective responsibility.

On the other hand, the effects might be negative, perhaps best explained by the following five mechanisms. Social media platforms can easily spread *false or misleading information* about COVID-19 (Li et al., 2020). Due to the ease of sharing and the lack of fact-checking, inaccurate information can go viral and might cause confusion, anxiety, and panic among users. Constant exposure to COVID-19-related content on social media can lead to *information overload* and contribute to heightened anxiety levels (J. Fan & Smith, 2021). The rapid spread of news, updates, and opinions can be overwhelming and might exacerbate existing stress or fears about the pandemic (Sharma et al., 2022). Social media platforms are known for fostering negativity, with users sometimes engaging in *cyberbullying and harassment*. Discussions around COVID-19 can become heated and polarized, leading to personal attacks and online conflicts. Such experiences threaten mental well-being and might contribute to feelings of distress and isolation. Social media often showcase the highlights and accomplishments of others, encouraging *social comparison* (Przybylski et al., 2013). During a pandemic, seeing posts about others' successes or seemingly perfect lives might intensify feelings of inadequacy or FOMO, especially when individuals are unable to participate in similar activities due to restrictions or personal circumstances (Sharma et al., 2022).

There is still little empirical research on how well-being is affected by social media use that is focused on COVID-19 specifically. Echoing the theoretical rationales outlines above, studies have yielded mixed results. Some studies found negative effects, indicating that excessive social media use for COVID-19 news led to compulsive behavior and increased stress levels, particularly due to upward social comparison (Stainback et al., 2020; Yue et al., 2022). Individuals who relied on social media as their primary information source reported higher levels of anxiety and depression symptoms (Bendau et al., 2021). Similarly, increased COVID-19-related media consumption was associated with higher psychological distress. On the other hand, some studies reported positive outcomes. Certain individuals experienced increased virtual community and social connectedness during the pandemic through social media, which contributed to their well-being (Guazzini et al., 2022). Additionally, engaging more on social media was associated with reduced feelings of loneliness (Latikka et al., 2022). Several studies reported mostly neutral effects of social media use on well-being indicators (Eden et al., 2020; Sewall et al., 2021). Overall, the literature demonstrates a mixed picture, highlighting both positive and negative effects of social media use focused on or during COVID-19 on well-being.

In conclusion, given these mixed empirical results, together with the observation that social media effects on well-being are very small in general, and that several plausible theoretical mechanisms exist for both positive and negative effects, I expect that COVID-19 related communication on social media should not be decidedly positive or negative. It seems most likely that both positive and negative coexist, but that on average using social media for COVID-19 related reasons should not have substantial effects on well-being.

> Hypothesis: The within-person effects of all measures of COVID-19 related social media use (types: reading, liking and sharing, posting; channels: Twitter, Instagram, Facebook, YouTube, WhatsApp) on all measures of well-being indicators (positive affect, negative affect, life satisfaction)—while controlling for several stable and varying covariates such as sociodemographic variables and psychological dispositions (see below)—will be trivial.

Smallest Effect Size of Interest

Exploring the hypothesis entails establishing the criteria for discerning a 'trivial effect size.' To achieve this, it is necessary to define the smallest effect size of interest (SESOI) (Anvari & Lakens, 2021). In this context, a trivial effect should fall below the threshold set by the SESOI (detailed below). Determining what constitutes a minimally intriguing, nontrivial effect is a matter with normative implications, making it challenging to arrive at a definitive, singular consensus. Nonetheless, it remains both essential and beneficial to strive for a reasonable benchmark. With that in mind, I propose the following SESOI as a suitable reference point for this study:

> SESOI: If a heavy user of COVID-19 related social media news suddenly *stops* using social media altogether, this should have a *noticeable* impact on their overall well-being.

What does this mean practically and how can it be operationalized? In this study, COVID-19 related social media use was measured on a 5-point scale, ranging from 1 = *never* to 5 = *several times a day.* Thus, a change of four units in social media use (e.g., a complete stop) should correspond to a noticeable change in well-being. According to Norman et al. (2003), people can reliably notice seven levels of change in satisfaction with health. So if satisfaction is measured on a 7-point scale, a four unit change in social media use should result in a one unit change in life satisfaction. In this study, life satisfaction was measured on an 11-point scale, and affect on a 5-point scale. Transposed to this scaling, the SESOI for life satisfaction is $b = \pm.30$, and for positive and negative affect $b = \pm.15$ (for more information, see online supplementary material).

Method

Preregistration

The hypotheses, the sample, the measures, the analyses, and the inference criteria (SESOI, p-value) were preregistered on the Open Science Framework, accessible here: https://osf.io/87b24/?view_only=b2289b6fec214fa88ee75a18d45c18f3. Because in this study I analyze data from an already existing large-scale data set, the preregistration was done prior to accessing the data. The preregistration was designed on the basis of the panel documentation online (Kittel et al., 2020). In some cases, it was impossible to execute the analyses as I had originally planned, for example because some properties of the variables only became apparent when seeing the actual data. The most relevant deviations are reported below, and a complete list of all changes can be found in the online companion website (https://XMtRA.github.io/Austrian_Corona_Panel_Project).

Sample

The data come from the Austrian Corona Panel Project (Kittel et al., 2020), which is a large-scale standalone panel study. The data are hosted on AUSSDA, are publicly available here (https://doi.org/10.11587/28KQNS), and consist of 34 waves. Participants were sampled from a pre-existing online access panel provided by the company Marketagent, Austria. Panel members were incentivized with 180 credit points for each wave of the study. The study was conducted between March 2020 and February 2023. Between March 2020 and July 2020, the intervals between waves were weekly, until May 2022 (wave 32) monthly, and afterward after 5 months. Each wave consists of at least 1,500 respondents. Panel mortality was compensated through a continuous re-acquisition of new participants. The sample size was $N = 3{,}641$, with overall 123,794 observations. For an overview of the study set-up, see Figure 1.

Achieved via quota sampling, the sample matched the Austrian population in terms

Wave	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
	27.03.20	03.04.20	10.04.20	17.04.20	24.04.20	01.05.20	08.05.20	15.05.20	23.05.20	29.05.20	12.06.20	26.06.20	10.07.20	14.08.20	11.09.20	16.10.20	13.11.20
Measures																	
Well-being (everyone)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Media use (everyone)	x	x						x									x
Media use (new users)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Description of waves																	
Participants	1541	1559	1500	1528	1515	1551	1517	1501	1502	1504	1510	1522	1532	1540	1581	1670	1592
Retention		86.2%	81.3%	78.1%	73.8%	74.3%	70.8%	69.1%	67.6%	65.5%	65.7%	61.3%	62.5%	55.8%	59.0%	63.6%	60.4%
Lockdown measures	x	x	x	x	x	x	x										x

Wave	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34
	11.12.20	15.01.21	12.02.21	12.03.21	16.04.21	21.05.21	25.06.21	24.09.21	22.10.21	26.11.21	14.01.22	18.02.22	18.03.22	22.04.22	20.05.22	21.10.22	17.02.23
Measures																	
Well-being (everyone)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Media use (everyone)						x					x						
Media use (new users)	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x	x
Description of waves																	
Participants	1567	1612	1574	1573	1533	1503	1513	1511	1514	1551	1524	1522	1507	1528	1557	1535	1536
Retention	56.4%	58.9%	58.2%	58.1%	55.8%	54.1%	50.3%	48.4%	50.9%	51.8%	49.5%	48.9%	48.4%	47.0%	46.0%	45.0%	45.0%
Lockdown measures	x	x			x												

Example items	
Affect positive	"In the last week, how often have you felt: calm and serene."
Affect negative	"In the last week, how often have you felt: anxious."
Life satisfaction	"All things considered, how satisfied are you with your life as a whole nowadays?"
Media use	"How often during the last week have you engaged in the following activities on social media? A) Reading the posts of others with content on the Coronavirus"

Figure 1

Overview of study set-up

of age, gender, region/state, municipality size, and educational level. In order to participate in the study, the respondents needed to be Austrian residents and had to be at least 14 years of age. All respondents needed to have access to the internet (via computer or mobile devices such as smartphones or tablets). Ethical review and approval was not required for the study in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study. The average age was 40 years, 49 percent were male, 14 percent had a University degree, and 5 percent were currently unemployed.

Data Analysis

The hypothesis is analyzed using the interval testing approach as proposed by Dienes (2014). To illustrate, let us consider the case of life satisfaction [SESOI: $\pm$.30]. Here, the null-region lies between -.30 and +.30. If the 95% confidence interval falls completely within the null-region (e.g., b = -.05, [95% CI: -.15, .05]), the hypothesis that the effect is trivial is supported. If the confidence interval falls completely outside of the null-region (e.g., b = -.40, [95% CI: -.45, -.35]), the hypothesis is rejected and the existence of a meaningful negative effect is supported. If the confidence interval and the null region overlap (e.g., b = -.30, [95% CI: -.35, -.25]), the hypothesis is not supported and the results are considered inconclusive, while a meaningful positive effect is rejected. If the confidence interval exceeds both sides of the null region (e.g., b = -.025, [95% CI: -.40, .35]), the hypothesis is not supported and judgement is suspended. For an illustration, see Figure 2.

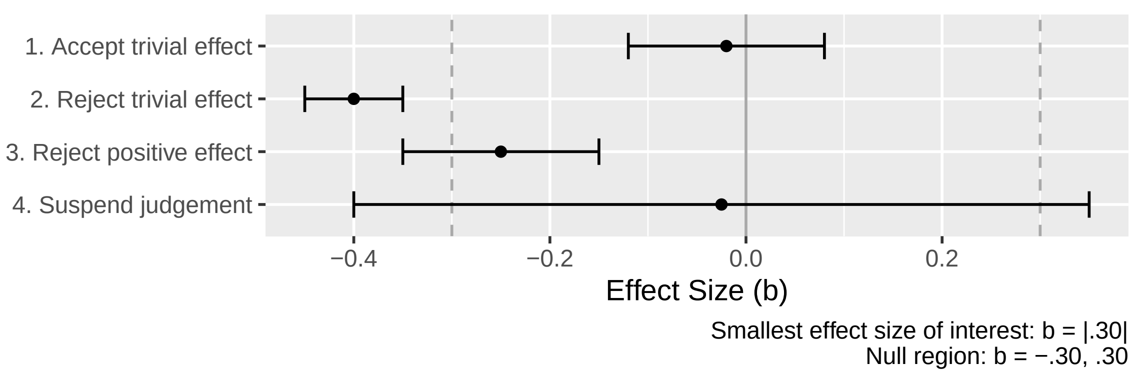

Figure 2

Using confidence intervals to test a null region. In this study, a trivial effect of social media use on life satisfaction is defined as ranging from b = -.30 to b = .30. Figure adapted from Dienes (2014).

Causality

When analyzing causality through longitudinal designs, it is important to address several critical aspects. An inherent requirement of analyzing causal effects within non-experimental designs is adopting an internal perspective, focusing on *within-person effects* (Hamaker, 2014). This entails evaluating how alterations in an individual's media consumption directly impact their well-being. Comparisons between individuals, as observed in longitudinal data, lack the granularity needed to understand these causal dynamics (Hamaker, 2014). Consequently, this study exclusively investigates within-person effects to shed light on this intricate relationship.

An essential strategy for isolating the genuine impact of variables is to *control for confounding factors* that influence both media use and well-being (Rohrer, 2018). In the context of within-person analysis, this necessitates accounting for time-varying confounders (Rohrer & Murayama, 2023). However, a cautious balance must be maintained by not controlling for variables that mediate the relationship (Rohrer, 2018), as their inclusion could distort the assessment of the causal effect. This study therefore incorporated several control variables. These encompass gender, age, education, place of birth and parental place of birth in Austria, Vienna residency, consumption of text-based and video-based news, household characteristics, health status, living space features, employment-related factors, income, outdoor activities, risk propensity, and locus of control (Eger & Maridal, 2015). These variables have demonstrated connections with both social media use and well-being and are not mediators.

A fundamental prerequisite for establishing causality is determining a *plausible temporal interval* (Dormann & Griffin, 2015). For instance, fluctuations in positive and negative affect call for shorter intervals, while the more enduring nature of life satisfaction implies longer intervals (Dienlin & Johannes, 2020).

In this study, I examine the linkage between changes in social media use and changes in affect within the same week. Specifically, I investigate if heightened COVID-19-related social media use during a week corresponds with enhanced or diminished affect during that same week. Additionally, I consider a longer interval for life satisfaction, examining whether increased COVID-19-related social media use over the course of a week influences one's life satisfaction at the week's end. This approach aims to uncover whether changes in social media consumption prompt simultaneous changes in affect and subsequent changes in life satisfaction.

Furthermore, the study's main analyses implement this temporal interval through item wording rather than relying on lagged measures from previous waves. Supplementary analyses extend this investigation to observe how media use might affect well-being one or four months later. In all instances, confounding variables are methodically controlled for, enhancing the study's capacity for causal interpretation.

Statistical model

The hypothesis was analyzed using random effect within-between models (REWB, Bell et al., 2019). Altogether three models were run, one for each dependent variable. The data were hierarchical, and responses were separately nested in participants and waves (i.e., participants and waves were implemented as random effects). Nesting in participants accounts for the longitudinal design. Nesting in waves controls for general exogenous developments, such as general decreases in well-being in the population, for example due to lockdown measures. Thus, there was no need additionally to control for specific phases or measures of the lockdown. Predictors were modeled as fixed effects. They included social media communication types and channels, separated into within and between-person factors, as well as stable and varying covariates. Between-person predictors are the predictors centered on the grand mean; within-person predictors are the predictors centered on the person's mean. Between-person predictors (which, measuring relations, are not of particular interest in this study) represent how the mean of one respondent differs from the mean of all the other respondents. The within-person predictors represent how much a person at one specific wave differs from their own mean. For example, we could find that on Wave 3 a person used social media more than usual, while also experiencing more negative affect than usual. All predictors were included simultaneously in each of the three models.

The factorial validity of the scales were tested with confirmatory factor analyses (CFA). Because Mardia's test showed that the assumption of multivariate normality was violated, I used the more robust Satorra-Bentler scaled and mean-adjusted test statistic

(MLM) as estimator. Mean scores were used for positive and negative affect. Missing responses were imputed using multiple imputation with predictive mean matching (five iterations, 30 data-sets), including categorical variables. All variables were imputed except the social media use measures, as they were not collected on each wave. All variables included in the analyses presented here were used to impute missing data. For the main analyses, results were pooled across all thirty data-sets.

To contextualize the results, I conducted additional exploratory analyses. I reran the analyses (a) with additional not-preregistered covariates such as trust in media or government, (b) without covariates, (c) with single imputation, and (d) without imputation. For more information on the analyses, a complete documentation of the models and results, and all additional analyses, see companion website.

Measures

For a complete list of all items and item characteristics, see companion website.

Well-being

Life satisfaction was measured with the item "All things considered, how satisfied are you with your life as a whole nowadays?", which comes from the European Social Survey. The response options ranged from 0 (*extremely dissatisfied*) to 10 (*extremely satisfied*).

To capture positive affect, respondents were asked how often in the last week they felt (a) calm and relaxed, (b) happy, and (c) full of energy (World Health Organization, 1998). The response options were 1 (*never*), 2 (*on some days*), 3 (*several times per week*), 4 (*almost every day*), and 5 (*daily*). The scale showed good factorial fit, $\chi^2(66) = 69.42$, $p = .363$, CFI = 1.00, RMSEA < .01, 90% CI [< .01, .02], SRMR = .01. Reliability was high, $\omega = .85$.

For negative affect, respondents were asked how often in the last week they felt (a) lonely, (b) aggravated, (c) so depressed, that nothing could lift you up, (d) very nervous, (e) anxious, and (h) glum and sad (World Health Organization, 1998). The response options were 1 (*never*), 2 (*on some days*), 3 (*several times per week*), 4 (*almost every day*), and 5 (*daily*). The scale showed good factorial fit, $\chi^2(471) = 4012.14$, $p < .001$, CFI = .98, RMSEA = .07, 90% CI [.07, .08], SRMR = .03. Reliability was high, $\omega = .91$.

All three variables were measured on each wave.

COVID-19 related social media use

COVID-19 related social media use focused on communication types was measured with the three dimensions of (a) reading, (b) liking and sharing, and (c) posting. The items come from Wagner et al. (2018) and were adapted for the context of this study. The general introductory question was "How often during the last week have you engaged in the following activities on social media?". The three items were "Reading the posts of others with content on the Coronavirus", "When seeing posts on the Coronavirus, I clicked 'like', 'share' or 'retweet' ", "I myself wrote posts on the Coronavirus on social media." Answer options were 1 (*several times per day*), 2 (*daily*), 3 (*several times per week*), 4 (*weekly*), 5 (*never*). The items were inverted for the analyses.

COVID-19 related social media use focused on channels was measured with five variables from Wagner et al. (2018), adapted for this study. The general introductory question was "How often in the last week have you followed information related to the Corona-crisis on the following social media?" The five items were (a) Facebook, (b) Twitter, (c) Instagram, (d) Youtube, and (e) WhatsApp. Again, the answer options were 1 (*several times per day*), 2 (*daily*), 3 (*several times per week*), 4 (*weekly*), 5 (*never*). Again, the items were inverted for the analyses.

Social media use was measured for all participants on waves 1, 2, 8, 17, 23, and 28 (see Figure 1). Freshly recruited respondents always answered all questions on COVID 19-related social media use. Because new respondents always provided data on media use, it was possible to include these data into the analyses. Hence, for the main analyses data from all 34 waves were used. In the additional analyses I tested longer intervals, namely if changes in social media use were associated with changes in well-being either one month of four months later. For these analyzes I used the predictors from waves 1, 2, 8, 17, 23, and 28, to see if they predicted changes in well-being either one month or four months later.

Control variables

The effects of COVID-19 related social media use were controlled for the following stable variables: gender (female, male, diverse), age, education (ten options), Austria country of birth (yes/no), Austria parents' country of birth (no parent, one parent, both parents), and household size. I also controlled for the following varying covariates: five items on current living conditions, including self-reported physical health, whether participants contracted COVID-19 since the last wave, current household income, working in home-office, and overall work hours; nine items measuring use of specific national text-based and video-based news outlets; five items measuring outdoor activities such as exercise or meeting friends; and two more psychological measures including locus of control and disposition to take risks.

Results

Descriptive Analyses

Looking at the variables from a descriptive perspective, aligned with set-point theory we can see that the level of all well-being measures were surprisingly stable during data collection (see Figure 3). COVID-19 related social media use, however, showed changes. Reading, sharing and liking COVID-19 related content decreased substantially (almost one scale point from 3 to 2). Posting about COVID-19 related content stayed the same. Using Facebook and WhatsApp for COVID-19 related content decreased. Instagram, YouTube, and Twitter stayed the same. The general initial decrease could be explained by the fact that the collection of data began at the end of March 2020, hence approximately three months after the pandemic's onset. After an initial uptick, COVID-19 related social media use might have already been declining at the time.

Using the average values across all waves, which provides a stable picture of the general relations, I next looked at the correlations between social media use and well-being

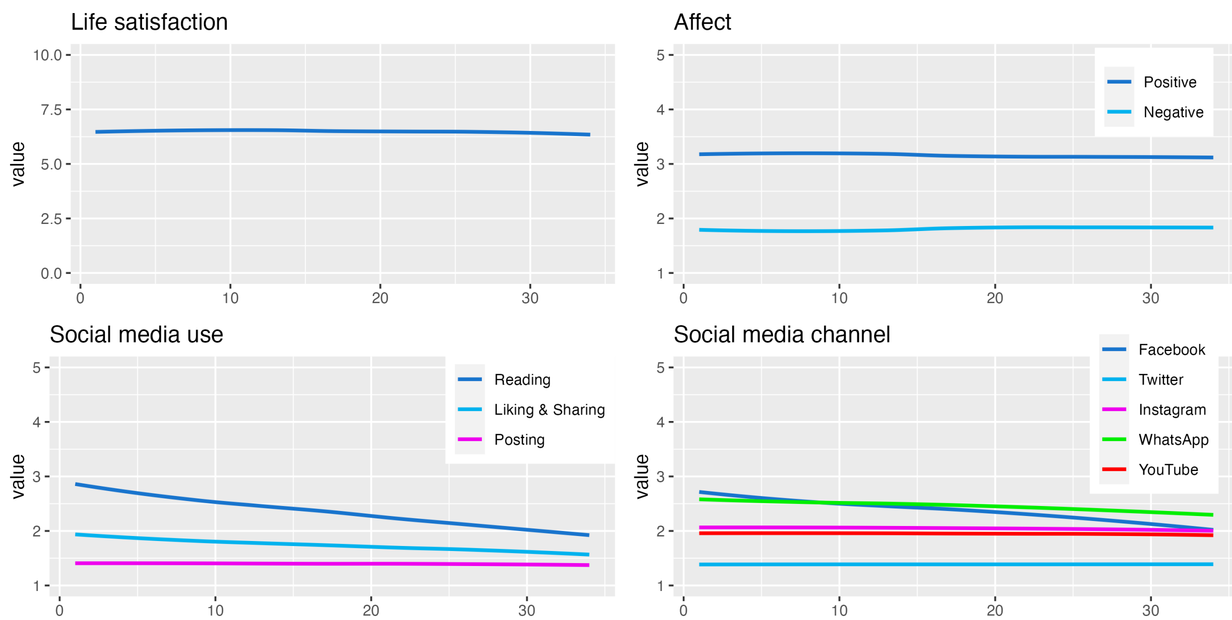

Figure 3

Well-being and media use across the 34 waves. Note. Values obtained from mixed effect models, with participants and waves as grouping factors and without additional predictors.

(see Figure 4). Several interesting patterns emerged. In general, people who spend more time engaging with COVID-19 related content on social media reported reduced well-being. Users who spend more time reading, liking and sharing, and posting COVID-19 related content were less satisfied with their lives. They also showed slightly less positive affect. This overall negative picture was even more pronounced for negative affect. People who engaged more with COVID-19 related content, including all types and channels of communication, reported substantially higher levels of negative affect. For example, people who were more likely to post COVID-19 content had much higher levels of negative affect (r = .61). Note that these results represent between-person correlations, not causal within-person effects.

Preregistered Analyses

The study's main hypothesis was that the causal effects of all types and channels of social media use on all facets of well-being would be trivial. Regarding the effects of

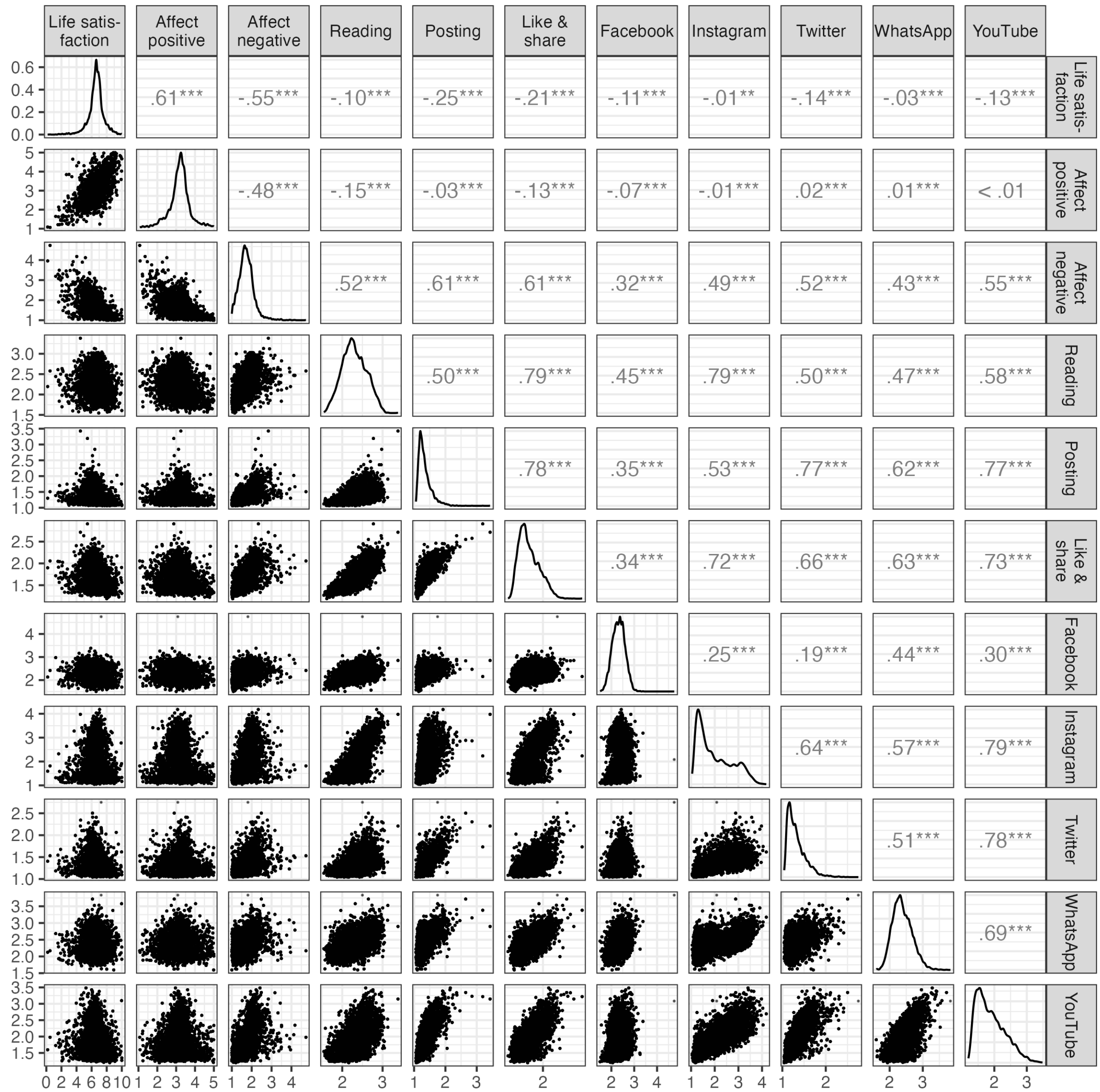

Figure 4

Descriptives of the main variables, capturing well-being and social media use with their average values across all waves. Upper triangle: correlation coefficients; diagonal: density plots; lower triangle: scatter plots.

different *communication types* (i.e., reading, sharing, of posting about COVID-19 related content), all within-person effects fell completely within the a-priori defined null region (see Figure 5). For example, respondents who used social media more frequently than usual to like or share COVID-19 related content did not show a simultaneous change in life satisfaction (b = -0.02 [95% CI -0.06, 0.01]). As a result, the hypothesis of trivial effects was supported for all COVID-19 related types of social media communication.

However, several effects stood out, as statistically they were significantly different from zero. Users who read more COVID-19 related content than usual reported slightly reduced levels of positive affect (b = -0.03 [95% CI -0.05, -0.02]). Users who liked and shared more COVID-19 related content than usual also experienced slightly more negative affect than usual (b = 0.05 [95% CI 0.04, 0.07]). Posting COVID-19 related content affected all types of well-being. Users who wrote more COVID-19 related posts than usual also reported slightly less life satisfaction than usual (b = -0.04 [95% CI -0.08, -0.01]) and slightly more negative affect than usual (b = 0.05 [95% CI 0.04, 0.07]). Interestingly, however, users who wrote more COVID-19 related posts than usual also experienced slightly *higher* levels of positive affect than usual (b = 0.02 [95% CI 0.01, 0.04]).

Regarding the COVID-19 related use of *social media channels* (i.e., Facebook, Instagram, WhatsApp, YouTube, and Twitter) the results were comparable (see Figure 5). Changes in the frequency of using different social media channels to attain information regarding COVID-19 were unrelated to meaningful changes in well-being. For example, respondents who used Facebook more frequently than usual to learn about COVID-19 did not show a simultaneous change in life satisfaction (b -0.01 [95% CI -0.04, 0.02]). In sum, the hypothesis of trivial effects was supported also for the COVID-19 related use of important social media channels.

That said, two effects differed statistically from zero. Respondents who used Twitter more frequently than usual to attain COVID-19 related news reported slightly higher levels of negative affect than usual (b = 0.02 [95% CI 0.01, 0.04]). Likewise, respondents who used YouTube more frequently than usual for COVID-19 related issues reported slightly higher levels of negative affect than usual ($b = 0.01$ [95% CI < 0.01, 0.02]). However, both effects were still completely inside of the null region, hence likely not large enough to be considered meaningful.

For an overview of all within-person effects, see Figure 5.

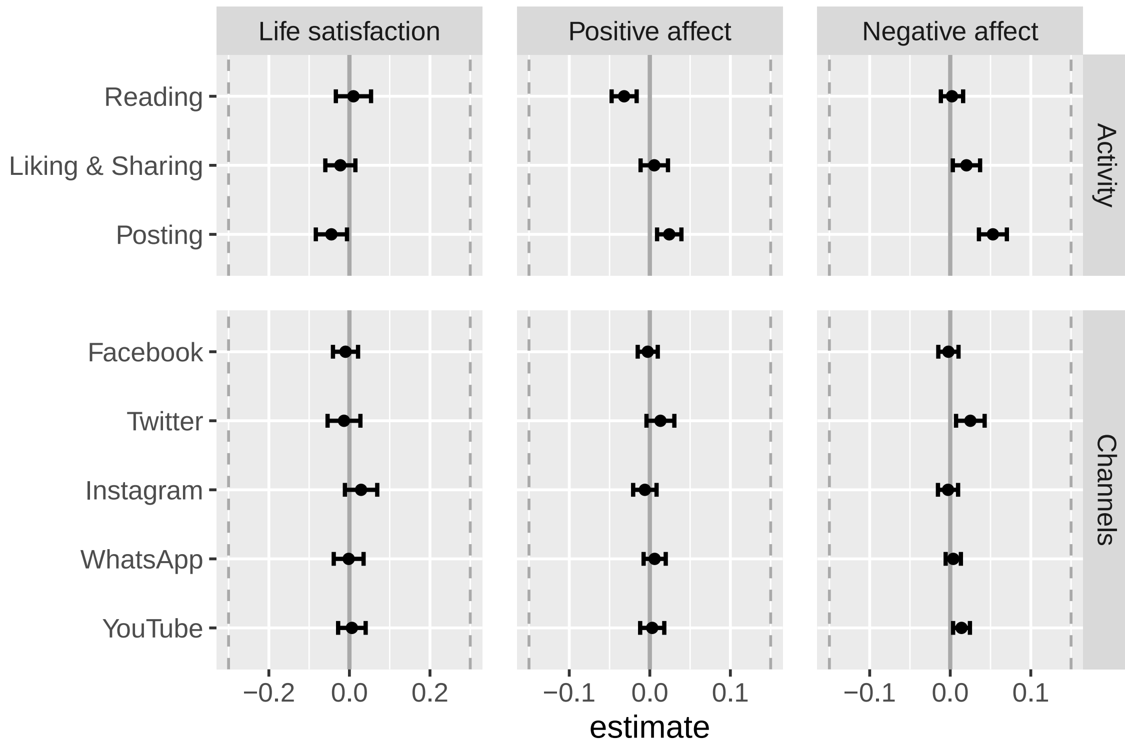

Figure 5

Unstandardized within-person effects of COVID-19 related social media use on well-being. Note. The SESOI was b = |0.30| for life satisfaction and b = |0.15| for affect. Hence, all of the reported effects are not considered large enough to be meaningful.

Exploratory Analyses

To contextualize the results reported above and to see if the study included any meaningful effects at all, I also looked at the effect sizes of the covariates. Because each variable featured different response options, which would require defining a SESOI for each variable, I hence report the results of the standardized scales, which allows for a better comparison across the differently scaled variables. Here, we can build on Cohen's convention that small effects begin at $r = |.10|$.

The results showed that several effects crossed or fell completely outside of the SESOI, and can hence be considered meaningful. For example, if physical health decreased, this had a meaningful detrimental impact on life satisfaction (β = .19 [95% CI .18, .20]), positive affect (β = .18 [95% CI .17, .19]), and negative affect (β = -.19 [95% CI -.20, -.18]). Spending more time outside to exercise meaningfully increased positive affect (β = .12 [95% CI .11, .14]). The strongest aspect affecting well-being was internal locus of control. If people felt more in control of their lives, this strongly increased both life satisfaction (β = .33 [95% CI .31, .35]) and positive affect (β = .28 [95% CI .27, .30]), while decreasing negative affect (β = -.29 [95% CI -.31, -.27]). For an overview, see Figure 6.

Because life satisfaction is more stable than affect, the effects of communication might materialize some time later. I hence also tested the effects across the longer intervals of one month and four months. Results showed that all effects disappeared. No effect remained significant, implying that at least in this case in this case effects take place on a shorter interval.

Finally, as suggested by the differential susceptibility of media effects model, media effects can depend on dispositional factors, developmental stages, or cultural norms (Valkenburg & Peter, 2013), such as gender and age (Orben et al., 2022). I hence reran the analyses, differentiating effects for boys and girls and for age cohorts. The results showed that effects did not differ across genders. The effects also did not depend on age. However, one effect stood out and was significant. Compared to the middle age category Generation X, results showed that if users from Generation Z posted more COVID-19 content than usual this lead to significantly more negative affect (β = .04 [95% CI .01, .06]).

Discussion

This study, based on a representative panel study spanning 34 waves within the Austrian population, investigated the impact of COVID-19-related social media usage on well-being. The between-person correlations revealed that increased engagement with

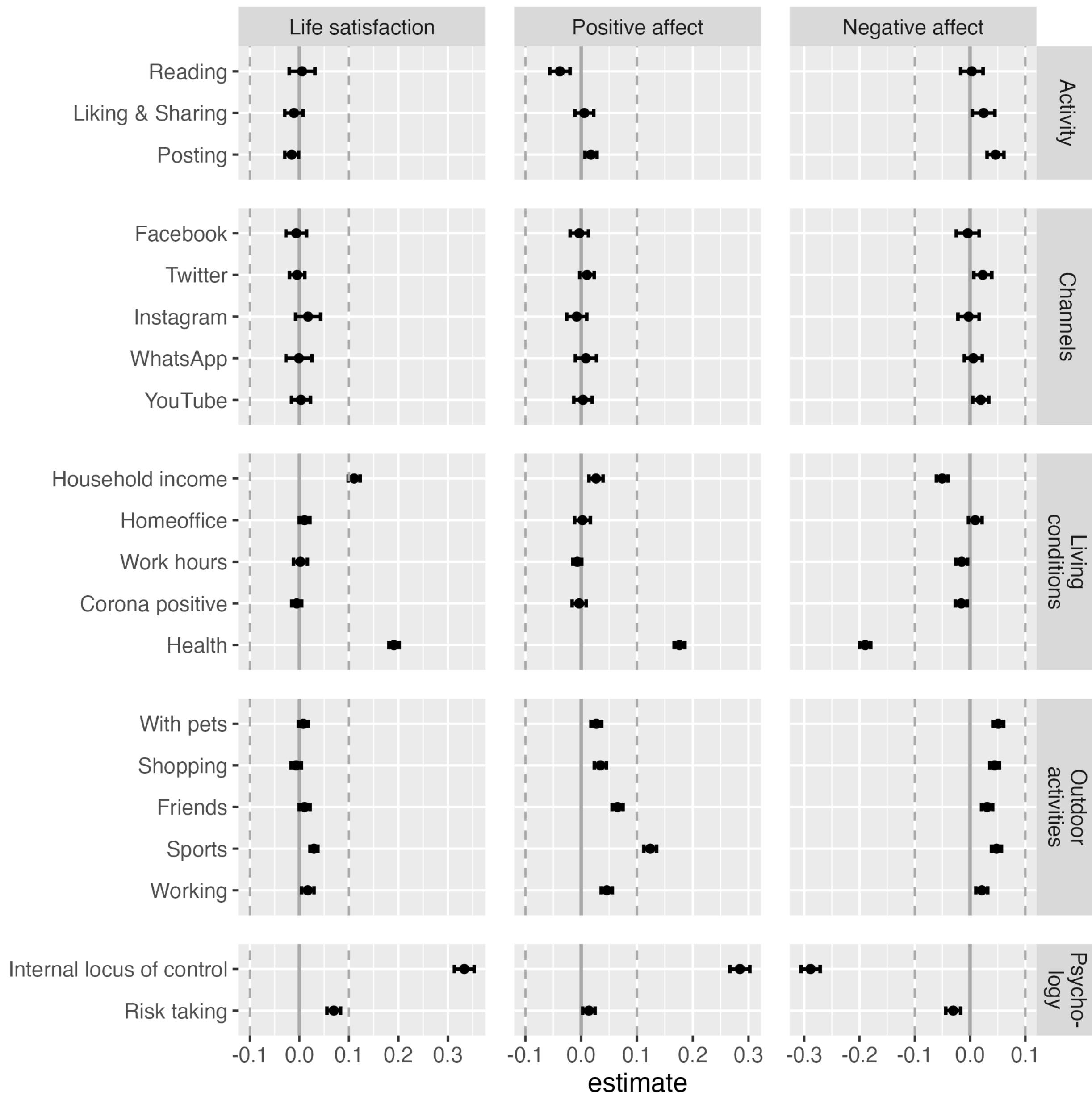

Figure 6

Results of main variables together with covariates to provide context. All variables standardized. SESOI: beta = |.10|

COVID-19 content on social media was associated with decreased well-being. For instance, individuals consuming more COVID-19-related content reported slightly lower life satisfaction, somewhat reduced positive affect, and notably elevated negative affect compared to others.

To explore if these between-person correlations translated into within-person effects, it was examined whether changes in media consumption corresponded with changes in well-being. Contrary to expectations, increased consumption of COVID-19 content did not significantly decrease well-being at a meaningful level. While several statistically significant effects emerged, their magnitudes were notably small. For instance, reading more COVID-19 posts than usual slightly decreased positive affect. Liking and sharing more COVID-19 content than usual were associated with slightly higher negative affect. Posting more COVID-19 content reduced life satisfaction slightly while elevating both positive and negative affect. The effects, although statistically significant, fell within a predefined range considered insignificant.

Further analysis demonstrated that factors such as health and physical activity, which would be expected to have substantial impacts on well-being, indeed showed significant influences. Additionally, extended assessments covering one and four months did not yield meaningful effects. In summary, the influence of COVID-19-related social media activity on well-being was not substantial. This counters popular concerns over excessive social media use during crises causing substantial well-being risks.

There is no consensus among scholars as to when effects become practically relevant and meaningful. If we adopt a more liberal and in cautious perspective, some general trends emerged. The study indicates a tendency for COVID-19-related social media usage to impact well-being negatively more frequently than positively. Notably several small yet statistically significant negative effects were observed, contrasting with a single positive effect. Furthermore, several significant associations were found between social media use and affect but only one with life satisfaction, a more stable measure.

These results align with prior research highlighting that social media usage is associated with elevated negative affect but not reduced life satisfaction [meierComputermediatedCommunicationSocial2020a]. The often extreme, negative, or aggressive tone of COVID-19 discussions on social media (L. Fan et al., 2020) could adversely impact active authors. The negative effects may be explained by the consumption of negative and misleading information.

Moreover, the study suggest that varying communication types and channels warrant separate analyses. For instance, reading content slightly reduced positive affect, while liking, sharing, and posting increased negative affect slightly. Posting COVID-19-related comments increased both negative and positive affect slightly, while reducing life satisfaction. This suggests that posting generates stronger reactions, both positive and negative. Together, this challenges the assumption that active use is inherently beneficial and passive use detrimental (Valkenburg et al., 2022). Notably, communication channels exhibited differences. Twitter and YouTube appeared more negative, whereas Instagram, WhatsApp, and Facebook maintained neutrality. Despite these nuanced findings, the effects remained small.

In conclusion, the study aligns with theoretical models and past research. It supports the notion of small media effects influenced by communication type and channel (Meier & Reinecke, 2020). The differential susceptibility model (Valkenburg & Peter, 2013) was supported, indicating that effects are small and dependent on communication factors. Age did not significantly moderate the effects, yet posting COVID-19 content was more negative for Generation Z, potentially reflecting broader negative effects of social media on this generation. The study also echoes mood management theory (Zillmann, 1988) and the uses and gratifications approach (Katz et al., 1973), implying that if the effects were highly negative, people would not engage with COVID-19 content as extensively.

Despite these insights, limitations exist. While the study's focus on within-person effects enhances causal understanding, challenges related to additional confounding variables (Rohrer, 2018), best definition of the SESOI (Anvari & Lakens, 2021), and exact measurement of media use (Scharkow, 2016). The study's results are applicable primarily to Western societies and may not hold true in different cultural contexts.

The study's findings conclude that COVID-19-related social media activity minimally affects well-being, with other factors playing more substantial roles. In light of these minimal effects, concerns over COVID-19-related social media engagement on well-being appear to be unwarranted.

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Competing Interests

I declare no competing interests.

Supplementary Material

All the stimuli, presentation materials, analysis scripts, and a reproducible version of the manuscript can be found on the companion website (https://XMtRA.github.io/Austrian_Corona_Panel_Project).

Data Accessibility Statement

The data are shared on AUSSDA, see https://doi.org/10.11587/28KQNS. The data can only be used for scientific purposes.

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