No effects of COVID-19 related social media use on well-being

Abstract

In times of crisis such as the Corona pandemic, it is important that citizens stay informed about recent events, the latest political decisions, or mandatory protection measures. To stay informed, many people use various types of media, and increasingly social media. However, because social media are particularly engaging, some find it hard to disconnect and cannot stop 'doomscrolling.' In this preregistered study, I investigate whether using social media for COVID-19 related topics might put personal well-being at risk. To this end, I analyze data from the Austrian Corona Panel Project, which consists of 24 waves with overall 3,018 participants. The data were analzed using random effects cross lagged panel models, controlling for several stable and varying covariates. Results showed that the effects of various types of COVID-19 related social media use on several types of well-being were very small, arguably too small to matter. The findings suggests fears that social media use during times of crisis might be detrimental for well-being are likely to be unfounded.

Keywords: COVID, well-being, affect, life satisfaction, social media use, news use, random effects within between model, panel study, longitudinal

No effects of COVID-19 related social media use on well-being

During the COVID-19 pandemic, numerous events unfolded in quick succession, and several open questions emerged. How dangerous is the virus? Is it spreading in my region? How is it transmitted, and how can I protect myself? Because for many it was (and still is) a matter of life or death, citizens had to stay informed regarding the latest developments. Governments around the world implemented safety measures, ranging from wearing masks or keeping physical distance to complete lockdowns. In this extraordinary situation, people hence used media excessively to stay informed, and especially social media were at an all time high (Statista, 2021). A new phenomenon termed "doomscrolling" emerged: People could not stop using social media to attain COVID-19 related news.

Several people reported that they were glued to their screens and could not pursue other relevant activities such as working, taking a break, or even care-work (Klein, 2021). As doomscrolling increased it became doubtful whether such a surge in social media use could still be considered useful and adaptive, or whether it created an additional and new psychological danger for the users' mental health (Sandstrom, Buchanan, Aknin, & Lotun, 2021). A study with 6,233 people from Germany found that "[f]requency, duration and diversity of media exposure were positively associated with more symptoms of depression and unspecific and COVID-19 specific anxiety" (Bendau et al., 2021), implying negative consequences for well-being.

As a result, with this study I want to build on this research and investigate the question whether COVID-19 related social media use during the pandemic affected the users' well-being. To this end I analyze a large-scale panel study from the Austrian Corona Panel Project (Kittel et al., 2020). The panel consists of 24 waves and an overall sample size of 3018, with at least 1,500 participants per wave, and it is representative of the Austrian population. The panel study collected a large number of variables. Being able to control for many confounding third variables, both stable and varying, together with the longitudinal design creates a unique opportunity to investigate causal effects.

Defining Well-being and Media Use

The underlying theories that guided the selection of variables for this study are the two-continua model of mental health (Greenspoon & Saklofske, 2001) and the hierarchical taxonomy of computer-mediated medation (Meier & Reinecke, 2020). According to the two-continua model of mental health, mental health consists of two dimensions: psychopathology and well-being. Well-being can be differentiated into subjective and psychological well-being (Diener, Lucas, & Oishi, 2018). Whereas subjective well-being emphasizes hedonic aspects such as a happiness and joy, psychological well-being focuses on eudaimonic aspects including fulfillment and meaning. Subjective well-being is primarily about achieving positive affect and avoiding negative affect. On of the most prominent indicators of well-being is life satisfaction. In my view, life satisfaction is a meta concept that combines psychological and subjective well-being and represents a meta-appraisal of one's life. Notably, life satisfaction is stable and fluctuates only little, whereas it's the exact opposite for affect (Dienlin & Johannes, 2020). To capture well-being in this study, I will thus build on life satisfaction, positive affect, and negative affect. Together, this should provide an encompassing perspective on media effects.

The hierarchical taxonomy of computer-mediated communication differentiates six levels of how people engage with digital technology: first, the device (e.g., smartphone); second, the type of application (e.g., social networking site); third, the branded application (e.g., Twitter); fourth, the feature (e.g., status post); fifth, the interaction (e.g., one-to-many); sixth, the message (e.g., content) (Meier & Reinecke, 2020). Whereas the first four levels are focused on the channel, the last two on the type of communication. To measure social media use for consumption of specific news, I here employ both the channel and the communication perspective, which together provides a more nuanced understanding of communication. First, I will analyze how using the most prominent branded applications affect well-being, and whether this effect changes across applications. According to Meier and Reinecke (2020), branded apps are separate entities with different effects. Therefore, Twitter might have a different effect than WhatsApp because of their different affordances. For example, Waterloo, Baumgartner, Peter, and Valkenburg (2018) found that it is more adequate to express negative emotions on WhatsApp than on Twitter or on Instagram. The branded applications investigated here are Facebook, Twitter, Instagram, WhatsApp, and YouTube. But because adopting only this position would be both too narrow and too general, I will secondly also investigate how different types of interaction affect well-being. Specifically, I will differentiate between active and passive use. I will distinguish (a) *reading* COVID-19 related social media use (passive), *posting* content regarding COVID (active), and *liking and sharing* COVID-19 related posts by others (both active and passive). Worth noting, this study is not about *general* social media during times of COVID, but on social media use focused on COVID-19 related news and interactions. Example of such media use include posting about the pandemic or retweeting COVID-19 related posts.

Effects of Social Media on Well-Being

In their study on the relations between media use and mental health during the pandemic, Bendau et al. (2021) found that people who used social media as a primary source of information reported on average "significantly more unspecific anxiety and depression [] and significantly more specific COVID-19 related anxiety symptoms" (p. 288). Hence, this might hint at potential negative effects of social media as news use—but note that this finding comes from a between-person relation stemming from a cross-sectional data (see below). Hence, we don't know whether the differences in mental health and well-being are due to social media use or other third variables, such as age or education. Eden, Johnson, Reinecke, and Grady (2020) analyzed the media use of 425 US college students during the first wave of the pandemic, and found both positive and negative relations with well-being. In a sample of 312 respondents collected via Amazon Mechanical Turk, it was found that people who used media to attain information were more lonely and less satisfied with their lives (Choi & Choung, 2021). Stainback, Hearne, and Trieu (2020) analyzed a large-scale study with 11,537 respondents from the US and found that increased COVID-19 media consumption was related to more psychological distress.

In general, so far there is only little empirical research on news-related social media use and well-being. On the other hand, the question of whether and how *general* social media use—or other, more specific types such as active or passive use—affect well-being is well-researched. A meta review (i.e., an analysis of meta-analyses), found that the relation between social media use and well-being is likely in the negative spectrum—but very small, potentially too small to matter (Meier & Reinecke, 2020). What determines whether an effect is considered trivial or small? If we refer to standardized effect sizes, according to Cohen (1992) small effect sizes start at $r = .10$. And indeed, several if not most meta-analyses find effect sizes below that threshold (Ferguson et al., 2021; Huang, 2017; Meier & Reinecke, 2020).

These overviews are well aligned with several individual new studies that employed the most advanced methods (Keresteš & Štulhofer, 2020; Orben, Dienlin, & Przybylski, 2019; Przybylski, Nguyen, Law, & Weinstein, 2021; Schemer, Masur, Geiß, Müller, & Schäfer, 2021). For example, Beyens, Pouwels, Driel, Keijsers, and Valkenburg (n.d.) reported that although for some users (roughly one quarter) the effects were negative, for almost the same number of users the effects were positive, while for the majority they were neutral. In conclusion, most effects are somewhere between trivial and small. I think it's most convincing to expect trivial to small effects also in the case of COVID-19 related social media use.

From a theoretical perspective, how could we explain how COVID-19 related social media use might affect well-being? In what follows, I outline potential arguments as to why the effect might be positive or negative, direct or indirect. In advance, there does not seem to be a clear winner, and it's likely that both positive and negative effects are equally strong.

First, one could reasonably assume a *direct* negative effect on well-being—especially on positive or negative affect, which is more volatile and fluctuating. Dangers, inequalities, corruption—these were the headlines across many countries worldwide. If one learns about such things, the initial reaction might be shock, fear, or dismay. Repeatedly consuming such news might be depressing, perhaps even changing some general perspectives on life, without any further mediating processes.

That said, because not all news were negative, because many people showed solidarity and compassion, there were also positive and potentially uplifting news.

There could be also indirect effects. When doomscrolling, users are captivated to such an extent that they cannot stop using social media. For example, during the pandemic social media use was at an all-time high in the US (Statista, 2021). As has been expressed by many before, it is most likely that moderate social media use is not detrimental (Orben, 2020). Overuse, however, is more critical, and several studies have shown more pronounced negative effects for extreme users (Przybylski & Weinstein, 2017). Overuse likely impairs well-being if it replaces other meaningful or functional activities such as meeting others, working, actively relaxing, or exercising. So if a society collectively overuses social media, there is potential for negative effects.

On the other hand, one can make the case that overuse can be beneficial *in times of a pandemic*, even if it's mainly COVID-19 related. Exchanging COVID-19 related messages with friends via WhatsApp might replace the in-person contact one would have otherwise, but which is effectively impossible at that time. At times where meaningful and functional activities are explicitly or implicitly prohibited, using social media to exchange about COVID-19 might not be the worst idea. In fact, given that nowadays a large number of experts, scientists, and politicians converse directly on social media, one can get first-hand information on the current developments.

Together, the strongest argument seems to be that *in general* effects of social media on well-being are, on average, small at best. Because this study looks at only *one part* of social media use—namely, COVID-19 related interactions—it is even more focused, and the overall potential of the effects should diminish even further. Whether or not using social media for COVID-19 related aspects is detrimental during a pandemic is also not entirely clear. Therefore, I expect to find that the effects of COVID-19 related news use on well-being will be not be meaningful or practically relevant.

Hypothesis: The within-person effects of all types of COVID-19 related social media use on all types of well-being indicators—while controlling for several stable and varying covariates such as sociodemographic variables and psychological dispositions—will be trivial.

Current Study

Smallest Effect Size of Interest

Testing this hypothesis, however, is not trivial. First, in contrast to most hypothesis typically posited in the social sciences, it implicitly contains an effect size, a so-called smallest effect size of interest (SESOI). Effectively testing this hypothesis hence necessitates to define what's considered a "trivial effect size" and what's not. Above I referred to standardized effect sizes. However, standardized effect sizes should only be a first step toward evaluating an effect's relevance (Baguley, 2009). Standardized effect sizes are determined by a sample's variance.[1] However, this is problematic: The question of whether or not social media use affects me personally in a relevant way should not depend on the variance in the sample in which my data were collected. Instead, it should depend on absolute criteria. What could be a minimally interesting, a nontrivial effect? I suggest the following SESOI for this research question:

[1] Consider the effect size Cohen's *d*: The mean's of the two groups that are to be compared are subtracted from one another and then divided by the sample's standard deviation (Cohen, 1992). Hence, if there is more deviation/variance in a sample, the effect size decreases, even if the difference of the group's means stays the same.

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

What would this mean practically and how could 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, the example from above would imply that a change of four units in social media use should correspond to a noticeable change in well-being. But what's a noticeable change in well-being? According to Norman, Sloan, and Wyrwich (2003), people can reliably differentiate between *seven* levels of satisfaction with health. So we could state that a four unit change in social media use should result in a one unit change in satisfaction. Statistically, in a regression, b estimates the change in the dependent variable if the independent variable increases by one point. Transferred to our example, we would hence expect $b = 1 / 4 = .25$.

In this study, life satisfaction was measured with 11 units, hence more than seven degrees people can reliably differentiate. We hence need to transform a 1-point change on a 7-point scale to an equivalent change on an 11-point scale. This is 11 / 7 = 1.57. Hence, we now expect $b = 1/4 * 11/7 = 0.39$. For affect, which was measured on a 5-point scale, our SESOI would therefore be $b = 1/4 * 5/7 = 0.18$. Because we are agnostic as to whether the effects are positively or negatively nontrivial, the null region will include negative and positive effects (in Bayesian terms, this is called the region of practical equivalence [ROPE]). In order not to exaggerate precision, and to be a bit less conservative, these numbers will be reduced to nearby thresholds. Note that other researchers also decrease or recommend decreasing thresholds for effect sizes when analyzing within-person or cumulative effects (Beyens, Pouwels, Driel, Keijsers, and Valkenburg (n.d.); Funder and Ozer (2019)). Together, this leads to an indifference region ranging from b = -.30 to b = .30 for life satisfaction, and b = -.15 to b = .15 for positive and negative affect.

Causality

The hypothesis explicitly states a causal effect. In non-experimental designs, longitudinal designs help investigate causality. Using longitudinal designs alone, however, is not sufficient for correct causal statements. In addition, we also need to control for third variables, and importantly also for *varying* third variables.

For example, imagine that a person suddenly starts using social media much more than usual, and then at the same time also become less satisfied with their lives. After some time, use recedes again, whereas life satisfaction returns to prior levels. If this happened to several people at the same time, in a longitudinal study we could then find a causal effect of social media use on life satisfaction. However, it could also be the case that during the study there was a major exogenous event (say, a pandemic) and a large part of the working population lost their jobs. Hence, the causal effect reported above was confounded, because in reality it was the pandemic that caused both social media use to rise and their life satisfaction to plummet.

Thus, only if we can control for *all* potential varying third variables, we can correctly estimate causality without any bias (Rohrer, 2018). Obviously, we can never be entirely sure to have included all varying covariates, which makes absolute statements regarding causality impossible. In addition, when determining the overall causal effect, we should *not* control for mediating variables (Rohrer, 2018). Doing so would bias and distort our assessment of the role of social media use. However, when controlling for relevant variables (that aren't mediators), we can be much more certain that we measured causality correctly. The aim should therefore be to collect as many *relevant* varying and nonvarying third variables as possible, while knowing that absolute certainty regarding causality cannot be reached.

When looking for suitable control candidates, ideally we find variables that affect both media use and well-being. Controlling for these factors will isolate the actual effect of social media use on well-being. We can also control for variables that affect *only* well-being. However, in doing so not much is gained or lost because the effects of social media use would remain virtually the same (Kline, 2016).

In this study, I hence plan to control for the following variables, which either have been shown or a likely to affect both social media use and well-being, while not being mediators. Gender, age, education, Austria country of birth, Austria country of birth of parents, text-based news consumption, video-based news consumption, residency Vienna, household size, health, living space, access to garden, access to balcony, employment, work hours per week, being in home-office, household income, outdoor activities, satisfaction with democracy, disposition to take risks, and locus of control. I will not control for variables such as trust in institutions or media, because these variables are likely influenced by social media use.

Next to including covariates, it is now increasingly understood that causal effects need to be analyzed from an internal, within-person perspective. If a specific person changes their media diet, we need to measure how this affects *them*. Between person comparison from cross-sectional data, where participants are interviewed only once, cannot provide such insights. In this study, I will hence differentiate between within-person effects and between-person relations. Because it is explicitly causal, in answering the hypothesis I will thus consider only the within-person effects.

One precondition of causality is temporal order. The cause needs to precede the outcome. To this end, finding the right interval when causes and effects are measured is crucial. For example, if we want to measure the effect of alcohol consumption on driving performance, it makes a big difference if driving performance is measured one minute, one hour, one day, or one week after consumption. Finding the right interval is difficult. If variables are more stable, longer intervals are needed, and if they fluctuate a lot, shorter intervals are necessary. In the case of well-being, to analyze affect we need shorter intervals, while for life satisfaction longer ones. Still, finding the right interval is challenging, because especially short intervals are practically hard to implement and require experience sampling measures (also known as in situ measurement or ambulant assessment).

In this study, I will adopt an intermediate perspective. I will analyze if, when a person changes their social media diet, are there simultaneous changes in well-being? When additionally controlling for both stable and varying covariates, we can then be more sure that the effect is indeed causal. This approach was implemented already by several other studies and is considered one of the best practices to analyze causality.

Method

This section describes the preregistration and how I determined the sample size, data exclusions, the analyses, and all measures in the study.

Preregistration

The hypotheses, the sample, the measures, the analyses, and the inference criteria (SESOI, p-value) were preregistered on the Open Science Framework. The (anonymous) preregistration can be accessed here: https://osf.io/87b24/?view_only=b2289b6fec214fa88ee75a18d45c18f3. Because in this study I analyze data from an already existing large-scale data set, the Austrian Corona Panel Project, all of these steps were preregistered prior to accessing the data. The preregistration was designed on the basis of the panel documentation online (Kittel et al., 2020). In some cases the analyses could not be executed as originally planned, because some properties of the variables only became apparent upon data analysis. The most relevant deviations are reported below, and a complete list of all changes can be found online.

Sample

The data come from the Austrian Corona Panel Project (Kittel et al., 2021). The study was conducted between March 2020 and October 2021. The contains 26 waves, and at the time of writing, the first 24 waves were available for download. Each wave consists of at least 1,500 respondents. The overall sample size was N = 3018, and 72432 observations were collected. Panel mortality was compensated through a continuous reacquistion of new participants. All respondents needed to have access to the internet (via computer or mobile devices such as smartphones or tablets). They were sampled from a pre-existing online access panel provided by Marketagent, Austria. Respondents were asked and incentivized with 180 credit points to participate in each wave of the panel.

The sample was representative of the Austrian population in terms 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 old. The average age was 42 years, 49 percent were male, 3.97 percent had a University degree, and NA percent were currently unemployed.

Because the data were analyzed post hoc, no sample size planning on the basis of a priori power analyses was conducted. The sample is very large, and it is hence well-equipped reliably to detect also small effects, which is why no exact post hoc power analysis were conducted. In addition, because such large samples easily generate significant p-values even for very small effects, this study builds on a smallest effect size of interest. To test the hypotheses, I will use the interval testing approach as proposed by Dienes (2014). On the basis of the SESOI, I will define a null region. For well-being, the null region will be between b = -.30 and b = .30. For example, if the 95% confidence interval lies completely within the null-region (e.g., b = .15, [95% CI: .05, .25]), the hypothesis that the effect is only trivial is be supported. If the effects interval and the null region overlap (e.g., b = .25, [95% CI: .15, .35]), the hypothesis is not supported and the results are considered inconclusive, whereas a meaningful negative effect is rejected. If the confidence falls completely outside of the null-region (e.g., b = .4, [95% CI: .35, .45]), the hypothesis is rejected and the existence of a meaningful positive effect is supported.

Respondents who answered less than 50% of all questions were removed. The remaining missing responses were imputed using predictive mean matching.

Data Analysis

The hypothesis was analyzed using mixed effects models, namely random effect within-between models (REWB)(Bell, Fairbrother, & Jones, 2019). Three models were run, one for each dependent variable. All predictors—that is, social media activities and social media channels, within and between-person factors, stably and varying covariates—were included in each of the three models. The data were hierarchical, and responses were nested in participants and waves (put differently, participants and waves were implemented as random effects). Nesting in participants allowed to separate between-person relations from within-person effects. Nesting in waves allowed to control for general developments, such as general decrease in well-being in the population, for example due to lockdown measures (hence, there was no need additionally to control for specific phases or measures of the lockdown).

For more information on the analyses, see companion website.

Measures

In what follows, I briefly list all variables that were collected. For the variables' means, range, and variance, see Table 1. For a complete list of all items and item characteristics, see companion website.

Well-being. Life satisfaction was measured with the item "Taken everything together, how satisfied are you currently with your life?" The response options ranged from 0 (*extremely unsatisfied*) 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. The response options were 1 (*never*), 2 (*on some days*), 3 (*several times per week*), 4 (*almost every day*), and 5 (*daily*).

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. The response options were 1 (*never*), 2 (*on some days*), 3 (*several times per week*), 4 (*almost every day*), and 5 (*daily*).

All three variables were measured on each wave.

COVID-19 related social media use. The COVID-19 related social media use focused on interaction was measured with three variables (a) reading, (b) liking and sharing, and (c) posting. The general introductory question was "How often during the last week have you engaged in the following activities on social media?" The three items read as follows: "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.

The COVID-19 related social media use focused on channels was measured with five variables. The general introductory question was "How often in the last week have you followed information related to the Corona-crisis in the following social media?" The five items were (a) Facebook, (b) Twitter, (c) Instagram, (d) Youtube, (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 everyone on waves 1, 2, 8, 17, and 23. Freshly recruited respondents always answered the questions on social media use.

Control variables. The effects of COVID-19 related social media use were controlled for the following stable variables: (a) gender (answer options: female, male, diverse), (b) age, (c) education (10 options), (d) Austria country of birth (yes/no), (e) Austria parents' country of birth (no parent, one parent, both parents). I originally planned to implement other variables as varying covariates. However, because they were not measured often enough or at the time when social media use was measured, I implemented them as stable variables using their average values across all waves. This includes (a) text-based media news consumption, (b) video-based media news consumption, (c) residency is Vienna, (d) self-reported physical health, (e) living space (in

Table 1

Descriptives of the main variables.

	sd	min	max	mean
Well-being				
Life satisfaction	1.68	6.39	6.79	6.59
Positive affect	0.57	3.05	3.29	3.15
Negative affect	0.39	1.66	1.81	1.73
Social media use				
Read	1.03	2.09	2.92	2.42
Like & share	0.86	1.61	1.92	1.78
Posting	0.63	1.33	1.47	1.39
Social media channel				
Facebook	0.96	2.34	2.68	2.45
Twitter	0.52	1.16	1.72	1.36
Instagram	0.82	1.85	2.65	2.09
WhatsApp	1.23	2.29	2.62	2.46
YouTube	0.88	1.77	2.32	2.01

squaremeter), (f) access to balcony, (g) access to garden, (h) employment status, (i) disposition to take risks, and (j) locus of control. I controlled also for the following varying covariates: (a) outdoor activities, (b) satisfaction with democracy. Because it lead to too much attrition in the sample, I did not control for (a) household size, (b) work hours per week, (c) home office, (d) household income.

Results

Preregistered Analyses

When looking at the variables from a descriptive perspective, we see that all well-being measures did not change substantially across the different phases of the pandemic. COVID-19 related media use, however, decreased during the beginning of the study and remained stable after approximately six waves. The initial decrease might be explained by the fact that the collection of data began in end of March 2020, hence approximately three months after the pandemic began. It could be that after an initial stark surge, COVID-19 related social media use was already declining, returning to more normal levels.

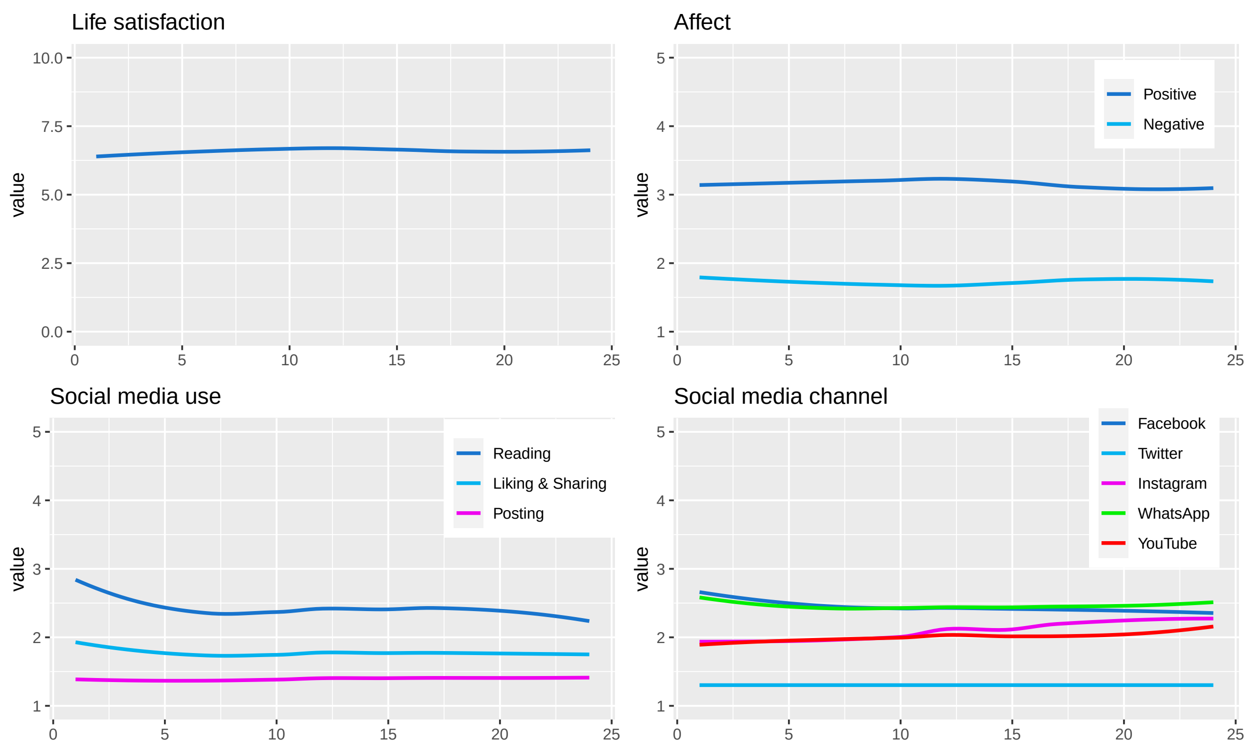

Figure 1. Development of well-being and media use measures across the pandemic. Values obtained from mixed effect models, with participants and waves as grouping factor and without additional predictors.

The study's hypothesis was that the effects of all types of social media use on well-being will be trivial. Regarding the different types of *communication*—that is, reading vs. sharing vs. posting—all within-person effects fell completely within the a-priori defined SESOIs (see Figure 2). For example, respondents who used social media more frequently than usual to read about COVID-19 related topics did not show a simultaneous change in life satisfaction (b = 0.04 [95% CI -0.02, 0.09]). All confidence intervals included zero; hence, all effects were non-significant. As a result, the hypothesis was supported for all types of COVID-19 related social media communication.

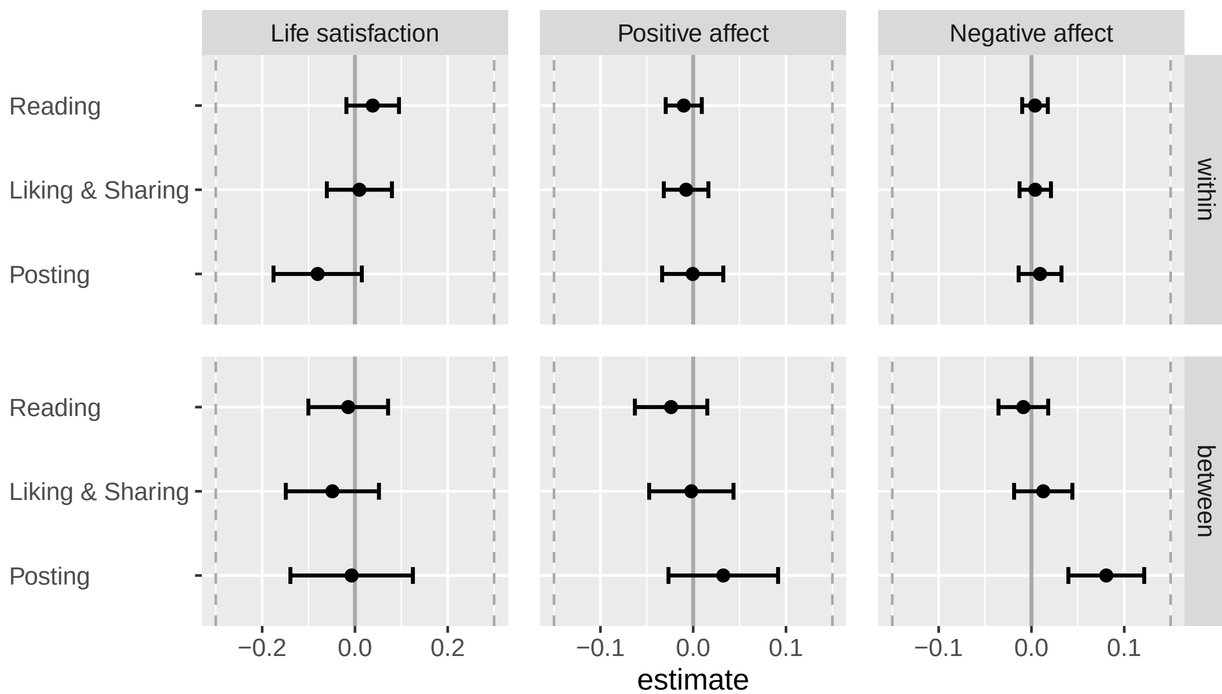

Figure 2. The effects of various types of social media use on three indicators of well-being. Effects are controlled for a large number of covariates (see text). The SESOI was 0.30 for life satisfaction and .15 for affects; hence, no effect is considered meaningful theoretically.

Regarding between-person relations, about which no hypotheses were formulated, only one effect didn't include zero. Respondents who across all waves used social media more frequently than others to write posts on COVID-19 reported higher levels of negative affect than others (b = 0.08 [95% CI 0.04, 0.12]). The effect was still completely inside of the null region, hence likely not large enough to be practically relevant.

Regarding the COVID-19 related use of social media *channels*, the results were very comparable. Changes in the frequency of using different social media channels to attain information regarding COVID-19 were unrelated to meaningful changes in well-being (see Figure 3). For example, respondents who used Facebook more frequently than usual to learn about COVID-19 did not show a simultaneous change in well-being (b = -0.04 [95% CI -0.1, 0.02]). Only two effects differed substantially from zero. Respondents who used Instagram more frequently than usual to attain COVID-19 related news reported slightly higher simultaneous levels of life satisfaction then usual (b = 0.08 [95% CI 0, 0.15]). Respondents who used Twitter more frequently than usual to attain COVID-19 related news reported slightly lower simultaneous levels of life satisfaction then usual (b = -0.15 [95% CI -0.27, -0.04]). However, both effects were still completely inside of the null region, hence not large enough to be considered meaningful. In sum, the hypothesis was supported for the COVID-19 related use of all types of social media channels.

In terms of between-person relations—which, again, weren't included in the hypotheses—no relations crossed or fell outside of the null region. Only one relation did not include zero, was hence statistically significant. Respondents who across all waves used YouTube more frequently than others for COVID-19 related reasons reported marginally higher levels of negative affect (b = 0.03 [95% CI $<$ 0.01, 0.05]). However, please note that this effect was not large enough to be considered practically relevant.

Exploratory Analyses

In what follows, I briefly report also the results of some covariates. Several variables showed large associations with well-being. Because each variable has a different scaling, we would again need to define a SESOI for each variable, which cannot be implemented here. But note that several variables would fall outside of such a SESOI. This includes for example internal locus of control, health, or employment. For a brief overview, see Figure 4.

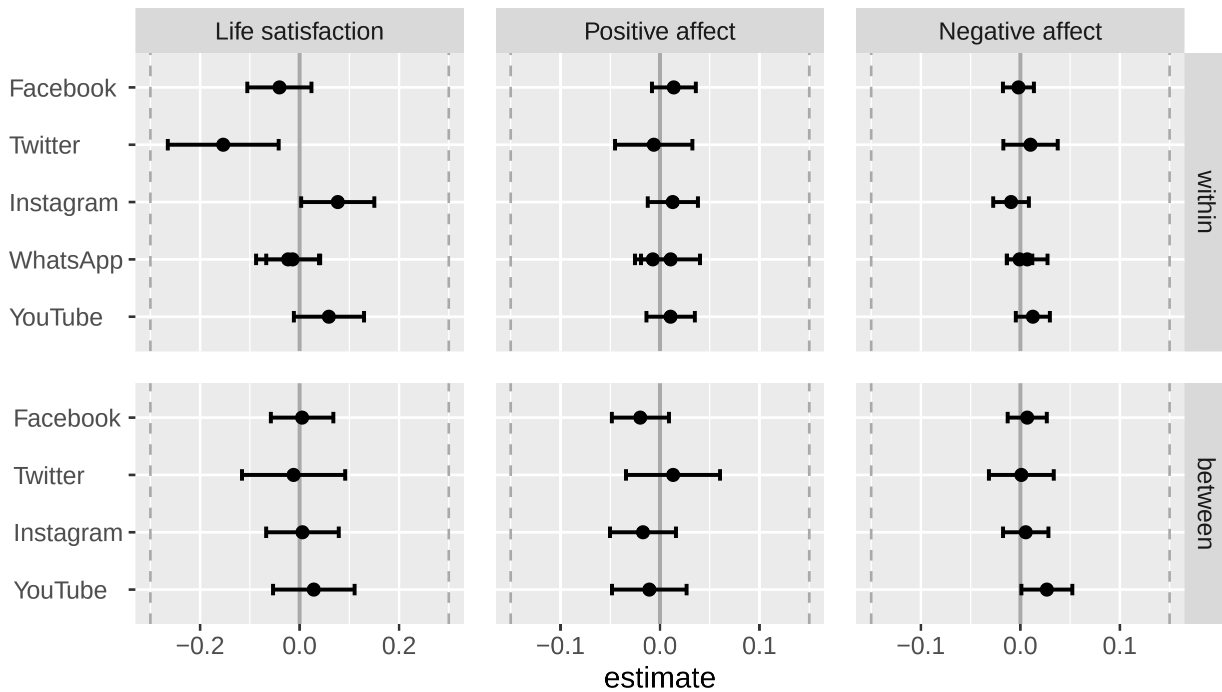

Figure 3. The effects of using various social media applications on three indicators of well-being. Effects are controlled for a large number of covariates (see text). The SESOI was 0.30 for life satisfaction and .15 for affects; hence, no effect is considered meaningful theoretically.

Discussion

In this study I analyzed the effects of COVID-19 related social media use on well-being. The data come from a panel study with 24 waves that is representative of the Austrian population. A random effect model, which separated between person relations from within-person effects and which controlled for several third variables, showed that within-person effects were trivial. People who used social media more than usual to learn about COVID-19 did not show changes in their well-being. As a result, the results imply that COVID-19 related social media use does not seem to be particularly relevant for people's well-being. Other factors among the third variables that were measured revealed larger effects or relations, implying that well-being is rather determined by aspects such as health, employment, or locus of control. According to this study, popular fears that

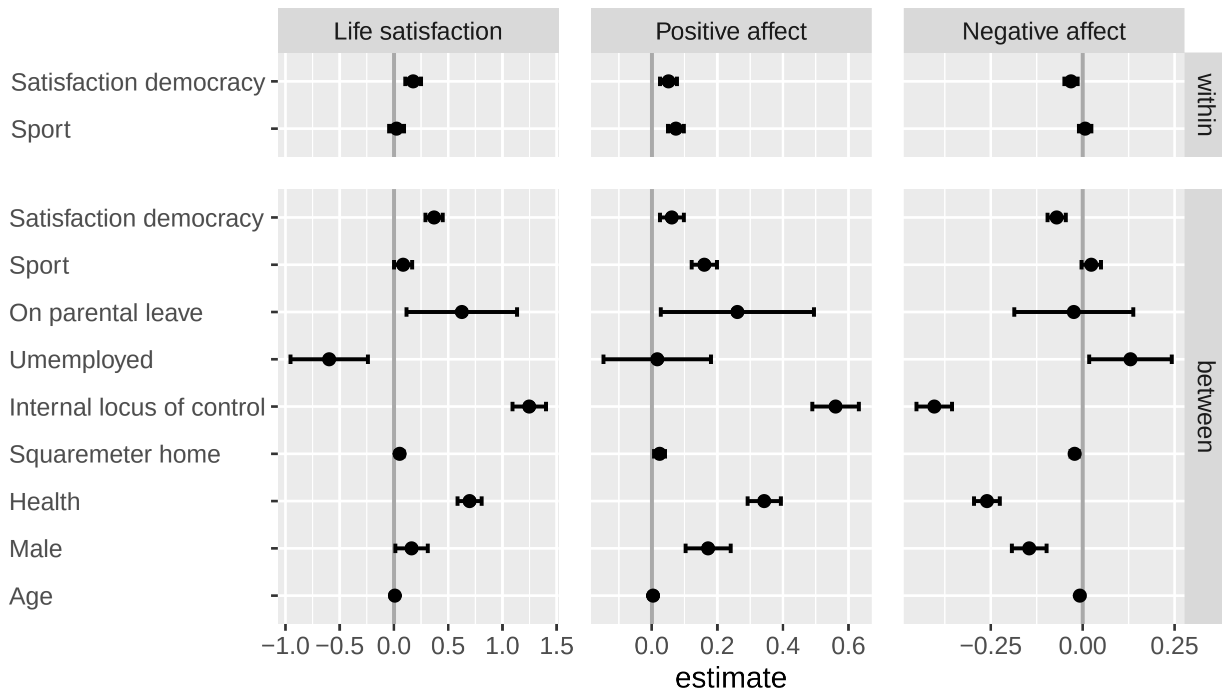

Figure 4. Results of selected covariates.

"doomscrolling" or overusing social media during times of crises do not seem to be justified.

The study is not aligned with a recent cross-sectional study by Bendau et al. (2021), which showed negative relations between social media and well-being. However, Bendau et al. (2021) analyzed cross-sectional data on a between-person level, while not controlling for third variables, which does not allow to make causal inferences. At the same time, this study is well-aligned with recent studies and meta-analyses from related research questions, which found that the effects of various types of social media use on several well-being indicators is small at best, often too small to matter (Ferguson et al., 2021; Meier & Reinecke, 2020; Orben, 2020).

Limitations

The current study analyzed whether changes in media use were related with changes in well-being, while controlling for several potential confounds. Together, this allows for a good perspective on potential causality. That said, causality necessitates temporal order, and the cause needs to precede the consequence. Regarding media use, such effects often happen immediately or shortly after use, necessitating intervals in the hours, minutes, or even seconds. Only experience sampling studies that ask users in the very moment can produce such knowledge. However, even then we don't know for certain if we actually measured the right interval. Hence, to document how effects unfold it needs future research employing different study designs with different time lags. In addition, more thought needs to be invested in what relevant stable and nonvarying factor to control for.

Although I had already reduced the predefined SESOIs to be less conservative, potentially they were still too large. Media use is only one aspect of several factors that simultaneously affect well-being. Is it realistic that extremely changing only *one* of these aspect (e.g., by completely stopping the use of social media) should already manifest in a detectable change in well-being? Or would it make more sense to expect that if people regularly start doing *two* activities (e.g. regularly exercising *and* establishing a reading habit) together should show in perceivable improvements to well-being? In other words, if the beneficial effect of a particular activity is large enough, people should actually feel a difference if they implement two of those activities. Practically, this would imply a SESOI half as large as I have defined here, that is $b = |.15|$ for well-being and $b = |.075|$. In this case, this would not make a difference, as even with these more liberal thresholds all but one effect would still be completely in the null region. However, at all events future research needs to start a discussion on what effect sizes are considered meaningful and relevant, and with this study I hope to provide some first concrete guidelines.

Both media use and well-being were measured using self-reports. Measuring well-being with self-reports is adequate, because it by definition requires introspection. However, it would be preferable to measure social media use objectively, because people cannot reliably estimate their use. That said, objective measures often cannot capture the content or the motivation of the use, and only very complicated tools that record the content that was used (such as the Screenome project) might produce such data. However, also these procedure introduce other problems, for example related to privacy. Hence, for this type of research question it seems necessary still to use self-reported measures.

The generalizability of the results are not large, because the data were collected in a single country. The results are hence potentially limited to the more Western sphere, and might not apply to other cultures, especially if they have a different media landscape or offer alternative social media. That said, because this is a large study, representative of a country's entire population, and because several waves were collected across a large time span, the results should be at least as generalizable as other typical empirical studies collected in the social sciences.

Conclusion

In this study, COVID-19 related social media use did not causally affect several indicators of well-being, including life satisfaction, positive affect, and negative affect. However, factors other than social media use were meaningfully related to well-being, such as physical health, employment, or believing that one is in control of one's life. If it's the aim to improve well-being, it might hence be fruitful not to focus on social media but to address other, potentially more pressing societal problems related to inequality or mental health.

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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/index.html).

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.