Social media and smartphone app use predicts maintenance of physical activity during Covid-19 enforced isolation in psychiatric outpatients

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Abstract

Public health professionals have raised concerns that the social and physical distancing measures implemented in response to the Covid-19 pandemic may negatively impact health in other areas, via both decreased physical activity and increased social isolation. Here, we investigated whether increased engagement with digital social tools may help mitigate effects of enforced isolation on physical activity and mood, in a naturalistic study of at-risk individuals. Passively sensed smartphone app use and actigraphy data, collected from a sample of psychiatric outpatients both before and during imposition of strict lockdown conditions (N=163), were analysed using Gaussian graphical models: a form of network analysis which gives insight into the predictive relationships between measures across timepoints. Within-individuals, we found evidence of a positive predictive path between digital social engagement, general smartphone use, and physical activity – selectively under lockdown conditions. Further, we observed a positive relationship between social media use and total daily steps across individuals during (but not prior to) lockdown. We interpret these findings in terms of individuals using these digital tools to harness online social support structures, which may help guard against negative effects of in-person social deprivation and other pandemic-related stress. Monitoring of these measures is low burden and unintrusive and therefore, given appropriate consent, could potentially help identify individuals who are failing to engage this mechanism, providing a route to early intervention in this and other vulnerable populations.

The novel coronavirus (Covid-19) pandemic is a major public health emergency. Responding to this crisis has required the implementation of unprecedented physical and social distancing measures, including the closure of non-essential businesses, travel restrictions, and stay-at-home and lockdown orders (*1*). As lockdowns become prolonged, researchers have drawn attention to potential negative effects of these measures on health (*2*, *3*), particularly in vulnerable populations (*4*). These potential negative effects are twofold: decreases in physical activity have been related to increased risk for cardiovascular disorders and other chronic health conditions (*5*, *6*), whilst social isolation has been related to increased all-cause mortality and poorer mental health (*7*).

Although social media and smartphone use have been proposed to have negative effects on mood and mental health – the strength and reliability of evidence for this assertion is disputed, and the reality is likely to be more nuanced (*8*, *9*). In particular, it has been suggested that these digital tools may help individuals to foster and maintain social support networks during periods of stress and isolation (*10*). Differences in use of online social and community support resources may therefore significantly influence the extent to which people experience 'social isolation' during enforced physical distancing (*11*). Further, the ability to engage such compensatory mechanisms may be particularly important for individuals likely to be more vulnerable to the effects of enforced isolation – such as those with pre-existing psychological disorders (*12*), and those with other chronic health conditions that may put them at increased risk from Covid-19 exposure (*13*).

Here, we tested the hypothesis that people who experienced greater digital social interaction would be less vulnerable to negative effects of strict social distancing measures imposed during the Covid-19 pandemic. Specifically, we investigated whether increased time spent engaging with social media apps would predict maintenance of higher physical activity levels, pre- *vs* post- imposition of lockdown conditions. To address this question, we analysed passively sensed app use and physical activity (step count) data, collected from a sample of psychiatric outpatients in Madrid, Spain (N=163 users). Data were available both before and after declaration of a national emergency in Spain – to date one of the world's countries most strongly affected by lockdown, in terms of measurable impact on physical activity (*14*, *15*). In a subset of participants (N=54 users), ecological momentary assessment of self-reported emotional state data were also available. This information was used to explore the idea that increased social media use may help protect against negative effects of lockdown-induced isolation on mood – either directly, or indirectly, via increased physical activity.

Data were analysed using a form of vector autoregression, where relationships between measures are represented as Gaussian graphical models (*16*, *17*). This dynamic network-based approach has previously been successfully applied to temporally-ordered data in order to examine which of a set of inter-related variables predict each other at successive timepoints – highlighting potential causal relationships between measures (*18*). Crucially, this method of analysis can be used to identify potential intervention points for users who fail to show adaptive behaviour patterns, and may therefore be at risk of poorer future outcomes (*3*).

Results

Study participants

Study participants are described in **Table 1**. In order to avoid differences in sample characteristics across models, only users who had enough data to contribute to both pre- and post- lockdown network estimates were included in the analysis. Subsequently, data from *N*=127 users (92 female) were used to estimate physical activity and smartphone use networks. The most commonly represented psychiatric diagnosis in the sample was an anxiety, trauma, or stress-related disorder (56%), followed by unipolar or bipolar depression (40%). 28% of participants had a history of suicidal behaviour (suicide attempt or emergency room visit as a result of suicidal ideation). A proportion of users (22%) also had a diagnosis of a medical condition that would put them at increased risk from Covid-19 infection (chronic pulmonary disease, chronic liver or kidney disease, cardiovascular disease, diabetes, hypertension, immunosuppressive disorder, clinical obesity, or cancer) (*13*).

Effect of lockdown on the relationship between physical activity and social media use

The population-level effects of lockdown and associated social distancing measures on daily activity in this cohort are explored in detail elsewhere (*19*). As reported previously, the introduction of these measures had a clear effect on both daily physical activity (decreased total step count) and social media usage (increased time spent using social and communicative apps such as Facebook and WhatsApp), **Figure 1a**. Here, we focus on how within-user changes in social app use were related to future physical activity (step count), and if the relationship between these measures was altered during enforced social isolation (lockdown).

To address this question, passively sensed smartphone use and actigraphy data were analysed using multilevel vector autoregression (VAR) (*17*). A key output of this analysis are Gaussian graphical models referred to as *temporal networks*: directed networks of regression coefficients that identify how well each variable predicts measures in the network across successive (lagged) time points (*16*, *17*). As there were clear effects of lockdown on daily activity levels, and VAR models assume stationarity (constancy of statistical properties over time), networks were estimated separately for the periods before and after declaration of a national emergency in Spain (*20*). Non-social (all other) app use was included in the models in order to account for potential nonspecific relationships between smartphone use and physical activity (as Gaussian graphical models are based on partial correlations, connections between nodes represent relationships that remain after adjusting for the values of all other variables in the network, (*21*)). Results of *between-subjects networks*, which represent the covariation of means across users, are also reported, in order to give insight into individual differences (*17*).

38 time points (days) were included in the pre-lockdown analysis, and 45 timepoints in the post-lockdown analysis. Model comparison was used to compare networks with different degrees of temporal lagging between observations. For both time periods this procedure favoured a 1-lag

model (pre-lockdown, mean Bayesian Information Criterion [BIC] across measures of 4976, compared to 5094 for a 1,2-lag model and 5269 for a 1,2,3-lag model; post-lockdown, mean BIC of 5141, compared to 5229 for a 1,2-lag model and 5417 for a 1,2,3-lag model). The temporal networks presented here therefore represent whether deviations from an individual user's mean for a particular measure on day n predict deviations in the value of other measures on day n+1.

Within-user temporal networks. Temporal networks depicting predictive relationships between changes in smartphone use and physical activity are shown in **Figure 1b**. In the pre-lockdown model, all three nodes had significant positive self-connections (auto-correlations) – indicating that an increase in number of steps taken, social media app use, or non-social smartphone app use on a given day predicted an increase in the same measure on the next day (fixed effect estimates [SE] of 0.176 [0.026], 0.259 [0.024], 0.190 [0.028], respectively; all p<0.001). Significant positive predictive paths also emerged from daily step count to social app use (fixed effect estimate 0.046 [0.019], p=0.014), and from social app use to non-social app use (fixed effect estimate 0.051 [0.023], p=0.030) – suggesting that increases in physical activity tended to predict increases in digital activity the next day (all other connections p>0.3; for full results see **Table S1**). Out-strength, a measure of which variables in the network are most strongly predictive of other network variables at the next time point, was equal for daily steps and social media use (both=0.055), and lower for non-social smartphone use (0.036).

In the post-lockdown model, positive self-connections for each node were still evident (fixed effect estimates [SE] of 0.195 [0.028], 0.361 [0.027], 0.259 [0.025], all p<0.001), but the direction of predictive effects *between* nodes appeared to have reversed. Specifically, the temporal network now revealed a positive predictive path from social to non-social app use (fixed effect estimate 0.088 [0.026], p=0.001), and from non-social app use to daily step count (fixed estimate 0.067 [0.021], p=0.001). There was also a mutually reinforcing loop from non-social back to social app use (fixed effect estimate 0.048 [0.020], p=0.017; for full results see **Table S2**). This suggests that, during lockdown, increased social media use tended to result in increased next day physical activity, via a positively reinforcing loop that included greater general smartphone use. Subsequently, in the post-lockdown temporal network, out-strength was greater for digital than physical activity variables (social app use, 0.104; non-social app use 0.115; total steps, 0.031).

Between-user networks. Between-users networks, representing the covariation of means across participants over all time points, provided further evidence for a relationship between social media use and physical activity levels, that emerged selectively during lockdown (**Figure 1c**). Users who, on average, spent more time engaging with social media apps, also, on average, took more daily steps – only in the *post*-lockdown network (post-lockdown correlation estimate=0.193, p=0.025; pre-lockdown correlation estimate=0.118, p=0.200; see **Table S1**, **Table S2**). The fact that this relationship was evident only in the second model suggests that it is unlikely to be purely the result of an unmeasured covariate that would be common across time periods – such as a tendency for greater physical activity and greater smartphone use in younger participants.

Effect of lockdown on the relationship between physical activity, social media use, and self-reported mood

As entering information about current emotional state was entirely voluntary, self-reported mood data were only available in a subset of users (*N*=54). Across this group, mood tended to be negative (mean emotional valence rating <0; **Figure 2a**), but was more likely to be negative following implementation of lockdown measures (*19*). Following restriction of users to individuals with enough data to be included in both models, *N*=22 users (14 female) provided enough emotional state information to be included in the pre and post lockdown networks for physical activity, smartphone use, and mood. This reduction in sample size is a result of the fact that many users stopped providing emotional state ratings during the lockdown period. As this dropout is unlikely to be at random (e.g., may represent users most psychologically affected by isolation conditions), we consider that users who continued to provide emotion ratings may be unrepresentative of the sample as a whole, and results of this analysis should be interpreted with caution. Demographic and clinical information for the mood subsample is available in **Table S3**.

The pre-lockdown model included 36 time points (days), and the post-lockdown model included 34 time points. Model comparison again favoured a 1-lag model (pre-lockdown, mean BIC across measures for 1-lag model 687, compared to 843 for a 1,2-lag model; higher lag models and >1lag models for the post-lockdown time period were inestimable due to too few observations).

Within-user temporal networks. Temporal networks depicting predictive relationships between changes in physical activity, smartphone use, and self-reported mood are shown in **Figure 2b**. In the pre-lockdown model of users who provided emotion data, only positive auto-correlations between activity measures were evident (total daily steps, fixed effect estimate [SD] of 0.215 [0.080], p=0.007; social app use, 0.241 [0.059], p<0.001; non-social smartphone use, 0.312 [0.062], p<0.001; mean emotional valence, p>0.6). In the post-lockdown model, there was a strong positive predictive relationship between social media use and next day step count (fixed estimate 0.423 [0.183], p=0.020), after adjusting for self-reported mean daily emotional valence. However, at this sample size, there was no strong evidence of increased daily physical activity (steps) predicting increases in mean emotional valence (mood) the next day (fixed effect estimate 0.182 [0.124], p=0.124), or of a direct pathway between physical activity and mood (p>0.5). Full statistics for pre- and post-lockdown networks incorporating mood are available in **Table S4** and **Table S5**.

Between-user networks. Between-user networks are depicted in **Figure 2c**. Similar to the results from the larger sample, after adjusting for covariance with self-reported mood,
there was a significant between-subjects association between physical activity and social media use in the post-lockdown network only (post-lockdown correlation estimate in users who volunteered emotional state information 0.699, p<0.001; pre-lockdown estimate in the same individuals 0.281, p=0.146). There was also a negative relationship between mood and non-social smartphone use, such that users who tended to report more negatively valenced emotions (across each day) also tended to spend more time each day using non-social smartphone apps.

Variable	***N***
Age (mean, SD)	45 (13.9)
Gender	
Male	35 (28%)
Female	92 (72%)
Family Status	
Single	44 (35%)
Separated	19 (15%)
Widowed	6 (5%)
Married or cohabiting for >6 months	58 (46%)
Employment Status	
Full-time student or housework	58 (46%)
Unemployed without subsidy	20 (16%)
Unemployed with subsidy	13 (10%)
Long-term disability	6 (5%)
Temporarily incapacitated	26 (21%)
Retired	4 (3%)
Currently living with children	43 (35%)
Currently living alone	19 (15%)
ICD-10 diagnosis	
Anxiety, stress, or trauma-related disorder	67 (56%)
Mood disorder (unipolar or bipolar depression)	47 (40%)
Personality disorder	23 (19%)
Substance use disorder	7 (6%)
Psychotic disorder	1 (1%)
Other psychiatric disorder	20 (17%)
History of suicidal behaviour	35 (28%)
Diagnosis of a comorbid medical condition that is a risk factor for Covid-19	23 (22%)

Table 1. Demographic and clinical information for the study sample (*N*=127). Data represent *N* and percentage of available data, unless otherwise specified. *N*=7 (5.5%) participants were missing information about psychiatric diagnoses; *N*=21 (16.5%) participants were missing information about medical comorbidities. *ICD-10*, International Classification of Diseases, 10th Edition. Psychiatric diagnosis categories are non mutually-exclusive. History of suicidal behaviour was defined as at least one suicide attempt or emergency room visit as a result of suicidal ideation. Comorbid medical conditions that were considered to place individuals at increased risk from Covid-19 were chronic pulmonary disease, chronic liver or kidney disease, cardiovascular disease, diabetes, hypertension, immunosuppressive disorder, clinical obesity, or cancer.

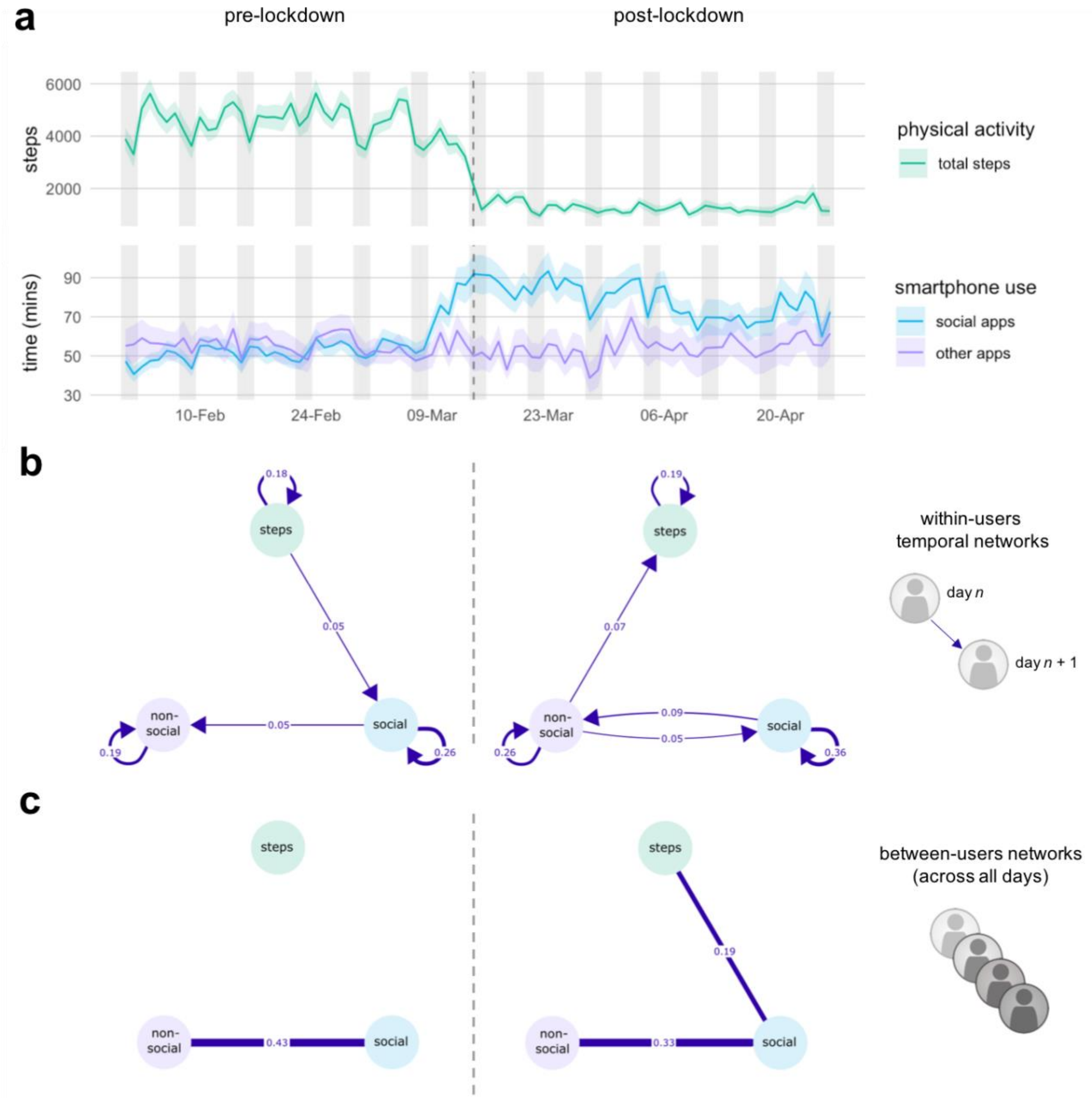

Figure 1. Effect of Covid-19 lockdown on the relationship between physical activity and social media use. a Mean (SE) of daily physical activity (step count), social, and non-social app use, as measured by passive smartphone sensing (eB2 monitoring app). The vertical dotted line represents the declaration of a national emergency (and associated lockdown measures) in Spain on 14/03/20. Vertical shading represents weekends (Saturday and Sunday). **b** Within-user temporal networks, pre- and post- imposition of lockdown conditions. The same N=127 users were included in each model. The pre-lockdown model included 38 time points (days), and the post-lockdown model included 45 time points. Blue lines represent positive predictive values for a given variable on day n on the value of the connected variable on day n+1, in the direction indicated by the arrowhead. Edges (connections between nodes) that do not significantly differ from 0 at alpha=0.05 are not depicted. **c** Between-users networks, representing covariance of means across participants, pre- and post-lockdown (derived from the same data as **b**).

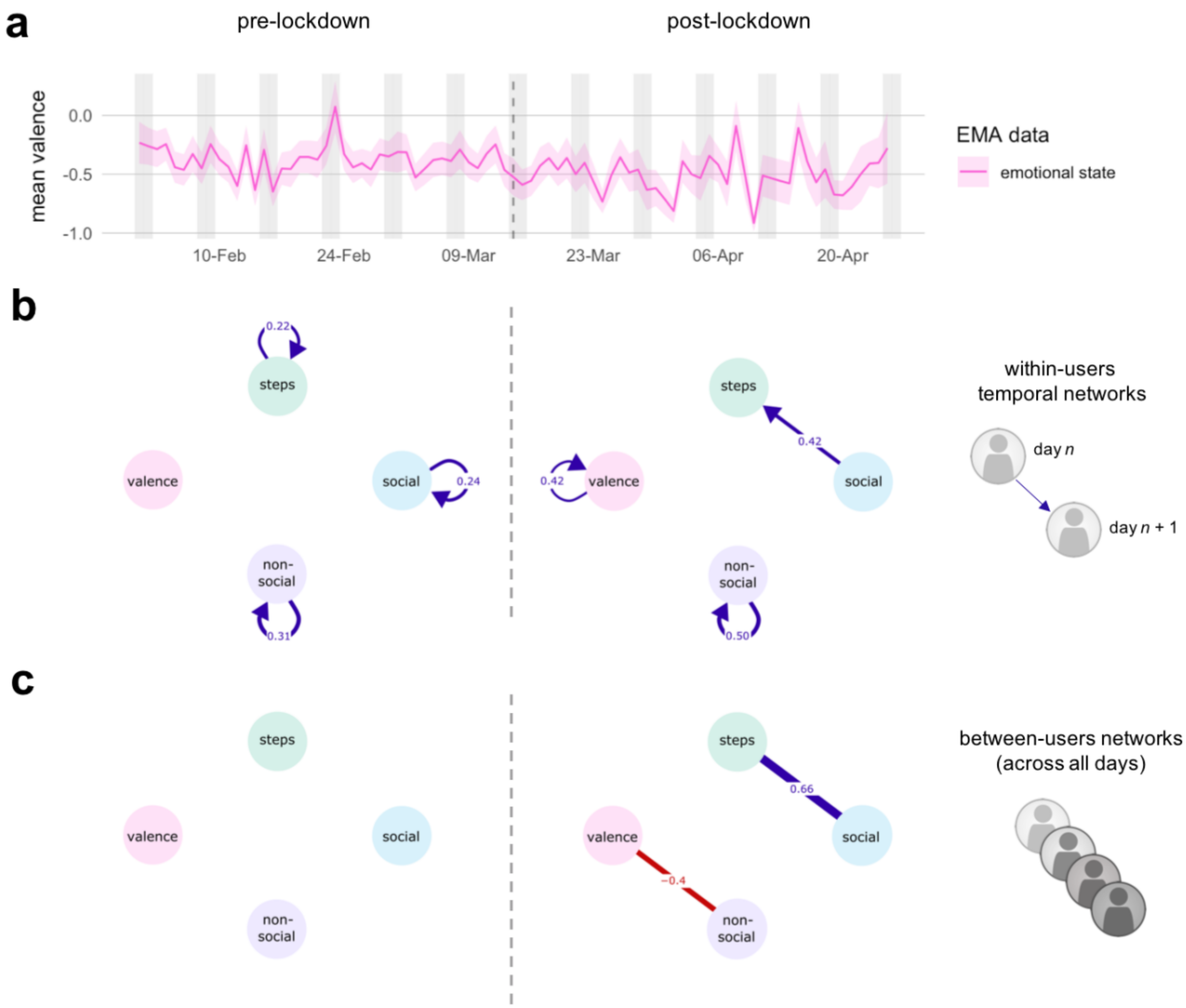

Figure 2. Effect of Covid-19 lockdown on the relationship between physical activity, social media use, and self-reported mood. a Mean (SE) of daily physical activity (step count), social, and non-social app use, as measured by passive smartphone sensing, and ecological momentary assessment (EMA) of emotional state data, as entered by users on an ad-hoc basis in the eB2 monitoring app. The vertical dotted line represents the declaration of a national emergency (and associated lockdown measures) in Spain on 14/03/20. Vertical shading represents weekends (Saturday and Sunday). **b** Within-user temporal networks, pre- and post- imposition of lockdown conditions. The same N=22 users were included in each model. The pre-lockdown model included 36 time points (days), and the post-lockdown model included 34 time points. Blue lines represent positive predictive values for a given variable on day n on the value of the connected variable on day n+1, in the direction indicated by the arrowhead. Edges (connections between nodes) that do not significantly differ from 0 at alpha=0.05 are not depicted. **c** Between-users networks, representing covariance of means across participants, pre- and post- lockdown (derived from the same data as **b**).

Discussion

The findings presented here have implications for gauging the value of social media and smartphone use to psychologically and medically vulnerable individuals during periods of enforced isolation. Within-individuals, we identified a specific pattern of behaviour during lockdown – whereby increased social media and smartphone use on a particular day predicted an increased number of steps recorded by that user the next day. The overall predictive effect of smartphone use variables in the temporal network (out-strength) was greater post- *vs* pre- lockdown, suggesting greater influence on physical activity under social distancing conditions. We also found evidence of a positive relationship between social media use and total daily steps *across* individuals during (but not prior to) lockdown, suggesting that – specifically during social isolation – users who, on average, spent more time using social media also, on average, took more daily steps.

We explain these findings in terms of individuals using these tools to harness online social support structures (*22*), which may mitigate against the negative effects of in-person social deprivation and other pandemic-related stress (*23*, *24*). Specifically, we propose that social interaction promotes engagement in physical activity by guarding against inertia and apathy associated with low mood (*25*, *26*). Possible mechanisms for this effect include stress-limiting effects of information-sharing or co-rumination (talking through problems together with others) (*27*, *28*), positive mood contagion (*29*, *30*), and general mood-boosting effects of social interaction (*31*, *32*). Although we found no strong evidence of a pathway between social media use, physical activity, and increased emotional valence in our EMA sub-sample, this analysis is likely to be severely underpowered, and a positive predictive association between physical activity and mood has been well-established in previous work (*31*, *33*). Importantly, increased physical activity may activate a positive feedback loop, whereby greater activity raises mood and therefore further enhances motivation to continue exercising. Indeed, both full-sample networks contained strong positive self-loops for total daily steps, suggesting that an increase in physical activity on day *n* is robust predictor of greater mean activity on day *n*+1. Other potential explanations for our findings include increased exposure to explicit pro-physical activity messages from trusted information sources (friends and family), or the influence of perceived social norms on the value of active behaviours (*34*).

Previous research has highlighted the importance of maintaining physical activity during periods of isolation, in terms of both physical and mental wellbeing (*2*, *5*, *6*). This is likely to be particularly important for people with pre-existing mental illness, as these individuals are already significantly less likely to meet guideline physical activity levels (*35*, *36*). Here, we present preliminary evidence of a positive path between digital social engagement and physical activity that could potentially be harnessed in other vulnerable populations. Importantly, given users' consent, monitoring of the relationship between social media and physical activity data could potentially help identify individuals who are failing to engage this mechanism, providing a route to early intervention (either via a clinician, or more informally, such as smartphone prompts to engage more with communication apps) (*3*).

An advantage of the data presented here is that it is truly prospective and longitudinal with respect to onset of the Covid-19 pandemic and associated social isolation period. The measures from which our major conclusions are drawn are passively sensed – requiring no active data submission on behalf of the participant – which may help guard against sampling-related biases (e.g. collider bias, (*37*, *38*)), whilst also decreasing measurement error (particularly compared to self-report, which may not be a very accurate measure of true online activity, (*39*)). Further, the sample was representative of the target population (85-87% recruitment rate from the outpatient clinic, (*40*)), and users were behaving naturalistically in the community, free from the influence of perceived experimenter demands.

Our study also has several important limitations. Consistent with previous observations, the predictive (cross-lagged) associations we observed *between* measures were substantially smaller than autocorrelation effects (*18*). Although fixed effect estimates for temporal models reported here were modest, the relatively large standard deviations of the random effects estimates indicate that the strength of these effects may vary significantly across individuals (e.g. fixed effects estimate of 0.088 with random effects SD of 0.159 for social -> nonsocial app use; and fixed effect estimate of 0.067 with random effects SD of 0.079 for nonsocial app use -> step count; Table S2). Unfortunately our sample size did not allow us to break down users by important between-subjects variables such as psychiatric diagnosis, age group, presence of a Covid-19 risk comorbidity, or household status, which might reasonably be expected to affect both baseline behaviour and moderate the impact of lockdown. If and how this pattern varies across these important between-subjects dimensions should be addressed in future research. Further, by focusing on total daily time as the unit of analysis for smartphone use, we may be masking more fine-grained effects of application type and usage patterns – such as differential effects of active communication/information-gathering and more passive browsing styles, which have previously been reported in some groups (*41–43*). Finally, we should employ the usual necessary caution when interpreting results of temporal dependence analyses in a causal manner. For example, it is possible that some unmeasured factor influenced both smartphone use and physical activity with varying time delays, resulting in spurious dependencies between the two (*44*).

In addition to having specific implications for how best to maintain physical and mental health under lockdown conditions, these results contribute to a broader discussion on the role of digital technologies in wellbeing. We second recent calls for a greater emphasis on nuance in this debate, in particular by focusing on longitudinal assessments, and paying greater attention to specific populations and contexts under which phenomena are observed (*45*).

Methods

Data and code availability statement

Data associated with this publication is not freely publicly available due to lack of participant consent for public sharing, but is available upon from the authors upon request. Code used to generate all results described here is available at https://github.com/agnesnorbury/app-use_physical-activity_covid19. Code is accompanied by synthetic data generated using the R package synthpop, in order to facilitate analytic reproducibility (*46*). All statistical analyses were carried out in R, version 3.6.1 (R Core Team, 2019). Version information for packages on which the analysis depended (R sessionInfo() output) is available at the above link.

Participants

Data were drawn from two ongoing studies of psychiatric outpatients in Madrid, Spain that involve remote smartphone monitoring (*47*, *48*). Both studies received ethnical approval from the Institutional Review Board at the Psychiatry Department of Fundación Jimenez Diaz Hospital, and all participants provided written informed consent. Participants were required to be age 18 or older, fluent in Spanish, and to possess a smartphone with internet access. Sociodemographic and clinical information were collected via an electronic health record tool (MEmind; (*49*)). For this analysis, participants were restricted to users with 20 or more days of physical activity data over the relevant time period, in order to enable stable network estimation.

Physical activity and smartphone use data

Physical activity (daily step count) and smartphone use (total time each day spent using applications) were collected using the Evidence-Based Behaviour (eB2) monitoring app (*50*). Following informed consent, the eB2 app was installed on participants' smartphones and configured with the assistance of a physician. After this time, the application passively collected smartphone use and actigraphy data, without requiring further input from the user (users were able to uninstall the app at any point). Social media app use was defined as time each day spent using apps from the 'communication' or 'social' app store categories (*51*). Examples of popular communication apps include WhatsApp, Facebook Messenger, and Gmail. Popular social apps include Facebook, Instagram, and TikTok (*52*). Non-social app use was defined as time each day spent using any other type of smartphone app (e.g., games, tools, travel apps, audiovisual media players).

Emotional state/mood data

In addition to passive activity sensing, users are able to open the eB2 app and enter information about their current emotional state, by selecting from a range of visual icons (see **Figure S1**). Entry of emotional state information was completely voluntary and un-prompted, and therefore was only available for a subset of users and days. As some of the available emotions were infrequently selected, emotions were grouped as positive (happy, delighted, motivated, relaxed), neutral (neutral), or negative (angry, sad, fearful, disgusted, tired, in pain, worried/overwhelmed). Emotions from each category were then scored +1, 0, or -1, respectively, and scores were averaged across each day to generate an index of mean emotional valence ("mood").

Network analysis of social media use and physical activity data

As physical activity and app use data exhibited significant weekly seasonality (lower values at weekends, see **Figure 1a**), these data were first adjusted for 7-day seasonality. Specifically, data were decomposed into weekly seasonal variation, overall trend, and residual time series components using the R function stl (*53*), following which the weekly seasonality component was subtracted from the overall time series. Plots of the mean detrended times series data are available in **Figure S2**. Physical activity, app use, and emotional valence data were also observed to be significantly skewed, and so were transformed prior to network estimation in order to meet assumptions of the Gaussian graphical model (nonparanormal transformation as implemented in function npn from the R package huge, (*54*)). Summary statistics and histograms visualizing the results of this transformation on distributions of observations across users are available in **Table S6**.

Networks were estimated using two-step multilevel vector autoregression (*17*), as implemented in the R package mlVAR, version 0.4.4 (*55*), using a two-step frequentist estimation procedure (mlVAR estimation option lmer). This procedure involves running sequential univariate multilevel regression models on previous measurements, with within-subject centred lagged variables as within-subjects level predictors, and the sample means of all other variables as between-subjects predictors (for full details of this procedure see (*16*, *17*)). This analysis yields three kinds of network: a *temporal network*, which consists of a directed network of regression coefficients between current and lagged variables; a *between-subjects network*, which describes relationships between the stationary means of subjects; and a *contemporaneous network*, which describes relationships within a single measurement occasion, after controlling for temporal effects (*17*). Here, we report findings from the first and second kind of networks, as we are primarily interested in how study variables predict each other over time, and how the extent to which this may vary across subjects. Findings for the third kind of network (contemporaneous) are reported in Supplementary tables for completeness, but are not discussed further. As the number of variables in our networks was small, random effects in temporal networks were allowed to be correlated. Bayesian Information Criterion (BIC) scores were used to compare models incorporating different numbers of time lags, penalized for model complexity. Out-strength was calculated as the absolute temporal edge weights extending out from each node, excluding autocorrelations, as per (*18*).

For clarity, edges that did not significantly differ from 0 at alpha=0.05 were not plotted. For the between-subjects networks, edges (connections between nodes) were considered significant according to an 'and' rule (i.e., only retained if both edges on which a connection was based were significant at alpha=0.05). Networks are depicted using the colourblind-friendly theme included in mlVAR: with positive edges coloured blue, and negative edges coloured red. Edges are drawn with line widths proportional to effect size.

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Supplementary material

Within-user temporal network:

from	to	lag	fixed effect estimate	SE	*p*	random effects SD
steps_total	steps_total	1	0.176	0.026	0.000	0.167
steps_total	social_usage	1	0.047	0.019	0.014	0.074
steps_total	nonsocial_usage	1	0.007	0.021	0.738	0.116
social_usage	steps_total	1	-0.004	0.021	0.837	0.048
social_usage	social_usage	1	0.259	0.024	0.000	0.133
social_usage	nonsocial_usage	1	0.051	0.023	0.030	0.130
nonsocial_usage	steps_total	1	0.016	0.022	0.460	0.046
nonsocial_usage	social_usage	1	0.020	0.022	0.361	0.060
nonsocial_usage	nonsocial_usage	1	0.190	0.028	0.000	0.180

Between-users network:

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.200	0.048	0.141	0.118
nonsocial_usage	steps_total	0.443	0.281	-0.081	-0.023
nonsocial_usage	social_usage	0.000	0.000	0.428	0.422

Within-user contemporaneous network (estimated post-hoc):

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.239	0.325	0.024	0.029
nonsocial_usage	steps_total	0.516	0.386	0.016	0.023
nonsocial_usage	social_usage	0.000	0.000	0.249	0.250

Table S1. Summary of pre-lockdown network analysis relating daily physical activity to smartphone use. *N*=127 participants and 38 time points (days) were included in the model. The temporal network included a 1-timepoint (day) lag for predictive relationships. *steps_total*, total daily step count; *social_usage*, total time spent using social media apps; *nonsocial_usage*, total time spent using any other app, per day; *SE*, standard error; *SD*, standard deviation; *pcor*, partial correlation; *cor*, correlation.

Within-user temporal network:

from	to	lag	fixed effect estimate	SE	*p*	random effects SD
steps_total	steps_total	1	0.195	0.028	0.000	0.216
steps_total	social_usage	1	-0.006	0.015	0.684	0.049
steps_total	nonsocial_usage	1	-0.025	0.018	0.169	0.079
social_usage	steps_total	1	-0.016	0.021	0.454	0.070
social_usage	social_usage	1	0.361	0.027	0.000	0.191
social_usage	nonsocial_usage	1	0.088	0.026	0.001	0.159
nonsocial_usage	steps_total	1	0.067	0.021	0.001	0.079
nonsocial_usage	social_usage	1	0.048	0.020	0.017	0.096
nonsocial_usage	nonsocial_usage	1	0.259	0.025	0.000	0.155

Between-users network:

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.025	0.023	0.193	0.192
nonsocial_usage	steps_total	0.640	0.696	-0.037	0.029
nonsocial_usage	social_usage	0.000	0.000	0.333	0.332

Within-user contemporaneous network (estimated post-hoc):

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.305	0.646	0.016	0.013
nonsocial_usage	steps_total	0.485	0.475	-0.015	-0.011
nonsocial_usage	social_usage	0.000	0.000	0.272	0.272

Table S2. Summary of post-lockdown network analysis relating daily physical activity to smartphone use. *N*=127 participants and 45 time points (days) were included in the model. The temporal network included a 1-timepoint (day) lag for predictive relationships. *steps_total*, total daily step count; *social_usage*, total time spent using social media apps; *nonsocial_usage*, total time spent using any other app, per day; *SE*, standard error; *SD*, standard deviation; *pcor*, partial correlation; *cor*, correlation.

Variable	*N*
Age (mean, SD)	47 (12.0)
Gender	
Male	8 (36%)
Female	14 (64%)
Family Status	
Single	10 (46%)
Separated	1 (5%)
Widowed	1 (5%)
Married or cohabiting for >6 months	10 (46%)
Employment Status	
Full-time student or housework	10 (46%)
Unemployed without subsidy	1 (5%)
Unemployed with subsidy	3 (14%)
Long-term disability	2 (9%)
Short-term disability	6 (27%)
Retired	0 (0%)
Currently living with children	6 (27%)
Currently living alone	6 (27%)
ICD-10 diagnosis	
Anxiety, stress, or trauma-related disorder	10 (50%)
Mood disorder (unipolar or bipolar depression)	10 (50%)
Personality disorder	4 (20%)
Substance use disorder	1 (5%)
Psychotic disorder	0 (0%)
Other psychiatric disorder	4 (20%)
History of suicidal behaviour	8 (36%)
Diagnosis of a comorbid medical condition that is a risk factor for Covid-19	2 (11%)

Table S3. Demographic and clinical information for the sub-sample of participants who provided emotional state data (*N*=22). Data represent *N* and percentage of available data, unless otherwise specified. *N*=2 (9%) participants were missing information about psychiatric diagnoses; *N*=3 (14%) participants were missing information about medical comorbidities. *ICD-10*, International Classification of Diseases, 10th Edition. Psychiatric diagnosis categories are non mutually-exclusive. History of suicidal behaviour was defined as at least one suicide attempt or emergency room visit as a result of suicidal ideation. Comorbid medical conditions that were considered to place individuals at increased risk from Covid-19 were chronic pulmonary disease, chronic liver or kidney disease, cardiovascular disease, diabetes, hypertension, immunosuppressive disorder, clinical obesity, or cancer.

Within-user temporal network:

from	to	lag	fixed effect estimate	SE	*p*	random effects SD
steps_total	steps_total	1	0.215	0.080	0.007	0.218
steps_total	social_usage	1	0.021	0.051	0.675	0.122
steps_total	nonsocial_usage	1	-0.059	0.037	0.111	0.030
steps_total	valence	1	0.004	0.061	0.942	0.166
social_usage	steps_total	1	-0.120	0.087	0.166	0.176
social_usage	social_usage	1	0.241	0.059	0.000	0.086
social_usage	nonsocial_usage	1	0.014	0.079	0.858	0.217
social_usage	valence	1	-0.064	0.073	0.385	0.159
nonsocial_usage	steps_total	1	0.071	0.105	0.495	0.267
nonsocial_usage	social_usage	1	0.014	0.061	0.824	0.087
nonsocial_usage	nonsocial_usage	1	0.312	0.062	0.000	0.101
nonsocial_usage	valence	1	0.155	0.105	0.141	0.331
valence	steps_total	1	-0.076	0.083	0.358	0.156
valence	social_usage	1	-0.087	0.050	0.082	0.018
valence	nonsocial_usage	1	-0.079	0.055	0.149	0.085
valence	valence	1	-0.035	0.068	0.610	0.172

Between-users network:

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.146	0.416	0.242	0.281
nonsocial_usage	steps_total	0.061	0.043	0.390	0.311
nonsocial_usage	social_usage	0.759	0.691	-0.008	0.070
valence	steps_total	0.098	0.009	0.373	0.301
valence	social_usage	0.721	0.980	0.031	0.118
valence	nonsocial_usage	0.272	0.011	-0.330	-0.205

Within-user contemporaneous network (estimated post-hoc):

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.791	0.825	0.004	-0.009
nonsocial_usage	steps_total	0.264	0.164	-0.076	-0.075
nonsocial_usage	social_usage	0.027	0.024	0.166	0.166
valence	steps_total	0.146	0.078	0.088	0.086
valence	social_usage	0.899	0.974	-0.005	-0.002
valence	nonsocial_usage	0.661	0.644	0.025	0.018

Table S4. Summary of pre-lockdown network analysis relating daily physical activity to smartphone use and self-reported mood. *N*=22 participants and 36 time points (days) were included in the model. The temporal network included a 1-timepoint (day) lag for predictive relationships. *steps_total*, total daily step count; *social_usage*, total time spent using social media apps; *nonsocial_usage*, total time spent using any other app, per day; *valence,* mean valence of emotions recorded each day (mood); *SE*, standard error; *SD*, standard deviation; *pcor*, partial correlation*; cor*, correlation.

Within-user temporal network:

from	to	lag	fixed effect estimate	SE	*p*	random effects SD
steps_total	steps_total	1	0.170	0.088	0.054	0.189
steps_total	social_usage	1	0.086	0.078	0.272	0.106
steps_total	nonsocial_usage	1	0.166	0.104	0.111	0.285
steps_total	valence	1	0.182	0.124	0.142	0.442
social_usage	steps_total	1	0.423	0.183	0.020	0.651
social_usage	social_usage	1	0.102	0.126	0.420	0.301
social_usage	nonsocial_usage	1	-0.047	0.102	0.645	0.236
social_usage	valence	1	-0.093	0.143	0.516	0.409
nonsocial_usage	steps_total	1	0.121	0.109	0.267	0.205
nonsocial_usage	social_usage	1	0.077	0.167	0.645	0.420
nonsocial_usage	nonsocial_usage	1	0.500	0.120	0.000	0.229
nonsocial_usage	valence	1	-0.013	0.205	0.948	0.642
valence	steps_total	1	-0.015	0.090	0.869	0.195
valence	social_usage	1	0.056	0.081	0.490	0.120
valence	nonsocial_usage	1	0.137	0.094	0.145	0.224
valence	valence	1	0.246	0.120	0.040	0.341

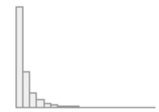
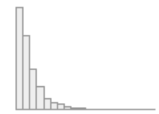
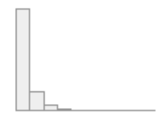
Between-users network:

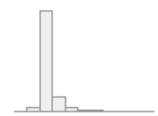
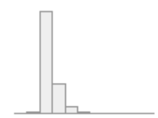
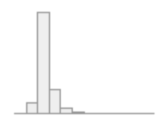
variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.000	0.000	0.658	0.699
nonsocial_usage	steps_total	0.060	0.110	0.233	0.348
nonsocial_usage	social_usage	0.916	0.095	0.090	0.318
valence	steps_total	0.006	0.852	0.162	0.039
valence	social_usage	0.521	0.742	-0.029	-0.024
valence	nonsocial_usage	0.048	0.003	-0.400	-0.366

Within-user contemporaneous network (estimated post-hoc):

variable 1	variable 2	*p* 1->2	*p* 1<-2	pcor	cor
social_usage	steps_total	0.106	0.138	0.155	0.101
nonsocial_usage	steps_total	0.009	0.024	-0.227	-0.189
nonsocial_usage	social_usage	0.001	0.037	0.262	0.233
valence	steps_total	0.391	0.600	0.068	0.035
valence	social_usage	0.791	0.671	-0.050	-0.008
valence	nonsocial_usage	0.200	0.188	0.148	0.130

Table S5. Summary of pre-lockdown network analysis relating daily physical activity to smartphone use and self-reported mood. *N*=22 participants and 36 time points (days) were included in the model. The temporal network included a 1-timepoint (day) lag for predictive relationships. *steps_total*, total daily step count; *social_usage*, total time spent using social media apps; *nonsocial_usage*, total time spent using any other app, per day; *valence,* mean valence of emotions recorded each day (mood); *SE*, standard error; *SD*, standard deviation; *pcor*, partial correlation; *cor*, correlation.

variable (raw data)	values	histogram
nonsocial_usage	mean (SD) : 3294.6 (5047.1) min < med < max: 0 < 1622 < 39007 IQR (CV) : 3059 (1.5)	
social_usage	mean (SD) : 3982.3 (4169.5) min < med < max: 1 < 2789 < 40000 IQR (CV) : 3956 (1)	
steps_total	mean (SD) : 2883.4 (3896) min < med < max: 0 < 1306 < 50000 IQR (CV) : 4028 (1.4)	

variable (seasonality adjusted)	values	histogram
nonsocial_usage	mean (SD) : 3395.5 (4976.8) min < med < max: -6302.5 < 1823.5 < 41484.7 IQR (CV) : 3047.4 (1.5)	
social_usage	mean (SD) : 4082.4 (3977.3) min < med < max: -5903.5 < 2974.5 < 43668.4 IQR (CV) : 3858.1 (1)	
steps_total	mean (SD) : 3006.7 (3691.4) min < med < max: -6047.6 < 1784.1 < 48854.4 IQR (CV) : 4107.9 (1.2)	

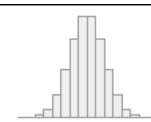
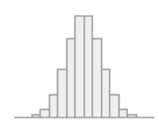
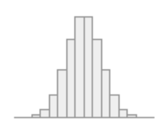
variable (seasonality adjusted and npn transformed)	values	histogram
nonsocial_usage	mean (SD) : 0 (1) min < med < max: -3.7 < 0 < 3.7 IQR (CV) : 1.3 (171180499863974752)	
social_usage	mean (SD) : 0 (1) min < med < max: -3.7 < 0 < 3.7 IQR (CV) : 1.3 (168302943547881888)	
steps_total	mean (SD) : 0 (1) min < med < max: -3.7 < 0 < 3.7 IQR (CV) : 1.3 (211267341144909664)	

Table S6. Effects of 7-day seasonality adjustment and nonparametric normal (npn) transformation on distribution of physical activity and smartphone use measures across users. Tables generated with R package summarytools. *steps_total*, total daily step count; *social_usage*, total time spent using social media apps; *nonsocial_usage*, total time spent using any other app, per day. *IQR*, interquartile range; *CV*, coefficient of variation (relative standard deviation)

Figure S1. Representative screenshots from the eB2 app. Left, screen showing daily activity summary data available to the user. Right, interface for ecological momentary assessment of emotional state within the app. Participants were able to open the app and enter information about their current emotional state at any point (as frequently or infrequently as they wanted), by selecting the relevant face icon (emoji). In the version of the app used for data reported here, the available emotions were happy, delighted, motivated, relaxed, neutral, angry, sad, fearful, disgusted, tired, in pain, and worried/overwhelmed. NB, for this study, all app text was in Spanish, therefore English terms represent approximate translations (Spanish language labels were *feliz, encantado, motivado, relajado, neutro, ira, tristeza, asustado, disgustado, cansado, dolor, agobiado*).

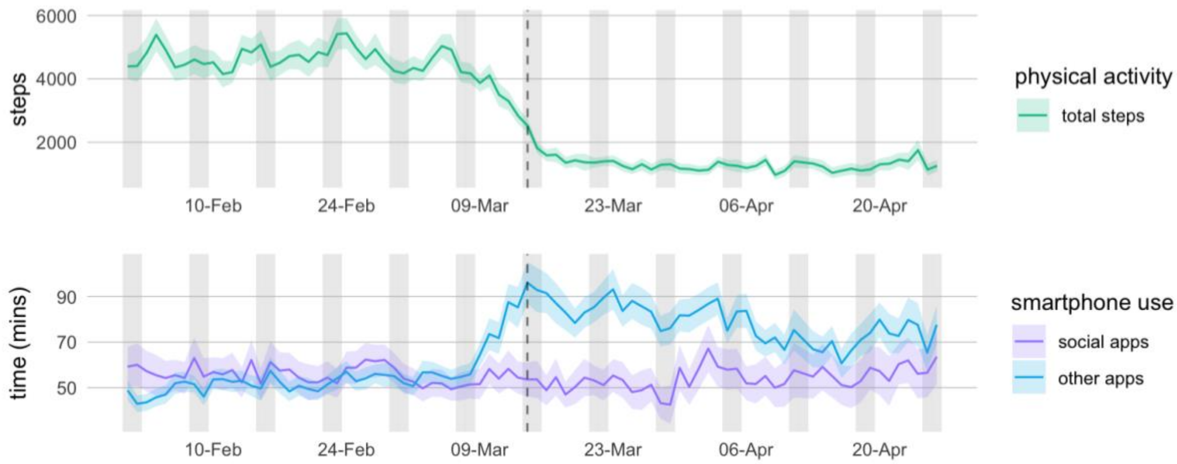


Figure S2. Physical activity and smartphone use data, following adjustment for weekly seasonality. Data represent mean (SE) of daily physical activity (step count), social, and non-social app use, following removal of the 7-day seasonality time series component. The vertical dotted line represents the declaration of a national emergency (and associated lockdown measures) in Spain on 14/03/20. Vertical shading represents weekends (Saturday and Sunday).