Title: The influence of working-from-home and digital device use on sleep, physical activity, and wellbeing following COVID-19 lockdown and reopening.

Stijn A. A. Massar^{1†}, Alyssa S.C. Ng^{1†}, Chun Siong Soon¹, Ju Lynn Ong¹, Xin Yu Chua¹, Nicholas I. Y. N. Chee¹, Tih Shih Lee², & Michael W. L. Chee^{1*}

¹ Sleep and Cognition Laboratory, Centre for Sleep and Cognition, Yong Loo Lin School of Medicine, National University of Singapore

² Laboratory of Neurobehavioral Genomics, Neuroscience and Behavioral Disorders Programme, Duke-NUS Medical School, Singapore

[†] These authors contributed equally.

* Corresponding Author

Michael W.L. Chee, Centre for Sleep and Cognition, Yong Loo Lin School of Medicine, 12 Science Drive 2, National University of Singapore, Singapore 117549.

Email: michael.chee@nus.edu.sg.

Abstract

The COVID-19 pandemic imposed massive changes to daily lives worldwide. While lockdowns arrived abruptly, the continuation of social-distancing measures like working from home could have longer-term influences. We longitudinally tracked lifestyle behaviors (sleep/physical activity/phone use) and mental wellbeing through lockdown and reopening in Singapore. Earlier sleep and increased physical activity benefited from offices reopening for in-person work. However, this was offset by higher stress and poorer mood. Changes were proportional to the degree of hybrid work adoption. Counter to expectation, smartphone usage did not decrease after reopening, and usage around bedtime increased marginally. Cluster analysis showed that while heavier bedtime smartphone use was associated with later sleep initiation and lower physical activity, intermediate bedtime usage was associated with more favorable wellbeing indicators. As hybrid work arrangements and expanded e-device use will likely persist during the pandemic and its aftermath, our findings could inform strategies on adapting to new societal norms.

Introduction

Social and mobility restrictions instituted to stem the spread of COVID-19 drastically altered the daily routines of individuals across the globe. Remote work and education have presented clear challenges, but also potential benefits in an era of vastly enhanced technology enabled work and social connectivity¹⁻³. Home confinement led to marked reductions in physical activity, with daily step counts dropping from close to the recommended 10,000/day to nearly half⁴⁻⁶. On the other hand, working from home has resulted in more flexible work schedules with less and less time spent on routine activities, such as commuting^{7,8}. This increased flexibility has contributed to shifts in sleep habits, resulting in later sleep timing and longer sleep duration⁹⁻¹³. Furthermore, with face-to-face communication severely limited, people have turned to digital technology to stay connected for social interaction, work/education, and entertainment¹⁴⁻¹⁷. Many of these acute changes were associated with a negative impact on health and mental wellbeing¹⁸⁻²².

In contrast to the abruptness of lockdowns, the process of reopening has generally been more gradual and protracted. Often measures to contain the spread of infection have been kept in place, even after lifting of strict lockdowns^{23,24}. Over the past year, it has become increasingly clear that there will be no quick resolution to the pandemic, and the need for intermittent restriction measures may persist for an extended duration^{25,26}. In this light, it is important to collect longitudinal data to evaluate health behavior and wellbeing outcomes over time, identify potentially mitigating and exacerbating factors, and formulate effective intervention strategies.

In this study, we objectively tracked lifestyle behaviors (physical activity, sleep, and phone use), and collected wellbeing data from a sample of students and working adults through the periods of lockdown (April-May 2020) and reopening in Singapore (June-July 2020). Data was collected through a combination of wearable, smartphone tracking, and ecological

momentary assessment (EMA) technology, to obtain detailed insights into the longitudinal changes over time. In particular, this allowed us to examine the impact of reopening after lockdown.

In short, our results showed that after lifting of the lockdown, lifestyle patterns shifted partially back towards commonly reported pre-pandemic patterns (i.e. shorter but earlier sleep, higher daily step count). However, this shift was accompanied by a deterioration in mood and increased stress. Daily reports of participants' work/study location after reopening showed that changes in sleep, physical activity and mood were most pronounced for those who worked more days outside the house. Participants who did not return to office/campus, however showed a sustained pattern of late sleep and low step count. Furthermore, smartphone use was not reduced after reopening. Rather, a small increase in pre-bedtime phone use was observed. Cluster analysis of pre-bedtime phone usage revealed how this behavior could predict sleep timing, physical activity, and wellbeing.

Results

One hundred and ninety-eight participants were recruited from a university population (staff: $N = 78$, students: $N = 120$, $M_{\text{age}} = 26.15 \pm 5.83$ years, 61 male), and enrolled during the Singapore COVID-19 lockdown (April-May 2020). Participants were studied for 8 to 16-weeks, during which they provided daily sleep, activity, and phone use records through a wearable device (Oura ring) and a phone usage tracking app (passively tracking touch-screen interactions and screen on/off events). They also provided twice daily self-reports of wellbeing (stress, mood), and thrice weekly self-reports of loneliness, through phone-based ecological momentary assessment (EMA). Participants were enrolled in batches over the course of 4 weeks, covering part of the lockdown and the subsequent reopening periods. For this report, analyses span the periods of 27 April-31 May (Lockdown), and 1 June-13 July (Post-lockdown).

Effects of reopening on lifestyle and well-being

We first evaluated changes in sleep, physical activity, well-being, and technology usage associated with the reopening period (See Supplementary Table 1 for details). Upon reopening, physical activity increased from an average of 5819 daily steps during lockdown to 7055 daily steps post-lockdown (mean Δ : +1135.6 steps/day; $p=0.001$). For sleep, the average bedtime and wake time advanced from lockdown to post-lockdown (bedtime Δ : -14.1 min; wake time Δ : -27.1 min, p 's <0.001). Time-in-bed (TIB) and total sleep time (TST) decreased from lockdown to post-lockdown (TIB Δ : -14.4 min; TST Δ : -11.4 min, p 's <0.001), resulting from larger advances in wake times than in bedtimes. The difference between weekend and weekday sleep timing increased (mean Δ : 7.9 min; $p=0.001$). Separately, sleep quality increased slightly but significantly from 2.56 points to 2.64 points (on a scale of 0 to 4; $p<.001$). Daily total

smartphone usage (total screen unlock time over 24-hours) was not significantly different between the lockdown and reopening periods (~5.7h/day), while smartphone use at bedtime was slightly increased from 27.51 minutes (in the hour before bedtime) during lockdown, to 28.32 minutes post-lockdown ($p = .036$). Concurrently, self-reported stress (reported twice daily in the daytime and evening via EMA on a scale of 0-100) increased after reopening by 4.13 points in daytime ratings, and by 3.64 points in evening ratings (p 's<0.001). Average mood score (reported on a scale of 0=Very negative to 100=Very positive) was significantly worsened at reopening only for evening ratings ($p<0.01$). No significant changes in loneliness were observed in self-reported loneliness ratings.

The effect of work arrangements during reopening

Several studies have indicated that the impact of lockdowns on daily routines was dependent on the work arrangements during lockdown (i.e. whether individuals were confined to work-from-home arrangements, or if they continued to work in-person)^{27,28}. Remote work may allow individuals to schedule (work and personal) activities more freely, increasing individual autonomy. However, workers may also feel socially disconnected or experience an increased claim on their time as work-life boundaries are blurred^{29,30}. Here, daily work arrangements upon reopening were assessed using EMA (see Figure 1 A). Over the first six weeks after reopening, most participants reported to work in-person (on campus or in office) some proportion of time (N=113), whereas a about a third continued to work-from-home fully (N=61). Of the participants who returned to their workplaces, N=58 reported to work in-person less than 50% of the time, while the other N=55 worked in-person on a majority of working days (>50%; see Figure 1B).

An additional twenty-four participants reported no working days during the post-lockdown period and were excluded from further analysis.

To examine the effects of returning to in-person work arrangements, we performed regression analyses for the sleep, physical activity, and wellbeing variables as dependent variables, and the proportion of on-campus/in-office work versus work-from-home days as a predictor (controlled for demographics: age, gender, student/staff; see Supplementary tables 2 and 3). The proportion of days worked in-person was associated with significantly earlier sleep timing (bedtime $B = -.66$, $p = .011$; wake time $B = -.90$, $p = .003$), but not with total sleep time or social jetlag (p 's $> .50$). More in-person work was also associated with increased daily step count ($B = 1911.81$, $p = .009$). While individuals working more in-person reported slightly worse morning and evening mood (morning $B = -5.76$, $p = .043$; evening $B = -5.467$, $p = .044$), no associations with other wellbeing variables were found.

Figure 1. The effect of Timeseries of lifestyle variables over the lockdown and post-lockdown periods, stratified by the proportion of days worked-from-home. A) Daily work location reports collected through ecological momentary assessment (EMA), B) Time series of physical activity and sleep over the lockdown and post-lockdown period. Data split by work location 100% work-from-home, < 50% work in-office, > 50% work in-office for visualization purposes. C) Number of valid recordings per day over lockdown and post-lockdown periods. Lines represent the daily average, shaded areas represent standard error of the mean.

The effect of phone use on sleep, physical activity, and wellbeing

We next evaluated the impact of smartphone usage on health and wellbeing. A high level of digital media usage during the pandemic has been associated with increased stress and anxiety^{20,31,32}. Furthermore, device usage near bedtime in particular, may negatively affect sleep related

health outcomes³³. On the other hand, digital devices are often the sole means to maintain social connection and offered a vital source of information and entertainment³⁴⁻³⁶, potentially offsetting the negative effects. As we observed a slight increase in phone usage after reopening around bedtime, we set out to further examine bedtime phone use patterns and their associations to sleep, activity, and wellbeing.

First, we created temporal profiles by quantifying each individual's active average phone usage across time, starting 3 hours before and ending 1 hour after their bedtime (in 10-minute time bins). Next, we performed a cluster analysis (k-means clustering), to identify common profiles of pre-bedtime phone usage patterns (for lockdown and post-lockdown separately). Three distinct profiles were observed (see Figure 2A). Cluster 1 ($N_{\text{lockdown}} = 73$, $N_{\text{post-lockdown}} = 56$) was characterized by low amounts of phone usage throughout the period before bedtime (see Figure 2B). Cluster 2 ($N_{\text{lockdown}} = 72$, $N_{\text{post-lockdown}} = 85$) showed moderate levels of phone usage at the start of the night, which ramped up in the hour before bedtime. For Cluster 3 individuals ($N_{\text{lockdown}} = 52$, $N_{\text{post-lockdown}} = 56$), high levels of phone usage were observed across the night. Examining specific types of apps used, Cluster 2 and 3 primarily showed an increase of social media, and browser apps towards bedtime, while Cluster 1 showed consistent low usage across all apps (See Supplementary Figure 1).

Regression analysis, controlling for demographics and work arrangements, indicated that these different bedtime phone use clusters were associated with differences in sleep timing, physical activity and wellbeing (See Figure 2C-E and Figure 3). Individuals with low bedtime phone usage (Cluster 1) had earlier wake times during lockdown ($09:25\text{AM} \pm 01:30 \text{ hh:mm}$) compared to high bedtime phone users (Cluster 3: $10:08\text{AM} \pm 01:49 \text{ hh:mm}$, $p = .015$; see Supplementary tables 4 & 6 for details). Post-lockdown, these differences between clusters were

maintained for wake time (Cluster 1: $08:43 \pm 01:36$ hh:mm, Cluster 3: $09:37 \pm 02:00$ hh:mm, $p = .010$)) as well as bedtime (Cluster 1: $01:09\text{AM} \pm 01:27$ hh:mm, Cluster 3: $01:55\text{AM} \pm 01:37$ hh:mm, $p = .012$).

Individuals with low phone usage profiles logged more physical activity, both during lockdown (Cluster 1: 6253 ± 4029 steps, Cluster 3: 5040 ± 2544 steps, $p = .029$), and post-lockdown (Cluster 1: 8438 ± 5221 , Cluster 2: 7111 ± 2971 , $p=.020$; Cluster 3: 6552 ± 3087 , $p = .009$).

Figure 2. Bedtime phone usage profiles during lockdown and post-lockdown, with A) Heat plot indicating peri-bedtime phone usage, identifying three distinct clusters of phone usage profiles, B) cluster average timeseries of bedtime phone usage, C) bedtime, D) wake time, and E) physical activity. Error bars represent standard error of the mean.

Mental wellbeing however, showed a different pattern (see Figure 3; Supplementary tables 5 & 7). Of interest, the cluster with intermediate phone usage, ramping up towards bedtime (Cluster 2) was associated with better mood in the evening both during lockdown (Cluster 1: mean = 55.14 ± 14.04 ; Cluster 2: mean = 59.23 ± 11.28 , $p = .045$) and post lockdown (Cluster 1: mean = 53.41 ± 14.06 ; Cluster 2: mean = 58.69 ± 12.53 , $p = .025$), as well as less loneliness post-lockdown (Cluster 1: mean = 36.93 ± 21.47 ; Cluster 2: mean = 28.41 ± 20.17 , $p = .025$). As similar pattern for post-lockdown evening stress rating did not reach significance (Cluster 1: mean = 46.96 ± 16.76 ; Cluster 2: mean = 40.07 ± 22.18 , $p = .075$). This pattern of results suggests that some phone use before bedtime might be beneficial.

Figure 3. Wellbeing variables during lockdown and post-lockdown showing differences between phone use clusters. Error bars represent standard error of the mean.

Is the observed shift in sleep timings desirable?

Previous studies have speculated that shifts to later sleep timings found during the lockdown compared to a pre-lockdown baseline may be the result of increased flexibility of work schedules arising from remote working arrangements, thereby enabling individuals to follow their own preferred sleep schedule³⁷. To probe this, participants were invited to report their preferred sleep timings in response to the question in our fourth week survey: *If you could choose your sleep schedule freely, what would be your... ideal bedtime/wake time/sleep duration?*

Responses were moderately correlated with the corresponding average actual observed sleep timings across the lockdown period ($r = .54$, $p < .001$) as well as reopening period ($r = .52$, $p < .001$; Figure 4a & b), suggesting that this measure was effective in capturing individual variations in preferred sleep timing. However, objective observed sleep timings tended to be delayed relative to participants preferred sleep timings, both during the lockdown ($t(175) = 13.88$, $p < .001$) as well as after reopening ($t(175) = 10.75$, $p < .001$). While this delay was reduced during reopening ($t(175) = 5.52$, $p < .001$), it remained significant, suggesting the persistence of social factors apart from lock-down related work-from-home arrangements that delay actual sleep timings relative to preferred times.

*Figure 4. Comparison of objectively observed sleep timing versus self-reported preferred sleep timing. (a) Scatter plots of observed mid-sleep times against preferred sleep time in lockdown and (b) post-lockdown (dashed line indicates equality). (c) Discrepancy between observed and preferred mid-sleep time. *** $p < .001$. Error bars represent standard error of the mean.*

Discussion

Increased physical activity, and earlier and shorter sleep upon reopening after lockdown, reflect a partial reversal of the robust lockdown-related changes in lifestyle as reported in a rapidly growing literature^{4,5,9,10,12,18,28,38,39}. Interestingly, smartphone usage was not significantly reduced upon reopening and there was also a slight increase in experienced stress, and a worsening of evening mood. Shifts in physical activity, sleep, and wellbeing across the sample were associated with the degree to which individuals returned to in-person work after lockdown, as well as patterns of peri-bedtime phone use.

Upon reopening, the majority of participants reported varying hybrid mixtures of in-person work and working-from-home, while a third continued to fully work-from-home. This heterogeneity in work arrangement is likely reflective of the phased reopening strategy that was adopted by the Singapore government (mandating continued remote work where possible in the first weeks after reopening)⁴⁰. We found a clear relationship between the proportion of days worked from home versus in-person and lifestyle factors. Sleep timing and daily step count returned towards more normal values for those individuals who reverted to in-person work most frequently. In contrast, participants who maintained working from home showed little change in activity and sleep timing after reopening.

Pandemic related lockdowns have revealed how much going to work influences habitual physical activity and sleep. A recent population survey demonstrated that commute and work-related activities strongly contribute to total daily physical activity in Singaporean adults (44.5% and 30.0% respectively, versus 25.5% for leisure time physical activity)⁴¹. Such commute and work-related physical activity may have beneficial long-term health effects (e.g. reduced obesity risk)^{42,43}. Our data also concur with reports that working from home (versus in-person work) is associated with later sleep timing^{27,28}. As daily schedules are less strongly dictated by office hours when working from home, time for other activities such as sleep could be more flexibly allocated³⁷. This may be beneficial for health as the observed sleep patterns under less constrained schedules might reflect the individual's biological tendencies³⁷. However

late sleep schedules, in general, are associated with negative health outcomes, and may reflect misalignment with natural night-day rhythms, due to reduced exposure to social and natural time cues^{11,28,44}. It is worth noting that in our data nearly all participants indicated that under ideal circumstances they would prefer to sleep earlier than they typically did.

Given the observed effects of working from home on physical activity and sleep, it will be key to closely monitor the long-term progression of these behaviors, and to devise recommendations and programmes to counteract negative wellbeing outcomes of these sustained behavioral patterns. Globally, the pandemic forced hundreds of millions of city dwellers to work-from-home. As the situation unfolds, many countries have experienced delays in reopening and/or multiple cycles of lockdown and reopening^{23,24}. Technological viability and economic considerations have led businesses to further embrace remote work arrangements and down-scale on physical office space. It is therefore expected that various hybrid work forms may remain in place for an extended duration, even after the pandemic is over^{45,46}.

A second set of findings is that patterns of smartphone usage were closely associated with sleep timing and physical activity. E-device use, especially around bedtime, can disrupt sleep by displacing time allocated to sleep, increasing pre-sleep arousal, and suppressing circadian sleep drive⁴⁷. The use of objective smartphone tracking allowed us to extract detailed temporal profiles of phone usage. Our cluster analysis confirmed that heavier phone usage around bedtime was associated with later sleep and wake timing. These associations persisted (and were even stronger) after reopening. Furthermore, heavier pre-bedtime smartphone usage was associated with lesser physical activity, both during lockdown and after reopening. From these findings it seems that heavy smartphone use is indeed associated with unfavorable health behaviors. When looking at self-rated wellbeing indicators however, a different picture emerged. Individuals who showed an intermediate pattern of phone usage, peaking near bedtime, reported better mood, and lesser loneliness compared to light phone users.

Taken together, these data suggest that there could be both disadvantages and benefits to pre-bedtime smartphone usage. Heavy bedtime usage may be a risk factor for delayed circadian timing and be related to low physical activity. However, moderate usage may be beneficial to mental wellbeing. While there has been much focus on the negative aspects of smartphone use, the smartphone can also be a vital tool in accessing information and maintaining social connectivity when communities are physically separated ^{48,49}. Moreover, access to online entertainment can help people to wind down after a day of work/study ⁵⁰. The finding that, prior to bedtime, time spent on social media, video, and browser apps most strongly increased, indeed suggests such leisurely usage. In practice, it is likely that the reliance on digital devices will only grow in the near future. In our data, we did not observe a reduction in phone usage after reopening (despite marked increases upon initial lockdown instatement, as documented in prior research) ^{15,16,18}. In order to arrive at effective and practicable recommendations, it seems necessary to take a more balanced approach, weighing both the positive and negative effects ⁵¹.

Several limitations of the current study should be noted. First of all, data were based on a convenience sample of University students and employees. As such, results may not be representative for the wider population. Our study sample contained a relatively high percentage of students (60.6%), and relatively more females (69.2%) than males (30.8%). Furthermore, most participants were single or married without children (93.9%), precluding a comparison of effects between individuals with and without parental caregiving duties ⁵². Importantly, the Singapore lockdown was announced before study recruitment was initiated. Therefore, no pre-lockdown data were collected in this study for comparison. However, highly consistent lockdown-related lifestyle changes have been documented across different populations and countries ^{5,53-55}. Prior studies in Singapore confirm these lockdown effects in wider samples of working adults and children ^{12,56}. As the pandemic situation has naturally impeded data collection from human subjects, much research has relied on survey data ⁵⁷. By combining objective tracking of activity, sleep and phone data, with participants' self-report through ecological momentary

assessment, the current study provides longitudinal insights, while minimizing reporting biases associated with (retrospective) surveys responses ^{14,58-61}

Conclusion

The current data shows a complex pattern of changes in lifestyle and wellbeing after lockdown measures were lifted involving shorter and earlier sleep, increased physical activity but also increased stress. These changes reflect a partial reversal of the lockdown-related changes as reported elsewhere. The addition of daily work location and phone use data uncovered persistent, heterogenous effects of residual mobility restrictions on sleep, activity, and wellbeing underscoring the utility of multimodal longitudinal behavioral data in informing strategies to better cope with an extended pandemic and its aftermath.

Methods

Ethics declaration

All procedures conducted were approved by the Institutional Review Board of the National University of Singapore (NUS-IRB Ref Code: N-20-039), and all participants signed written informed consent before commencing the study.

Participants and procedure

A total of 200 young adults, working or studying at the National University of Singapore or working at the National University Hospital of Singapore, were recruited via online platforms to participate in an 8 to 16-week observational study. Participants joined the study in four batches separated by 1-week intervals during the circuit breaker. The present report examines data collected from each participant's enrollment (April 2020) until the sixth week, post-lockdown (13th July 2020), which encompasses the transition from lockdown to the gradual easing of mobility restriction measures at post-lockdown. All participants were observed for a minimum of 2 weeks during lockdown, and a minimum of 3 weeks post-lockdown.

Participants were briefed on study procedures remotely via a short instructional video, after which consent was obtained electronically. Participants were emailed instructions to install the smartphone applications (Oura app, Z4IP ecological momentary assessment app [EMA], phone monitoring app [TapCounter, Quantactions GmbH⁶²]) onto their primary mobile device, and received a sleep and activity tracking device (Oura ring, sized by ring finger measurements provided by the participant) via courier. Over the study period, participants were instructed to wear the ring at all times and to complete short questionnaires and cognitive assessment games

on an EMA application twice daily. To motivate compliance, participants could earn 10 dollars per week for logging the minimum of 4 days of data on the study applications, with an additional \$20 bonus paid to them upon completion of the study. Feedback was provided each week on their progress.

Every 4 weeks, participants were invited to complete a standardised online survey. Participants responded to questions about their work hours, daily routines, causes of stress, and comfort of the wearable trackers over the previous four weeks.

Ethical approval for all study procedures was obtained from the National University of Singapore Institutional Review Board.

Sleep metrics

Wearable based sleep measures were extracted daily from the commercial Oura ring (Oura, Health Oy, Oulu, Finland). This device tracks users' heart rate, temperature changes, and movement through photoplethysmography sensors, temperature sensors and an accelerometer. As per the proprietary Oura algorithm, sleep information was extracted from Oura's cloud API. A minimum of 3 hours was required for Oura's sleep identification.

Daily self-reports of sleep timings and ratings of sleep quality on a 5-point Likert scale (0=Very poor to 4=Very good), were also collected through a phone-based ecological momentary assessment (EMA) application (Z4IP). A third measure of sleep timing was derived from an application which recorded participant's screen interactions and thus mobile device

usage (tappigraphy) throughout the day. These were used to corroborate sleep and wake timings obtained using the Oura ring, and are not reported here, however.

In the survey administered at the 4th week of study, participants were additionally asked to provide their ideal sleep timings (bedtime, wake time and sleep duration), were they free to choose their sleep schedule.

Well-being and performance

Participants rated their levels of stress and mood twice daily (once in the morning and once in the evening), and loneliness thrice a week (once in the evening every Monday, Thursday, and Saturday) in response to a short questionnaire administered on the EMA phone application. Responses were collected on a rating scale of 0 to 100 (0=Not at all, 100=Very much for stress and loneliness scales, 0=Negative and 100=Positive for mood scale). In conjunction with the morning questionnaire, participants completed a short set of three cognitive assessments daily: 3-min psychomotor vigilance test, dot memory test, and symbol search test (adapted from ⁶³). Data from these tests are not presented here.

Work location

For the lockdown period, participants were asked to report their work arrangements in the survey administered at the 8th week of the study. At the end of the lockdown, a new question was included in the EMA short questionnaire enquiring participants work location on that day (*“From what location did you work/attend lessons today?”*). Responses were obtained daily to

account for varying work arrangements across employers and the flexibility with which students and staff were allowed to return to their workplaces. Participants could select from the four options: 'Home', 'Office/hospital/university', 'Others' or 'Did not have to work/attend lessons'. In the present analyses, the two categories: 'Office/hospital/university' and 'Others' were collapsed into one.

Mobile device usage

Smartphone usage was measured using a smartphone application which tracked touchscreen interactions and screen on/off events, as well as the name of the active application (TapCounter by QuantActions GmbH, Lausanne, Switzerland, www.quantactions.com)⁶². This application operates passively in the device background. Each touchscreen interaction is recorded as a timestamped event along with the active app on the user's screen at the point of the touch.

Information about total screen unlock time, considering all screen unlock till lock events with a minimum of one detected tap, as well as the number of taps in one day were extracted. Data from one participant who used an auto tap generation application was removed from analyses of mobile device usage.

Physical activity

Step count as extracted from the Oura ring was used as an indicator of daily physical activity.

Based on the daily non-wear time provided by Oura, we excluded step count from days where subjects had more than 3 hr in which they were not using the Oura device. **Analyses**

Across all participants, 12088 nights containing Oura sleep information were collected. Sleep outcome variables provided by Oura included bedtime, wake times, time-in-bed (TIB), and total sleep time (TST). Sleep efficiency was calculated as $100 \times \text{TST} / \text{TIB}$, and mid-sleep times were calculated as the midpoint between bedtimes and wake times on the same night. Social jetlag was calculated as the difference between weekday and weekend mid-sleep times ($\text{MST}_{\text{WE}} - \text{MST}_{\text{WD}}$). Sleep variability was taken as the overall standard deviations of bedtime, wake time and midsleep time for each participant.

Our first investigation aimed to identify changes in sleep, physical activity, well-being scores and mobile device usage patterns resulting from the reopening after lockdown. To achieve this, participants step count, bedtime, wake-time, TIB, TST, sleep variability and social jetlag, as well as average daily stress and mood rating (morning and evening) were averaged across each time period (lockdown and post-lockdown) and compared using two-tailed paired sample t-tests and non-parametric tests (i.e., Wilcoxon signed rank test) in cases where the assumption of normality was violated.

We expected changes in sleep and well-being after the reopening to be moderated by changes to participant's work arrangements enabled by the lifting of social distancing measures. Some workplaces and university classes opted to continue work from home arrangements and home-based learning for an extended period. To account for varying arrangements, work location was reported daily from the first day of reopening. To examine the effects of work arrangements the proportion of days worked in-person (over the total number of working days) was calculated. This proportion was entered in multiple regression analyses, with sleep, activity, and wellbeing measures as dependent variables, controlled for demographics (age, gender, staff/student).

Identification of bedtime phone usage patterns

To assess bedtime phone usage patterns during and after the lockdown, two separate k-means clustering analyses were performed using individuals' average phone use in the period surrounding their bedtime as features (in 10 min time bins starting 3hr before bedtime till 1hr after); once during the lockdown and once after the lockdown. One subject was removed from the analysis due to the use of tap generating apps which interfered with phone usage calculation

(resultant $N = 197$). Clustering was conducted on Matlab version 2017b (Mathworks, Natick, MA) using the k-means++ algorithm with the squared Euclidean distance metric for center initialization of clusters. Based on the elbow plots, obtained from assessing within-cluster sums of squared distance of various cluster numbers ($k=2-10$), an optimal cluster number was selected for the analyses ($k=3$)

Comparing individuals based on bedtime phone usage cluster

Individuals were assigned separate groupings based on the obtained cluster solution for both the period during lockdown and post-lockdown. Subjects were compared based on their sleep metrics, daily well-being, and daily step count using multiple regression analysis with Cluster groups as regressors of interest (Cluster 1 as reference). Demographics (age, gender, staff/student) and work arrangements were included as control variables. For the period during the lockdown, work arrangement was defined by whether individuals reported returning to the office on a regular basis (>3 days). For the period after the lockdown, work arrangement was defined by the proportion of days worked in-person. Twenty-four individuals who did not report any working days in the post-lockdown period were excluded from this analysis (resultant $N_{\text{post-lockdown}} = 173$). Two individuals during the lockdown period and seven individuals from the post-lockdown period were removed from the step count analysis as they did not use the wearable during the day.

Data availability

The data used for statistical tests in this study are available from Open Science Framework:
<https://osf.io/f43h6/>.

Code availability

Statistical analyses were performed using standard packages in Matlab version R2017b and SPSS version 26. Associated code is available from the corresponding author upon reasonable request. Syntaxes for statistical tests is available from Open Science Framework:
<https://osf.io/f43h6/>.

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Author contribution

S.M. and A.N. contributed equally to this work. S.M., A.N., and M.C. conceptualized and designed the study. S.M., A.N., and X.Y. coordinated and performed the data analysis and visualization. S.M., and A.N. wrote the first draft of the manuscript. C.S., J.O., X.C., N.C., and M.C. led the preparation and development of the data collection platforms. A.N. and S.M. coordinated participants recruitment and communication. N.C. and J.O. coordinated distribution of wearable devices to participants. X.C., N.C., A.N. monitored data collection and integrity during the study. T.L. provided critical input to the manuscript. S.M., A.N., and M.C. wrote the final version of the manuscript. All the authors have approved the final submitted version of the manuscript.

Competing Interests

Michael Chee sponsored the development of the Z4IP Ecological Momentary Assessment App, and is advisor for QuantActions Ltd, Lausanne, Switzerland. Software and data collection services from QuantActions were used to monitor smartphone activity. Stijn Massar, Alyssa Ng, Chun Siong Soon, Xin Yu Chua, Ju Lynn Ong, Nick Chee, and Tih Shih Lee have no competing interests to declare.

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