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# Mental Health and Social Contact During the COVID-19 Pandemic: An Ecological Momentary Assessment Study

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**Abstract**

Students are at elevated risk for mental health problems. The COVID-19 pandemic and public health responses such as school and university closures caused once-in-a-lifetime disruptions of daily life for most students. In March 2020, during the beginning of the outbreak in the Netherlands, we used Ecological Momentary Assessment to follow 80 bachelor students 4 times a day for 2 weeks. Despite rapidly increasing rates of infections and deaths, short-term dynamics revealed slight decreases of mental health problems, COVID-19 related concerns, and loneliness, especially in the first few days of the study. Students showed no changes in the frequency of in-person social activities. Dynamic network models indicated that social activities were negatively related to being at home, and identified reinforcing vicious cycles among mental health problems and being alone, which in turn predicted concerns about COVID-19. Findings and implications are discussed in detail.

**Statement of Relevance**

There is a considerable body of research on student mental health. Prospective stress research is less common, and there is little work monitoring students closely during periods of intense stress. Here we report results of a unique prospective stress dataset collected during the outbreak of the COVID-19 pandemic, a period of dramatic disruptions of students' daily life. In March 2020, we queried 80 students in the Netherlands on mental health variables 56 times over 2 weeks using a smartphone application, in addition to baseline and exit surveys. Results indicate no changes on global mental health outcomes from baseline and exit, and reductions on many daily mental health problems, including mood, loneliness, and worries about COVID-19, especially in the first days. Although shocking events such as the pandemic may have rapid adverse short-term effects, our results suggest that many students may be surprisingly resilient, at least in the timespan we observed.

## Introduction

About 75% of all severe mental health problems develop before the age of 24 (Kessler et al., 2005), and many studies have documented that students report consistently higher levels of mental health problems than the general population (Denovan & Macaskill, 2016; Gaspersz et al., 2012; Mortier, Auerbach, et al., 2018; Stallman, 2010; Tomoda et al., 2000; Tran et al., 2017; Williams et al., 2018). Paired with the fact that student samples are convenient to recruit, this has led to a considerable body of research on understanding, predicting, and preventing stress and mental disorders in students.

The WHO Mental Health Survey documented 1-year incidence rates of mental illness among students of about 20%, with anxiety and mood disorders among the most prevalent problems (Auerbach et al., 2016). The College Health Intervention Project estimated that one in four college students experience symptoms of depression, and one in ten suicidal thoughts (Mackenzie et al., 2011). In data of over 2,500 college freshmen collected in Belgium, the 1-year incidence rates were about 7% for Major Depression (Ebert et al., 2018), 5% for suicidal thoughts and behaviors (Mortier, Demyttenaere, et al., 2018), and 10% for non-suicidal self-injury (Kiekens et al., 2019). Longitudinal work indicates that problems increase during the first semester in freshmen (Besser & Zeigler-hill, 2014). Mental health problems in students are related to considerable impairment of functioning, decreased academic performance and life satisfaction, higher levels of physical comorbidities, increased college dropout, and increased levels of smoking, alcohol, and drug abuse (Ebert et al., 2018; Ribeiro et al., 2017).

While the literature on student mental health has been growing rapidly, only a minority of work consists of prospective stress studies that follow participants during periods of considerable stress, such as residency in medical students (Fried et al., 2014). Of those, there are only a handful of studies to date that used Ecological Momentary Assessment methods, e.g. via smart phones, to assess the impact of stressors on students' daily lives. The few existing studies have focused on US presidential elections and other US events like the Las Vegas shooting (Frank et al., 2019; Roche & Jacobson, 2019).

The etiology of mental health problems in students is diverse, and includes stressors such as including financial problems (Heckman et al., 2014), academic pressure (Misra & McKean, 2000), adjusting to new social and geographical environments (Montgomery & Cote, 2003), relationships, life-stage transitions, and time management (Wilks et al., 2009). One massive recent stressor is the COVID-19 pandemic, and early work indicates increases of mental health problems across the globe (Jacobson et al., 2020; Nelson et al., 2020). In the Netherlands, where we collected our data, the pandemic led to severe disruptions of public life. Requests for public transport information in March dropped by 75%, while the number of COVID-19 infections and deaths grew rapidly from 10 to 12,595 and 0 to 1,038, respectively (**Figure 1**). The pandemic was accompanied by public health measures announced by the Dutch government (The Dutch Government, 2020), potentially causing novel, once-in-a-lifetime stressors for students, including: ban of public gatherings; ban of non-essential international travel; closing of, among others, universities, schools, restaurants, cinemas, and gyms; shortage of some basic supplies due to mass purchases; health concerns about family and friends; and economic concerns. Our goal was to study the impact of these stressors on student mental health.

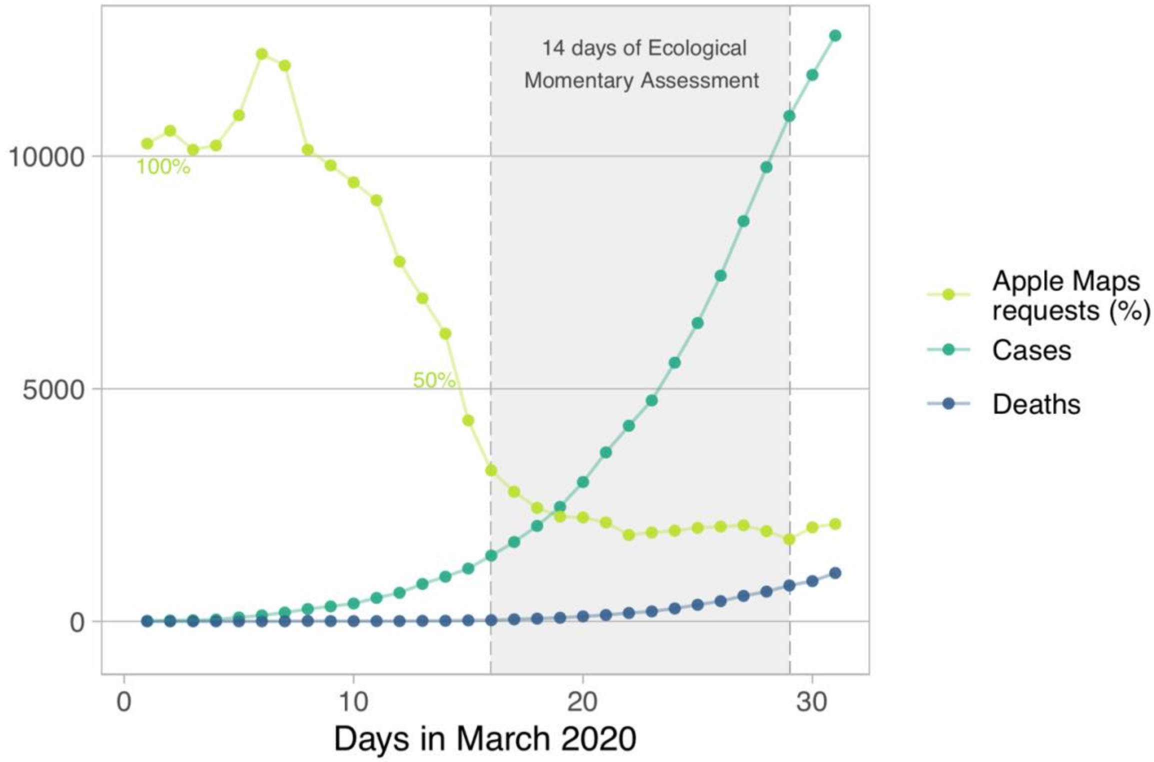


**Figure 1**: We conducted a 2-week prospective stress study in the Netherlands. We plot Apple Maps requests for public transport in the Netherlands as proxy for disruption of normal daily life, in % compared to January 2020 (from: https://www.apple.com/covid19/mobility), as well as increase of COVID-19 cases and deaths in the Netherlands (https://www.worldometers.info/coronavirus/country/netherlands).

We followed 80 bachelor students enrolled at Leiden University closely over the course of 2 weeks, using Ecological Momentary Assessment (EMA). After a battery of questions at baseline, we queried students about mental health problems, social contact and isolation, and concerns about the pandemic. We concluded the study with a short exit survey, including information on COVID-19 diagnosis, mental health, implementation of social distancing and personal hygiene behaviors, and whether students felt well informed by Leiden University and the Dutch government.

This data allows us to answer three questions. First, what is the general frequency of mental health problems, social behaviors, and pandemic-related concerns in the 2 weeks following a university shut down—and do these variables change over time? Second, what variables predict changes in mental health over the 2-week study period? And third, what are the potential causal relations among these variables (e.g., do concerns COVID-19 lead to higher levels of mental health problems at the next measurement point)? We answer the last question by estimating dynamic network models, consistent with the network approach to mental health problem (Borsboom, 2017; Fried & Cramer, 2017).

Given the novelty of the COVID-19 pandemic and little previous work studying prospective stressors via EMA, we have no a priori hypotheses except that the pandemic has adverse effects on student mental health. Our primary goal for this paper is to faithfully report on the collected data in an exploratory way. We share all data, code, and measures in the supplementary materials.

## Methods

### Procedure

The study took place between March 11 and April 04 2020, and was conducted in three parts. First, participants completed a 45-minute baseline assessment, required to continue to the second stage: 2 weeks of EMA. This stage lasted from Monday March 16 (University closed on Friday March 13) to Sunday March 29. During this period, participants received a prompt on their smart phones four times per day (noon, 3 pm, 6 pm, and 9 pm). Each assessment lasted approximately 2.5 minutes, and participants had to answer the prompt within 60 minutes, after which it expired. Third, participants completed a 20-minute post-assessment survey, available from March 29 to April 5. No manipulations took place. All assessments were conducted via

*Ethica Data*, a data collection platform available on both Android an iOS that participants installed on their smart phones.

## Participants

We recruited participants in the week following March 4, through online advertisements on social networks, posters and flyers distributed in the Faculty of Social Sciences of Leiden University, or directly approached by the researchers. Participants were students at Leiden University, and were reimbursed for participation with study credits and the chance to win one of four 25€ vouchers. Students received credits proportional to completed EMA surveys. Out of the 100 initially recruited participants, 84 completed the baseline survey, 79 completed the EMA surveys and 80 completed the post assessment; we include the 80 participants who completed both pre and post assessments in this study. The study was approved by the Ethics Board of Leiden University, Faculty of Social and Behavioral Sciences.

## Measures

All measures can be found in the supplementary materials. Importantly, the current paper only reports on a number of selected items of specific interest for our research questions; full data is available online, with the exception of some data we deleted to guarantee anonymity.

### Baseline and follow-up assessments

The baseline survey consisted of 159 questions, in which participants were asked, among others, about their age, gender, relationship status, employment status, nationality, and prior mental health issues. In addition, we assessed several constructs for which we used in part adapted or shortened versions of original scales to decrease participant burden: last-week problems regarding depression, anxiety, and stress (Depression Anxiety Stress Scale; DASS-21; (Lovibond & Lovibond, 1995)); last-month perceived stress (10-item Perceived Stress Scale

(Cohen & Williamson, 1988); general loneliness (5 items from the 8-item revised UCLA loneliness scale; ULS-8 (Russell et al., 1980)); general frequency of social in-person activities (1 item); and self-efficacy (10-item General Self-Efficacy Scale (Schwarzer, R., & Jerusalem, 1995); All scales were modified to range from 1 through 5 for consistent assessment. Due to these differences compared to the original scales, we refer to the adapted DASS-21 score as Global Mental Health score, and the adapted ULS loneliness scale as loneliness score, for the remainder of the manuscript.

During follow-up, we queried participants on 74 items. These comprised COVID-19 related symptoms, diagnoses of the participant, diagnosis of close family members and friends; perceived impact on mental health, and whether actions taken by Leiden University had impact on their stress levels; and how well-informed students felt by Leiden University and the Dutch government. In addition, we queried students again on our adapted DASS-21 and loneliness scales.

EMA

For all 14 variables, we queried participants how much, over the last 3 hours, they endorsed a certain feeling or behavior (not at all, slightly, moderately, very, extremely), or how much time they spend on a certain activity (0 minutes, 1-15 minutes, 15-60 minutes, 1-2 hours, over 2 hours); see **Table 1**. The mental health items were adapted from the DASS-21/DASS-42 (Lovibond & Lovibond, 1995)and the Generalized Anxiety Disorder Scale (Spitzer et al., 2006); other items were created for the purpose of this study, based on our experiences with prior EMA studies we conducted in 2018 and 2019 with student populations in the Netherlands.

**Statistical analyses**

All analyses were carried out in the free statistical environment R. Data and syntax are available in the supplementary materials.

**Table 1.** Ecological Momentary Assessment items, queried 4 times per day over 2 weeks.

| # | Abbreviation | Item |
|---|---|---|
| 1 | Relax | I found it difficult to relax |
| 2 | Irritable | I felt (very) irritable |
| 3 | Worry | I was worried about different things |
| 4 | Nervous | I felt nervous, anxious or on edge |
| 5 | Future | I felt that I had nothing to look forward |
| 6 | Anhedonia | I couldn't seem to experience any positive feeling at all |
| 7 | Tired | I felt tired |
| 8 | Alone | I felt like I lack companionship, or that I am not close to people |
| 9 | Social_offline | I spent ___ on meaningful, offline, social interaction |
| 10 | Social_online | I spent __ using social media to kill/pass the time |
| 11 | Outdoors | I spent __ outside (outdoors) |
| 12 | C19_occupied | I spent __ occupied with the coronavirus (e.g. watching news thinking about it talking to friends about it) |
| 13 | C19_worry | I spent __ thinking about my own health or that of my close friends and family members regarding the coronavirus |
| 14 | Home | I spent __ at home (including the home of parents/partner) |

**Note:** Range of all items 1-5. Items 1 through 8: not at all, slightly, moderately, very, extremely. Items 9 through 14: 0min, 1-15 minutes, 15-60 minutes, 1-2 hours, over 2 hours.

We used paired t-tests to investigate whether Global Mental Health and loneliness changed in the 2 weeks between baseline and exit surveys. We estimated a multiple regression model to predict changes in Global Mental Health from pre to post, using the predictors gender, age, nationality, relationship status, working, prior mental health issues, self-efficacy, perceived stress, loneliness, and being socially active, controlling for Global Mental Health at baseline.

For estimation of dynamic network models, we used two-step multilevel vector auto-regression (two-step mlVAR; (Epskamp et al., 2018)), a model in which all variables at a given timepoints are regressed on variables of the previous assessment. Predictors are within-person centered and sample means are added as predictors to separate within- and between-person variance; residuals are used in a second step to investigate contemporaneous relationships. This leads to two networks. (1) The *temporal* network, that estimates lag-1 associations between all items after controlling for all other lagged associations. This provides statistical relations that can be interpreted as Granger-causal: how well does an item predict other items at the next time point after taking into account all other variables (Granger, 1969). (2) The *contemporaneous* network, that partials out all temporal relations, and then estimates the unique relations among all items within the same time window. A third network returned by two-step mlVAR, the between-persons network, was not investigated due to our relatively low sample size. We visualized the results of network models in graphs that contain nodes (variables) and edges (statistical relationships described above). The temporal model features directed edges, the contemporaneous network undirected edges. Stronger relations are depicted as thicker and more saturated edges; positive edges are blue, negative red. Two-step mlVAR requires stationarity. We detrended the data by fitting fixed-effects linear regression models to each variable, regressing out a linear trend on day number (i.e. general increases in variables over time), and a categorical effect on measurement per day (i.e. fluctuations of variables from morning to evening), at an alpha of 0.05.

The obtained linear trends from the detrending procedure (i.e. the question whether slopes were different from 0) were utilized in determining whether EMA items changed over time. To investigate whether individuals differed in these trends, we used univariate multilevel regression models, including fixed and random effects, detailed in the supplementary materials.

## Results

### Sample descriptives

Of the 80 students, 60 identified as female, 19 as male, and 1 as other, with an age mean of 20.38 (SD=3.68, range 18-48), and a mix of 19 nationalities, the most common of which were Dutch (*N*=36), German (*N*=16), and Finnish (*N*=7). Most students were single (*N*=50), fewer in a relationship (*N*=27) or married (*N*=3), and the large majority of students were first-year bachelor students (*N*=68) enrolled in psychology (*N*=70). Seventeen students reported having suffered from mental health problems in the past, or having taken psychiatric drugs; 26 students were employed. Abbreviations for all EMA items discussed in the subsequent sections are detailed in **Table 1**.

### Mental health comparison of baseline and exit surveys

We identified no changes for Global Mental Health scores in the 2 weeks from baseline (M=36.03, SD=9.08) to study exit (M=35.57, SD=8.75), $t(76)=0.45$, $p=0.66$, and, interestingly, decreases for loneliness scores from pre (M=11.65, SD=3.92) to post (M=10.86, SD=3.90), $t(76)=3.14$, $p=0.002$.

We predicted change in Global Mental Health scores from pre to post by gender (*N*=60 female, *N*=19 male), age, nationality (*N*=36 Dutch, *N*=44 international), relationship status (*N*=50 single, *N*=30 partnered), working (*N*=54 no, *N*=26 yes), prior mental health issues (*N*=59 no, *N*=17 yes), self-efficacy (M=28.9, SD=3.93) perceived stress (M=30.34, SD=3.36), loneliness (M=11.65, SD=3.93), and in-person social activities (M=3.78, SD=1.3). None of the variables predicted significant changes, except for a negative coefficient for Global Mental Health scores at baseline that we controlled for ($b$=-0.66, t(62)=-5.12, $p$<0.001; overall, F(11,62)=3.71, $p$<0.000, adjusted $R^2$=0.29). The negative relation can likely be explained by regression to the mean, where higher baseline scores predict decreases, i.e. negative changes.

**EMA variables**

Investigating the slopes of 14 EMA variables over the 56 measurement points revealed that items were either stable across time, or decreased somewhat in magnitude. As visualized in **Figure 2**, 10 items significantly decreased over the 2 weeks, one item significantly increased (*Home*); the remaining four variables (*Anhedonia*, *Social_offline*, *Outdoors*, *Home*) remained stationary. We observed the largest decreases for the items *C19_occupied* (standardized coefficient -0.18), *C19_worry* (-0.16), *Nervous* (-0.13), and *Worry* (-0.12), all $p$<0.001; the increase for *Home* was 0.03 ($p$=0.03). We also identified significant cyclic patterns within days for the five variables *Tired*, *Social_Offline*, *Outdoors*, *Home* ($p$<0.001), and *Worry* ($p$=0.02), most of which are clearly visible in **Figure 2** (e.g. students have more social contact in the afternoon and evening).

Zooming into the item with the strongest decrease, *C19-occupied*, reveals that on day 1, nearly no students indicated the lowest response category, while nearly half of the students endorsed this response on the last day of the study 2 weeks later (**Figure 3**). We used univariate multi-level regression models to get further information for individual participants, and found that 83% of the students had a negative slope for *C19-occupied*, and 57.6% had a negative slope with a standardized coefficient below -0.1. Results were similar for *C19-worry*, with 76.2% and 50.6%, respectively (see supplementary materials for details on all items). We can therefore rule out that decreases on the group-level were driven by few individuals.

**Figure 3** further reveals small peaks following days 4 and 8. We speculate that this is related to university and government announcements on March 19 (day 4) and March 23 (day 8), because similar peaks can be observed for other EMA items on the same days, and are especially for *Future* and *Worry* (see supplementary materials).

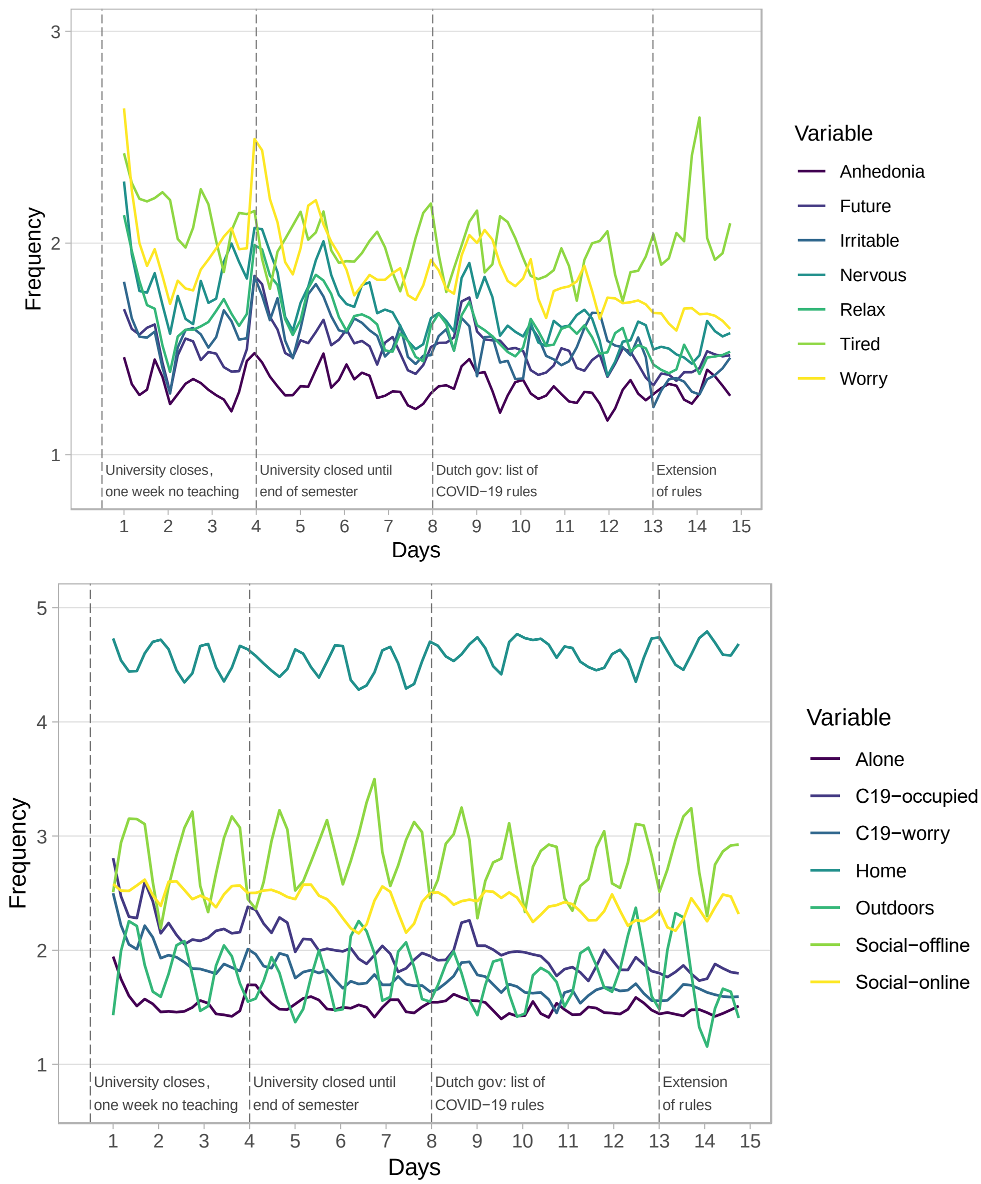


**Figure 2.** Means of 14 Ecological Momentary Assessment items, assessed 4 times per day over 14 days on a 1-5 scale (higher scores: more severe or frequent). Top: mental health related variables. Bottom: social and COVID-19 related variables. Note that we adapted the y-axis range in the upper figure to increase interpretability. Detailed item descriptions can be found in Table 1.

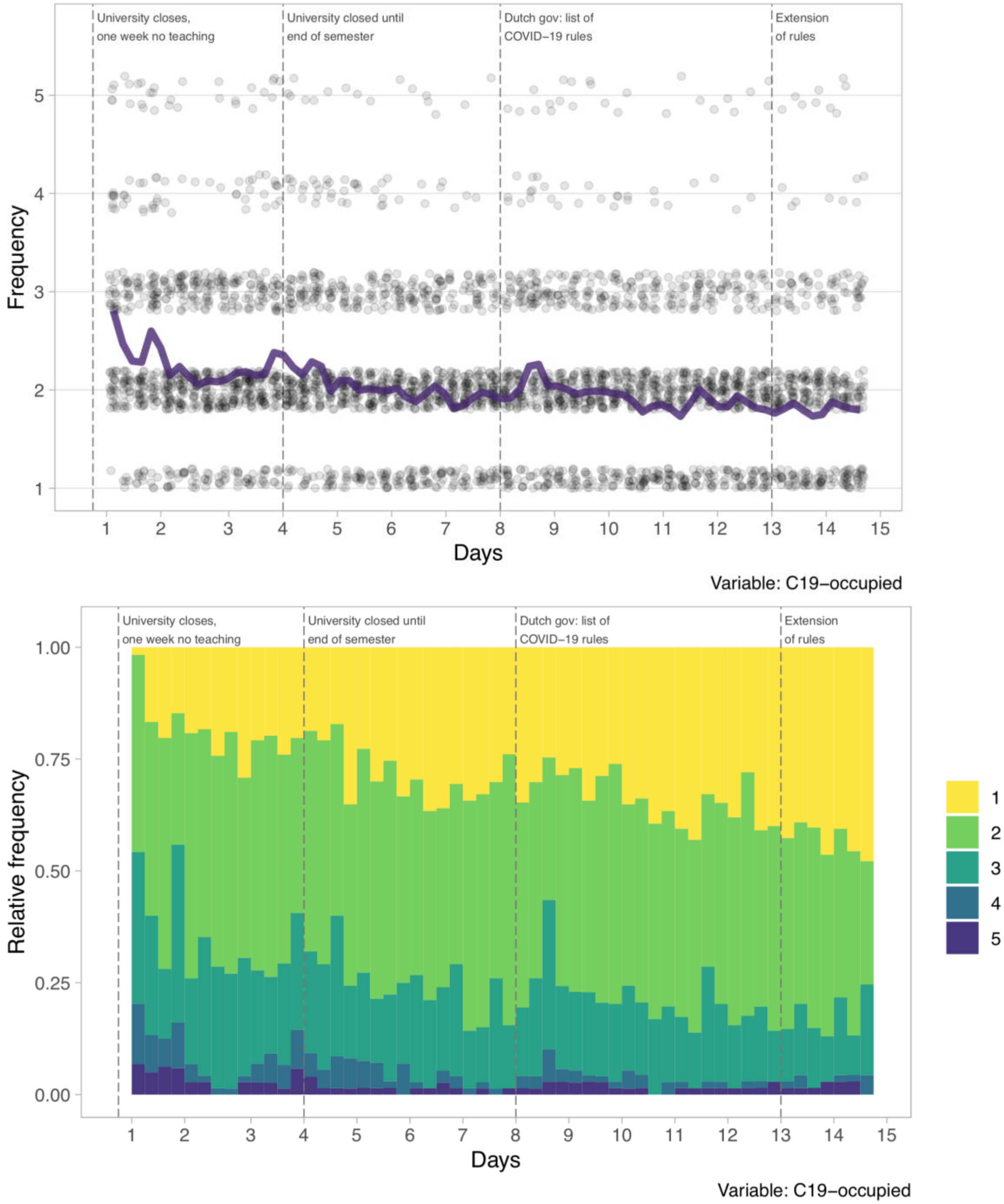


**Figure 3.** Time course of the Ecological Momentary Assessment item "in the last 3 hours, I spent __ occupied with the coronavirus (e.g. watching news, thinking about it, talking to friends about it)", which exhibited the largest decreases of all items in our study, with the answer options 1 (0m.), 2 (1-15m.), 3 (15-60m.), 4 (1-2hrs.), and 5 (>2hrs.). Top: individual item responses per day as dots, plus mean score over time. Bottom: Relative frequencies of ordinal responses. Small peaks can be observed on days 4 and 8, potentially following announcements of Leiden University and the Dutch government

## Network model

The evolution of means over time in **Figure 2** indicated some strong patterns, for instance, there seemed a strong inverse relation between the means of *Social_offline* and *Home*. To investigate these relations further, we estimate contemporaneous and temporal network models that depict conditional dependence relations of all variables in **Figure 4**.

In the contemporaneous network (i.e. relations among items within the last 3-hour duration of a given beep), we identified many expected relations among items, such as a negative relation between *Social_offline* and *Social_online*; a negative relation between *Alone* and *Social_offline*; and a strong negative relation between *Outdoors* and *Home*. Further, we found that mental health items generally clustered together; *C19_occupied* and *C19_worry* were related; *Alone* was related to (concerns about) *Future* as well as *Anhedonia*; and *Outdoors* was positively (and *Home* negatively) related to *Social-offline*.

In the temporal network (i.e. lag-1 relations from one 3-hour measurement period to the next), we identified positive autoregressive coefficients for all nodes (i.e. variables predict themselves, which is very common in these models); largely positive relations among mental health variables; and some vicious cycles, e.g. between (worry about) *Future* and *Anhedonia*, (unable to) *Relax* and *Anhedonia*, and *Future* and *Alone. Nervous* was followed by participants being less *Alone* at the next measurement point. Interestingly, *Alone* predicted *C19-worry*, which was followed by *C19-occupied*, which in turn predicted a range of mental health variables.

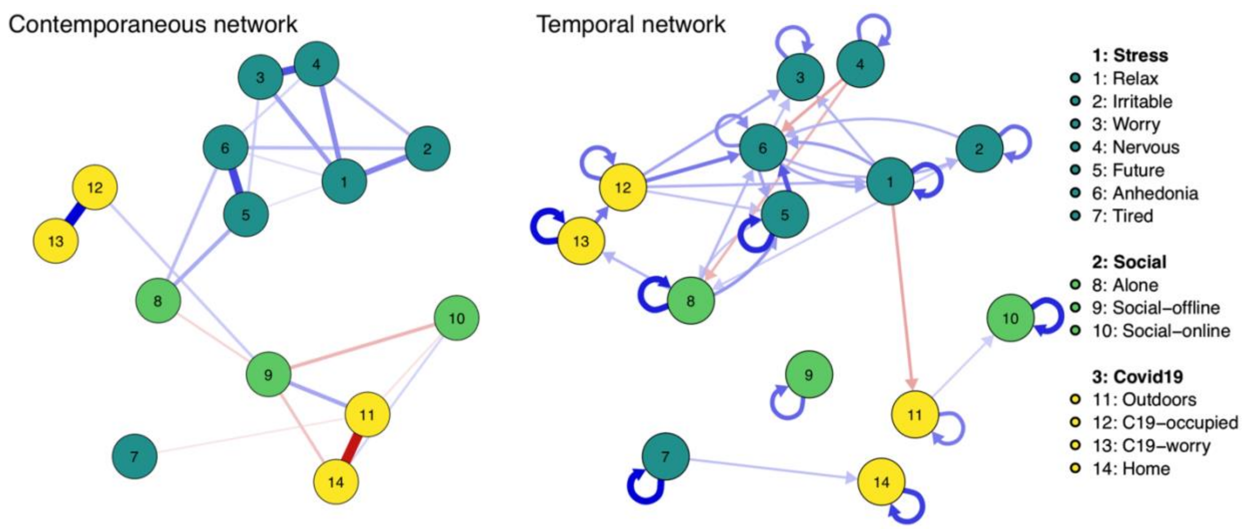


**Figure 4.** Contemporaneous (left) and temporal (right) relations among 14 Ecological Momentary Assessment variables gathered 4 times a day over the course of 2 weeks, estimated with a multilevel vector-autoregressive model and depicted as a graph where nodes are variables, and edges are partial correlations among variables. Thicker and more saturated edges depict stronger relations; positive relations in blue, negative relations in red.

## Post assessment

At the post assessment, 19.5% of students indicated that they had had symptoms during the last 3 weeks that could indicate a COVID-19 infection, such as fever, cough, or shortness of breath; none had received a formal diagnosis, however. Only 4 students indicated that a close friend or relative had received a COVID-19 diagnosis. Participants further indicated, on a 5-point Likert scale ranging from 1 (totally disagree) to 5 (totally agree), with 3 being neutral, that: they started washing their hands more frequently during the study period (M=3.49 [3.32-3.67]); they avoided social activities with many people (M=3.70 [3.56-3.84]); the pandemic impacted their mental health negatively (M=3.34 [3.06-3.62]); they felt somewhat well informed by Leiden University (M=3.39 [3.11-3.67]) and the Dutch government (M=3.39 [3.11-3.67]); and that the actions taken by Leiden University and the government had had no impact on their stress levels (M=2.88 [2.60-3.16]).

## Discussion

We closely follow 80 students during the early days of the COVID-19 pandemic in the Netherlands, during a time of fairly dramatic changes. Many of these were once-in-a-lifetime disruptions of students' daily lives, such as banning all public gatherings, banning non-essential international travel, and closing down Universities, schools, restaurants, cinemas, gyms, and all jobs that are contact-based and cannot guarantee sufficient distance among people (The Dutch Government, 2020).

The unique COVID-19 pandemic, as well as our unique EMA data, make the results somewhat difficult to compare to prior work. Nonetheless, in the following we summarize our main results and connect them to previous research.

First, we found no increases in global mental health problems over the course of the 2-week study. This was the case for mental health measures collected via typical pre-post surveys, but also via smartphone applications 4 times a day. Prior work reported considerable adverse effects on mental health during outbreaks, such as during the Severe Acute Respiratory Syndrome (SARS) epidemic in 2003, although data were largely retrospective self-report (J. Lau et al., 2005). Among others, being in quarantine, and knowing people with SARS diagnoses, predicted adverse effects (Hawryluck et al., 2004). None of our students received a COVID-19 diagnosis, and only four participants reported having close friends or family members with diagnoses, which may have mitigated adverse mental health outcomes. Interestingly, participants reported at the exit measurement point on a 1-item screener that the pandemic had affected their mental health adversely. We identified no substantive predictors of changes of global mental health outcomes over the study period.

Second, when comparing baseline to exit surveys, we identified a decrease in loneliness. This was corroborated by EMA data, which also showed decreases in state loneliness. During the SARS epidemic, the subjective well-being of adults in Hong Kong (especially younger adults) remained within normative range compared to an assessment a year before the outbreak, and participants reported increases regarding ‘feeling part of the community’ (A. L. D. Lau et al., 2008), which may be consistent with our findings of decreasing loneliness. This also seems plausible with regard to the fact that students showed no decrease in in-person social activities. Based on our own observations, we speculate that students may have also engaged in deeper and more meaningful social contact, such as talking to close family members and friends (e.g. on the phone) more often than usual.

Third, we identified decreases for most mental health related EMA items, including items concerning students’ worry about their own health and that of family members, and students’ occupation with COVID-19. This occurred in a time in which the pandemic dominated the media landscape, with rapid increases of infections and deaths. One interpretation is that the initial drop in mental health outcomes in our data, observable especially in the first three days, represents a quick recovery towards baseline after a brief elevation, implying that we may have missed the peak a few days before. This interpretation may be consistent with a 14-day EMA study in US students which revealed short-lived increases in adverse mental health outcomes after the 2016 presidential election (Roche & Jacobson, 2019). Another interpretation is that government clarity and action may have calming effects by reducing uncertainty. A study that examined US Google searches for mental health outcomes during the week of March 16 2020, coinciding with first week of our EMA data (Jacobson et al., 2020), suggests that after dramatic initial increases in mental health related searches, the implementation of stay-at-home-orders led to quick stabilization of searches in less than 4 days. A final possibility is response shift bias, i.e. that participants changed the way they understood and answered EMA items; future work on response shift bias for EMA, an assessment form that has seen rapid increases in use, is urgently needed.

Fourth, meaningful in-person social activities remained stationary of the 2-week EMA period, which is somewhat surprising, given the closure of Leiden University, and strict public health policies implemented by the Dutch government during our study. Time spent at home did increase over the same time period, however. Consistent with that, students reported at the exit survey that they had started avoiding social activities with many people.

Fifth, the main findings of the two network models were that mental health items clustered together and yielded some vicious cycles; that loneliness was positively related to mental health problems and concerns about COVID-19, which in turn predicted mental health outcomes; and that being outdoors was related to meaningful in-person social activities. This indicates that in-person social contact during the EMA study period was not only with co-inhabitants.

Finally, there was evidence for small peaks of state mental health problems on days 4 and 8, following university and government announcements. From a dynamical systems perspective (Borsboom, 2017; Robinaugh et al., 2019), these peaks can be thought of as perturbations of the students' mental health systems caused by events in the external field. This view offers the possibility that, especially in vulnerable students, timely interventions on elements of the dynamical system (such as loneliness and worry) may have positive outcomes and prevent transitions into more severe problems. This calls for future research utilizing time series data to investigate dynamical systems of mental health during stressors, and the potential benefits of prevention and intervention strategies targeting such systems using methods like control theory (Henry et al., 2020).

**Limitations and future directions**

Our study comes with a number of limitations. First, we largely focused our investigation on the group level, and did not explore inter-individual differences in detail. Such idiographic follow-up work is important, but beyond the scope of the present work. Second, to limit the burden of an already time-intensive study for students and minimize dropout, we could not assess many variables of interest, and shortened or adapted some scales such as the DASS-21. Further, we created the EMA items for our study, given that there is no validation work in the context of EMA measurement as of yet. Third, while the sample is a diverse sample in terms of nationalities, it is largely limited to European students, and is a convenience sample of psychology bachelor students living in the Netherlands. The Netherlands is a first world country, and has scored rank 1 in Europe several times in the last decade in terms of healthcare consumer satisfaction (Watson, 2012). It is an open question how well our results generalize to other populations, given the nature of the COVID-19 pandemic. Finally, research on compliance rates in EMA data may elucidate ways to reliably gather data over longer assessment periods. Combining longer EMA periods with passive sensing and digital phenotype data collection, for instance, via smart watches, will provide more fine-grained and objective data than we were able to collect.

**Open Practices Statement**

The study was not formally preregistered. We made all data, measures, and code available online: https://osf.io/kd936/?view_only=e530e47a1e7c4e88b2401a237de30614]

**Author contributions**

EIF designed the study. FP cleaned and prepared the data for analysis. EIF and SE analyzed the data. EIF wrote the first manuscript draft. All authors revised and approved the final draft.

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