Article title: Self-Perceived Loneliness and Depression During the COVID-19 Pandemic: a Two-Wave Replication Study

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Dear Editor,

Please find attached our manuscript titled "Self-Perceived Loneliness and Depression During the COVID-19 Pandemic: a Two-Wave Replication Study" submitted for consideration in *UCL Open: Environment – Special Issue: COVID-19 and Mental Health (paper 1 for webinar 1)*. The authors of this paper are Alessandro Carollo, Andrea Bizzego, Giulio Gabrieli, Keri Ka-Yee Wong, Adrian Raine, and Gianluca Esposito. The manuscript has been read and approved by all authors and by the responsible authorities where the research study was conducted. The paper is not under consideration for publication elsewhere and, if accepted, it will not be published elsewhere in the same form, in English or in any other language, including electronically without the written consent of the copyright holder.

In this paper, we present a replication study about the effect of time spent in lockdown on people's physical and mental health. In particular, we adopted a data-driven machine learning approach to identify the most affected index by time spent in lockdown during the wave 1 of UK national lockdown. Furthermore, the paper tries to extend the results found by Carollo et al. (2020) on the second wave of UK lockdown by using a statistical approach to study the distribution of self-perceived loneliness. Theoretical fundamentals, aims, methods, data analysis and statistics, three figures and two tables, results, discussion, limitations and future directions are reported.

The pre-registration for this study can be found on the Open Science Framework at https://osf.io/4nj3g**.** The analysis scripts are available upon request to the corresponding author. The study has been conducted in accordance with the ethical principles stated in the Helsinki declaration and informed consent was obtained from all participants. We hope you can consider our paper for publication in the *UCL Open: Environment*.

Best regards,

Gianluca Esposito, PhD

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Self-Perceived Loneliness and Depression During the COVID-19 Pandemic: a Two-Wave Replication Study

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Abstract

COVID-19 studies to date have documented some of the initial health consequences of lockdown restrictions adopted by many countries. Combining a data-driven machine learning paradigm and a statistical analysis approach, our previous paper documented a U-shape pattern in levels of self-perceived loneliness in both the UK and Greek populations during the first lockdown (17 April to 17 July 2020). The current paper aimed to test the robustness of these results. Specifically, we tested *a*) for the dependence of the chosen model by adopting a new one - namely, support vector regressor (SVR). Furthermore, *b*) whether the patterns of self-perceived loneliness found in data from the first UK national lockdown could be generalizable to the second wave of the UK lockdown (17 October 2020 to 31 January 2021). The first part of the study involved training an SVR model on the 75% of the UK dataset from wave 1 (n total = 435). This SVR model was then tested on the remaining 25% of data (MSE training = 2.04; MSE test = 2.29), which resulted in depressive symptoms to be the most important variable - followed by self-perceived loneliness. Statistical analysis of depressive symptoms by week of lockdown resulted in a significant U-shape pattern between week 3 to 7 of lockdown. In the second part of the study, data from wave 2 of the UK lockdown (n = 263) was used to conduct a graphical and statistical inspections of the week-by-week distribution of scores regarding self-perceived loneliness. Despite a graphical U-shaped pattern between week 3 and 9 of lockdown, levels of loneliness were not between weeks of lockdown. Consistent with past studies, study findings suggest that self-perceived loneliness and depressive symptoms may be two of the most relevant symptoms to address when imposing lockdown restrictions.

Keywords: COVID-19; depression; lockdown; loneliness; global study; machine learning; SARS-CoV-2

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1. Introduction

Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a novel and highly pathogenic coronavirus that originated in bats and hosted by pangolins before the spillover to humans [1, 2, 3, 4]. SARS-CoV-2 disease was first documented in the Hubei province of China in December 2019. Since then, SARS-CoV-2 has rapidly spread throughout the world with the World Health Organization declaring it a pandemic on 11 March 2020 [5]. As of September 2021, over 224 million people have been infected by COVID-19 and more than 4.6 millions of deaths have been reported globally [6].

With no available vaccine to prevent COVID-19, many countries were initially forced to adopt lockdown restrictions to slow down the spread of the virus. Between countries, restrictions varied in period, length, and strictness. In particular, the UK's first lockdown imposed on 23rd March 2020 encountered a 'must-stay-home' order [7]. Leaving the house was allowed only once a day and for essentials only like shopping, exercising, medical needs, caring duties, and essential travel for work [8]. These restrictions were accompanied by social distancing measures, which were aimed at reducing the person-toperson transmission of the virus by encouraging the population to stay at least 2 meters away from others [9]. Though these policies were effective at reducing the number of new cases and the spread of the airborne virus, individuals had to endure long periods of social isolation, skepticism towards others, and little to no contact with others (e.g., friends, parents, siblings, partners) that may have had short and longer-term impacts on their health.

Considering the impact of social isolation on people's physical and mental health [10, 11, 12, 13], we hypothesized that lockdown measures, specifically lockdown duration (in days), may impact several important aspects of individual's daily lives. Globally, studies have documented links between restrictions and poorer mental health, such as more post-traumatic stress symptoms, anxiety, depression, insomnia, and trust in others [14, 15, 16, 17, 18]. Similarly, in a previous data-driven study, we identified that by using a machine learning model, self-perceived loneliness was most impacted by the time in lockdown, over and above other mental health indicators [19]. Further statistical analyses testing the variations in levels of self-perceived loneliness found a statistically significant U-shaped pattern of significantly different levels of self-perceived loneliness by lockdown duration (in weeks) in both the UK and Greece. An effect of restrictions on the perceived loneliness during the first lockdown period was replicated and substantiated by other COVID studies in the literature [20, 21, 22, 23].

Building on previous findings, the current study aims to replicate and extend on the previous results. In particular, the current study consists of two parts: to test whether the result by Carollo et al. [19] *a*) depended on the chosen machine learning model, we applied a new model on the same set of UK data from the first lockdown period; and *b*) depended on the wave of lockdown, we analyzed perceived loneliness distribution by week on data from the second UK national lockdown, with data collected from the UCL-Penn Global COVID Study between 17 October 2020 and 31 January 2021 [24]. The current study provides a unique opportunity to replicate whether self-perceived loneliness is again most impacted by time in lockdown or not, and to uncover other aspects that may be significantly influenced by the lockdown restrictions in both the first and second waves of lockdown.

2. Methods

2.1. Questionnaire

The current study is based on survey data from the UCL-Penn Global COVID Study, a 12-month study of COVID-19's impact on mental health in adults conducted between 17 April 2020 and 31 July 2021 [24]. Specifically, this study will use data from wave 1 collected between 17 April 2020 and 10 July 2020, and data from wave 2 collected between 17 October 2020 and 31 January 2021. Briefly, the survey was available in 8 languages and anyone 18 years and above with access to the survey link through several social media channels (website - www.GlobalCOVIDStudy.com -, email, LinkedIn, Whatsapp, Instagram, Facebook, and Reddit) was able to take part in the study. Participants received a randomized presentation of 13 standardized questionnaires assessing mental health including self-perceived loneliness, anxiety, depression, aggression, physical health, social relationships (empathy), living conditions, and background variables. For this study 12 indices derived from the previous questionnaires were included in the analytic sample (see Table 1). This study received ethical approval from the University College London Institute of Education Research Ethics Committee (REC 1331; April 2020).

2.2. Participants

Participants from the first wave of lockdown

During the first period of lockdown, a total of 2,276 adults from 66 different countries participated in the study. As in Carollo et al. [19], we excluded participants who: i) dissented to take part (n = 32), had incomplete (n = 712) or missing data (n = 165); ii) did not complete the survey within two

Score	**Description**	**Reference**	**Domain**	**Cronbach's Alpha (C.I. 95%)**
Mild Activity Difference	Difference between days of mild physical activity post- and pre- COVID-19 lockdown.	*International Physical Activity Questionnaire – Short Form* (IPAQ-SF, 6-items) [25]	Physical Activity	Not applicable
Mild Activity Time Difference	Difference between minutes of mild physical activity post- and pre- COVID-19 lockdown.	*International Physical Activity Questionnaire – Short Form* (IPAQ-SF, 6-items) [25]	Physical Activity	Not applicable
Moderate Activity Difference	Difference between days of moderate physical activity post- and pre- COVID-19 lockdown.	*International Physical Activity Questionnaire – Short Form* (IPAQ-SF, 6-items) [25]	Physical Activity	Not applicable
Sleep Quality	Self-reported sleep quality and quantity, where higher scores reflect better sleep quality.	*Pittsburgh Sleep Quality Index* (2-items) [26], *Epworth Sleepiness Scale* [27], *Subjective and Objective Sleepiness Scale* [28]	Sleep Quality	0.73 (0.7-0.77)
Empathy	Self-reported affective, cognitive, and somatic empathy, where higher scores reflect higher empathy.	*Cognitive, Affective, Somatic Empathy Scale* (CASES, 30-items) [29]	Empathy	0.87 (0.85-0.88)
Anxiety	Higher scores reflect higher anxiety.	*General Anxiety Disorder-7* (GAD-7) [30]	Anxiety	0.89 (0.88-0.91)
Depression	Higher scores reflect higher depression.	*Patient Health Questionnaire-9* (PHQ-9, 9items) [31]	Depression	0.87 (0.86-0.89)
Perceived Loneliness	Higher scores reflect higher perceived loneliness.	*Loneliness Questionnaire* (LQ, 20-items) [32]	Perceived Loneliness	0.94 (0.93-0.95)
Living Conditions/Environment	Higher scores reflect more chaotic home environments.	*Chaos, Hubbub, and Order Scale and Health Risk Behaviors* (CHAOS, 6-items) [33]	Demographic Information	0.66 (0.62-0.67)
Beliefs	Perceived effectiveness of government guidelines on social distancing, schools closing, face masks and gloves as protection. Higher scores reflect stronger beliefs.	Summed 9-items on COVID-19 beliefs	Worries and Beliefs	0.81 (0.78-0.83)
Schizotypal Traits	Higher scores reflect more schizotypal traits.	Schizotypal Personality Questionnaire–Brief [34]	Social Suspicions and Schizotypal Traits	0.73 (0.7-0.77)
Reactive-Proactive Aggression	Higher score reflects more aggression.	Reactive-Proactive Aggression Questionnaire [35]	Aggression	0.86 (0.84-0.87)

Table 1: Variables that are computed to quantify participants' mental and physical health and living environment during lockdown. Cronbach's Alphas are reported referring to the scores collected during the first wave of lockdown.

days from the start date (n = 76); iii) filled in the survey from a country that was different from their original country of residence (n = 132). Criterion ii) was applied to exclude possible confounds in the amount of time passed from the start to the end of survey completion. This was a particularly key point in the data processing procedure since we were interested in the effects that the amount of time in lockdown had on people's mental and physical health. Similarly, criterion iii) was applied to exclude confounds of different types of lockdown restrictions that were adopted by the various countries of the world. All of these participants were excluded from the final analysis.

To consider the time spent in lockdown (independent variable), we computed "Weeks in lockdown" by taking the difference between the date in which the specific country adopted lockdown preventive measures and the survey completion date, for countries that had lockdown restrictions in place. This new numerical variable referred to the week of lockdown into which the single participant completed the survey.

In contrast to Carollo et al. [19], the current study examined UK participants only. After also excluding the participants who completed the survey after week 9 of lockdown (n = 40), the analytic sample (N = 435) had the following demographic features: female = 345 (79.31%), male = 81 (18.62%), non-binary = 4 (0.92%), prefer not to say = 2 (0.46%), self-identified = 3 (0.69%); age: Mean = 37.62, SD = 13.83 (missing = 1) (see Table 2).

Wave of lockdown	Before Week 3	Week 3	Week 4	Week 5	Week 6	Week 7	Week 8	Week 9	After Week 9	TOT
Wave 1	0	42	100	80	76	110	23	4	0	435
Wave 2	244	5	2	3	1	0	0	4	4	263

Table 2: Number of participants from the UK by week during the first and second period of lockdown.

Participants from the second wave of lockdown

With regard to the second wave of lockdown, 2,280 participants completed the survey. The same exclusion criteria described in the section above were applied to wave 2 data. Thus, 1,341 and 140 participants were excluded because they had incomplete and missing data respectively. The other 206 were excluded because they did not complete the survey within two days.

Finally, 43 did not filled in the survey from their original country of residence and, therefore, were excluded from the analysis. Again, the variable "Weeks in lockdown" was computed for each participant by referring to the date in which the second period of lockdown began in their country.

To be consistent with the sample used in our previous study, the statistical analysis applied to uncover the pattern of self-perceived loneliness in wave 2 was conducted uniquely on the UK participants (n = 263). The sample had the following demographic features: female = 216 (82.13%), male = 39 (14.83%), non-binary = 5 (1.90%), prefer not to say = 2 (0.76%), self identified = 1 (0.38%); age: *Mean* = 38.28, *SD* = 13.74 (missing = 2) (see Table 2).

2.3. Data Analysis

Using data from waves 1 and 2 of the UCL-Penn Global COVID Study and the same health variables across both time-points, we conducted two sets of analyses to answer our research questions: *a*) to test whether results in Carollo et al. [19] depended on the chosen machine learning model, we used wave 1 data and we adopted a data-drive machine learning approach with a different model to identify the most influential health variable (out of the 12 indices included). This was followed by a statistical approach with significance tests corrected for multiple comparisons. Conversely, *b*) to test whether the patterns of self-perceived loneliness found in Carollo et al. [19] were unique to wave 1 of lockdown, we used wave 2 data and applied the same statistical method to try to replicate the U-shaped pattern found in wave 1.

Data-driven and statistical replication of the results in wave 1

The current paper first adopted a machine learning approach to test whether the results in Carollo et al. [19] were specific to the RandomForest model or whether we would replicate the result using a new model, Support Vector Regressor (SVR) [36]. Data from 12 variables of interest (outlined in Table 1) were included in the SVR model to predict weeks in lockdown. First, we applied a standardized 10x5fold cross-validation scheme [37] to train the SVR model on 75% of the data. Once the model was established, we then applied the SVR model to the remaining 25% of data, the 'testing set' data, to test its accuracy by comparing real and predicted values. The SVR model's performances were evaluated by Mean Squared Error (MSE), where a lower MSE value corresponds to a higher overlap between the real and predicted data. For every training iteration, the variables were ranked by their absolute coefficient value to reflect their influence on the model's built. On all the training' rankings, we computed a Borda count [38] to determine the most important variable for the model's prediction of the Weeks in lockdown - the most informative variable in the model's training process. By comparing the several training-evaluation iterations, we derived the optimal hyper-parameter C to set in the final SVR model, specifically C = 0.01. This final model was then trained by using all the data from the training set and its performance was evaluated on the testing set data.

Next, focusing on the most influential variable, we applied a KruskalWallis test to assess whether the variable changed over the lockdown period and if there were significant differences in scores week-on-week. If the Kruskal-Wallis test comparing weeks 3 (since at the beginning of the data collection, the UK lockdown was already started) to 7 highlighted the existence of significant weekly variations, we conducted multiple pairwise KruskalWallis tests with Bonferroni correction to compare week 7 scores to other weeks.

Statistical replication of the results in wave 2

To test whether the distribution of weekly self-perceived loneliness levels were unique to wave 1 of lockdown, a graphical and statistical analysis of self-perceived loneliness levels was conducted on wave 2 data. Again, participant's scores were clustered by week of lockdown and a Kruskal-Wallis test was computed to compare scores from week 3 to 6 (weeks 7 and 8 were not considered because they did not include any participant), and week 9. For significant comparisons, additional multiple pairwise Kruskal-Wallis tests with Bonferroni-bias correction were conducted.

3. Results

3.1. Replication of the results in wave 1

The MSEs for the SVR performances were 2.04 and 2.29 for the training and test data, respectively. While the performance on the training set is slightly worse than in Carollo et al. [19], the performance on the test is in line with the previous paper. Furthermore, depression scores were found to be the most informative for the model's training, above and beyond the other variables in the model (see Figure 1).

A closer look at depressive symptoms divided by week found that the data reflected a U-shaped pattern. Specifically, self-reported symptoms of

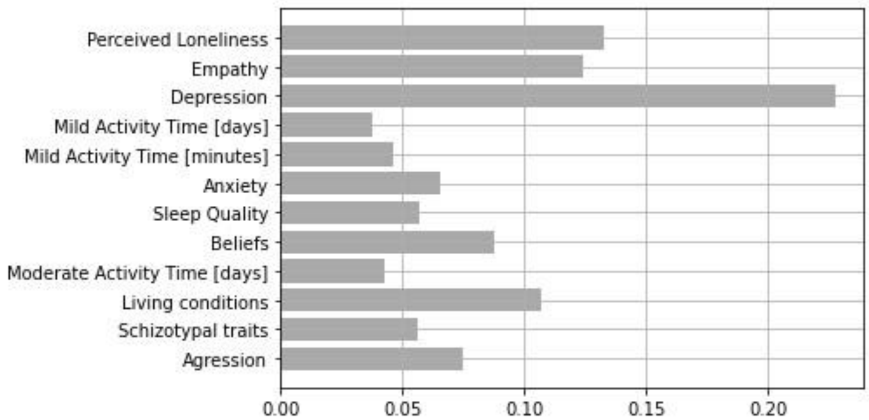

Figure 1: Average importance of the selected variables when training a Support Vector Regressor model on data from the first lockdown period.

depression during weeks 4 and 5 were lower compared to weeks 3 and 7 of wave 2 lockdown (see Figure 2).

A Kruskal-Wallis test confirmed that at least one week (in the period from the 3rd to the 7th week of lockdown) differed significantly from the others in terms of depressive symptoms (H=22.03, $p < 0.001$). Specifically, symptoms from week 4 to week 7 (H=22.52, $p < 0.001$), and week 5 to week 7 (H=9.69, p=0.002) were statistically different. Conversely, the comparisons between week 3 to week 7 (H=4.64, p=0.031), and week 6 to week 7 (H=4.02, p=0.045) were not significant after applying the Bonferroni bias-correction.

3.2. Statistical replication of the results in wave 2

A graphical inspection of boxplots with self-perceived loneliness scores divided by week suggests that, between week 3 to 9 of wave 2 UK national lockdown, another U-shaped pattern could be reported. Specifically, participants who took part at the study during the 4th and 5th week of lockdown

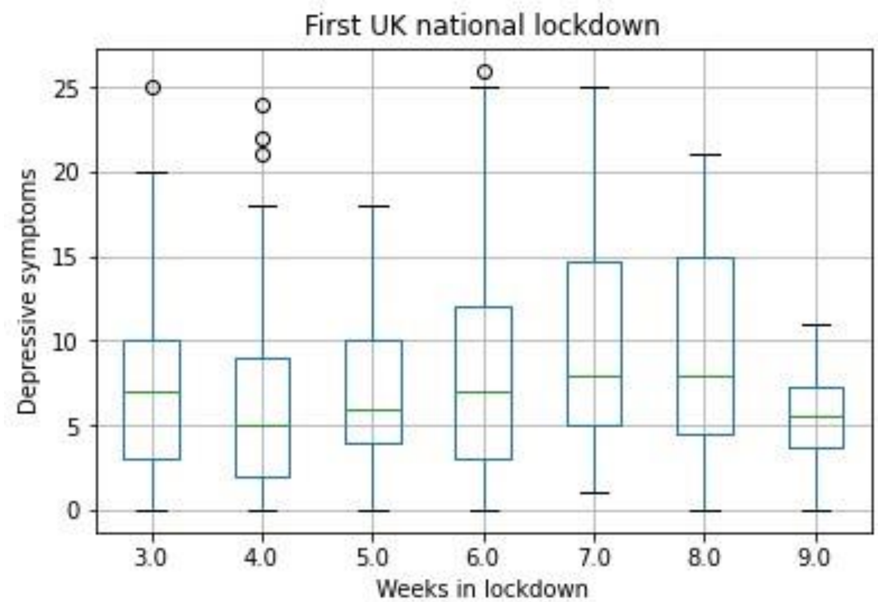

Figure 2: Symptoms of Depression reported by week during the first UK national lockdown.

reported lower levels of self-perceived loneliness than did participants in the survey during week 3. Although there were not enough participants for week 6, 7, and 8, self-perceived loneliness scores during week 9 were reportedly higher again (see Figure 3).

Despite a graphical U-shaped pattern, the multiple comparison KruskalWallis test on weeks 3 to 6, and week 9, showed no difference in scores (H=2.75, p=0.60).

4. Discussion

This study applying a machine learning approach alongside a statistical approach to data from waves 1 (17 April to 31 July 2020) and 2 (17 October

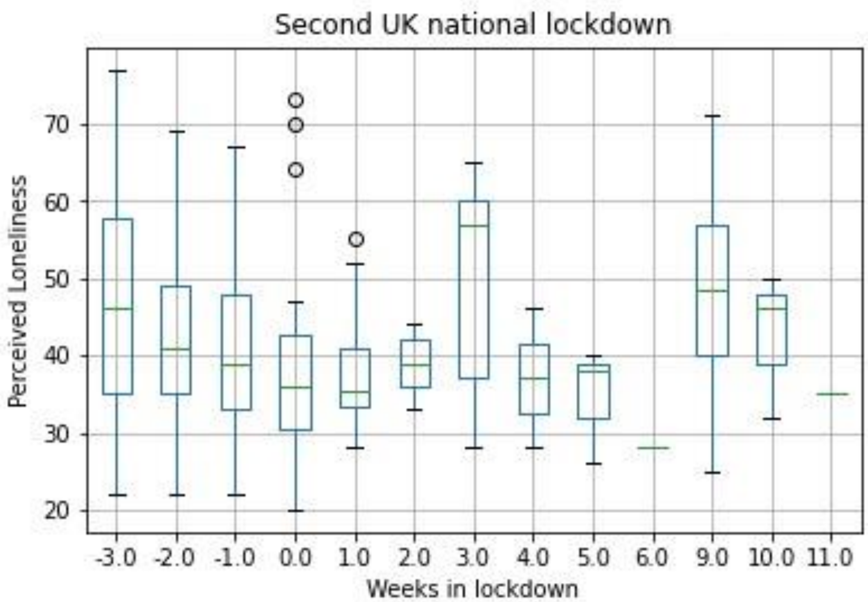

Figure 3: Reports of Perceived Loneliness by week during the second UK national lockdown.

2020 to 31 January 2021) of the UCL-Penn Global COVID Study [24] identifies the mental health variable(s) most influential in predicting UK lockdown duration, and how the variable varies by week. With the aim of replicating and extending the results from our previous paper, Carollo et al. [19], we applied a Support Vector Regressor (SVR) model instead of a RandomForest model to predict participant's weeks in lockdown. We found that depressive symptoms, over and above the other 11 health indices in the model, were the most important variable for the SVR model when determining the model best-fit to the data and was the best at predicting lockdown duration in weeks. Specifically, depressive symptoms reported across the 9 lockdown weeks resulted in a U-shaped pattern where symptoms were lowest during weeks 4 and 5 compared to week 7.

Variation in the population's depressive symptoms during lockdown has been reported by past studies as depressive symptoms have been a key mental health issue during the COVID-19 pandemic [39, 40, 41, 42]. Specifically, Ammar et al. [43] compared the scores pre- and post-lockdown symptoms of depression and found higher depressive symptoms as a result of home confinement. Notably, this study relied on self-report ratings of depression from participants internationally (e.g., Asia, Europe, and Africa), thus further substantiating the reliability of our finding. This is not surprising, given that social isolation is a common precursor of poorer mental and physical health [44], with increased risk for depression [45, 46, 47]. In another study by Delmastro and Zamariola [48] of lockdown in Italy, people living alone, or not being allowed to leave the house to go to work, tended to have higher depressive symptoms. Like self-perceived loneliness, symptoms of depression have varied during the first UK lockdown. Self-report data from the US during their first three-months of lockdown also showed that self-perceived loneliness was positively correlated with depression and suicide ideation at various time-points [49]. In fact, during the COVID-19 pandemic, self-perceived loneliness - a discrepancy between desired and perceived social connection - seemed to be one of the most important risk-factors for depression (and anxiety) [50], and social trust [18]. Specifically, higher perceived social support during lockdown - in other words, lower self-perceived loneliness - was associated with lower depressive symptoms [51]. After such periods, instead, self-perceived loneliness appeared to act as a moderator between stress and depression [52].

While we did not find significant week-by-week contrasts for self-perceived loneliness in wave 2 data as we did in wave 1 [19], it is worth noting that a similar

U-shaped pattern of self-perceived levels of loneliness did emerge again across the lockdown weeks. Again, the self-perceived levels of loneliness were low during weeks 4 and 5, and highest during the third and ninth weeks of the lockdown period. In fact, significant differences between weeks in wave 2 may not have been found given the small sample of participants that completed the survey in those weeks. Nonetheless, our study findings suggest that local and nation-wide initiatives to help reduce self-perceived loneliness and increase solidarity and community cohesion may be helpful at improving people's mental health during lockdowns.

Of course, "why" both perceived levels of loneliness and depression follow U-shaped patterns will necessarily involve the examination of individual-level characteristics, or other variables, that were not assessed and explored in the current study. For the same aim, a longitudinal investigation - opposed to the cross-sectional design of the current study - could also result useful. Although these limitations, the present study has also some clear strengths. First of all, a wide range of mental and physical variables could be studied in a data-driven fashion thanks to the adopted machine learning approach. In this way, we were able to identify and, in a second phase, statistically characterize the index that varied the most accordingly to the time spent in lockdown. Moreover, given the differences across lockdown restrictions, cross-cultural comparisons of the impacts of COVID-19 on populations are challenging. Thus, a strength of the current study is to focus just on the UK. Generally, the study highlighted the importance of considering the potential weekly variation in mental health across a wide range of variables and the variation that may exists across individuals and countries with different lockdown restrictions.

Author contribution

Conceptualization: A.B., G.G., K.K.W., G.E.; Data curation: A.C., A.B., G.G., K.K.W.; Data analysis, Data interpretation, Writing: A.C., A.B.; Revision: A.C., A.B., G.G., K.K.W., A.R., G.E.; Supervision: G.E. All authors read and agreed to the published version of the manuscript.

Conflicts of interest

The authors declare no conflict of interest.

Ethics

This study was pre-registered (https://osf.io/4nj3g/) on 17 April 2021 and ethical approval for the COVID-19 Social Study was granted by the University College London Institute of Education Ethics and Review Committee in April 2020 (REC 1331; [24]). The study is GDPR compliant.

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