



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

**Authors:** Alessandro Carollo[1], Andrea Bizzego[2], Giulio Gabrieli[3], Keri Ka-Yee Wong[4], Adrian Raine[5], Gianluca Esposito[6]

**Affiliations:** Department of Psychology and Cognitive Science, University of Trento, Italy[1], School of Social Sciences, Nanyang Technological University, Singapore[2], Department of Psychology and Human Development, University College London, London, UK[3], Departments of Criminology, Psychiatry, and Psychology, University of Pennsylvania[4], Department of Psychology and Cognitive Science, University of Trento, Italy; School of Social Sciences, Nanyang Technological University, Singapore; Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore[5]

**Orcid ids:** 0000-0002-2737-0218[1], 0000-0002-1586-8350[2], 0000-0002-9846-5767[3], 0000-0002-2962-8438[4], 0000-0002-3756-4307[5], 0000-0002-9442-0254[6]

**Contact e-mail:** gesposito79@gmail.com

**License information:** This is an open access article distributed under the terms of the Creative Commons Attribution License (CC BY) 4.0 <https://creativecommons.org/licenses/by/4.0/>, which permits unrestricted use, distribution and reproduction in any medium, provided the original author and source are credited.

**Preprint statement:** This article is a preprint and has not been peer-reviewed, under consideration and submitted to UCL Open: Environment Preprint for open peer review.

**Links to data:** [www.doi.org/10.5522/04/16583861](http://www.doi.org/10.5522/04/16583861)

**Funder:** UCL Global Engagement Fund

**DOI:** 10.14324/111.444/000095.v1

**Preprint first posted online:** 08 October 2021

**Keywords:** COVID-19, depression, lockdown, loneliness, global study, machine learning, SARS-CoV-2, Health

Rovereto, October 8<sup>th</sup> 2021

*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

University of Trento (Italy)

Nanyang Technological University (Singapore)

# 1 Self-Perceived Loneliness and Depression During the 2 COVID-19 Pandemic: a Two-Wave Replication Study

3 Alessandro Carollo<sup>a</sup>, Andrea Bizzego<sup>a</sup>, Giulio Gabrieli<sup>b</sup>, Keri Ka-Yee Wong<sup>c</sup>,  
4 Adrian Raine<sup>d</sup>, Gianluca Esposito<sup>\*a,b,e</sup>

5 *<sup>a</sup>Department of Psychology and Cognitive Science, University of Trento, Italy <sup>b</sup>School of  
6 Social Sciences, Nanyang Technological University, Singapore <sup>c</sup>Department of Psychology  
7 and Human Development, University College London,  
8 London, UK*

9 *<sup>d</sup>Departments of Criminology, Psychiatry, and Psychology, University of Pennsylvania*

10 *<sup>e</sup>Lee Kong Chian School of Medicine, Nanyang Technological University, Singapore*

11 \_\_\_\_\_

## 12 **Abstract**

13 COVID-19 studies to date have documented some of the initial health  
14 consequences of lockdown restrictions adopted by many countries. Combining a  
15 data-driven machine learning paradigm and a statistical analysis approach, our  
16 previous paper documented a U-shape pattern in levels of self-perceived  
17 loneliness in both the UK and Greek populations during the first lockdown (17  
18 April to 17 July 2020). The current paper aimed to test the robustness of these  
19 results. Specifically, we tested *a*) for the dependence of the chosen model by  
20 adopting a new one - namely, support vector regressor (SVR). Furthermore, *b*)  
21 whether the patterns of self-perceived loneliness found in data from the first UK  
22 national lockdown could be generalizable to the second wave of the UK lockdown  
23 (17 October 2020 to 31 January 2021). The first part of the study involved training  
24 an SVR model on the 75% of the UK dataset from wave 1 (n total = 435). This  
25 SVR model was then tested on the remaining 25% of data (MSE training = 2.04;  
26 MSE test = 2.29), which resulted in depressive symptoms to be the most important  
27 variable - followed by self-perceived loneliness. Statistical analysis of depressive

28 symptoms by week of lockdown resulted in a significant U-shape pattern between  
29 week 3 to 7 of lockdown. In the second part of the study, data from wave 2 of the  
30 UK lockdown (n = 263) was used to conduct a graphical and statistical inspections  
31 of the week-by-week distribution of scores regarding self-perceived loneliness.  
32 Despite a graphical U-shaped pattern between week 3 and 9 of lockdown, levels  
33 of loneliness were not between weeks of lockdown. Consistent with past studies,  
34 study findings suggest that self-perceived loneliness and depressive symptoms  
35 may be two of the most relevant symptoms to address when imposing lockdown  
36 restrictions.

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

39

---

40 Correspondence: #04-14, 48 Nanyang Avenue, Singapore 639818, Singapore.  
41 (+65) 6592 1573. gianluca.esposito@ntu.edu.sg

## 42 **1. Introduction**

43 Severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) is a novel  
44 and highly pathogenic coronavirus that originated in bats and hosted by pangolins  
45 before the spillover to humans [1, 2, 3, 4]. SARS-CoV-2 disease was first  
46 documented in the Hubei province of China in December 2019. Since then, SARS-  
47 CoV-2 has rapidly spread throughout the world with the World Health  
48 Organization declaring it a pandemic on 11 March 2020 [5]. As of September  
49 2021, over 224 million people have been infected by COVID-19 and more than  
50 4.6 millions of deaths have been reported globally [6].

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

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

77 on the perceived loneliness during the first lockdown period was replicated and  
78 substantiated by other COVID studies in the literature [20, 21, 22, 23].

79 Building on previous findings, the current study aims to replicate and extend  
80 on the previous results. In particular, the current study consists of two parts: to test  
81 whether the result by Carollo et al. [19] *a)* depended on the chosen machine  
82 learning model, we applied a new model on the same set of UK data from the first  
83 lockdown period; and *b)* depended on the wave of lockdown, we analyzed  
84 perceived loneliness distribution by week on data from the second UK national  
85 lockdown, with data collected from the UCL-Penn Global COVID Study between  
86 17 October 2020 and 31 January 2021 [24]. The current study provides a unique  
87 opportunity to replicate whether self-perceived loneliness is again most impacted  
88 by time in lockdown or not, and to uncover other aspects that may be significantly  
89 influenced by the lockdown restrictions in both the first and second waves of  
90 lockdown.

## 91 **2. Methods**

### 92 *2.1. Questionnaire*

93 The current study is based on survey data from the UCL-Penn Global COVID  
94 Study, a 12-month study of COVID-19's impact on mental health in adults  
95 conducted between 17 April 2020 and 31 July 2021 [24]. Specifically, this study  
96 will use data from wave 1 collected between 17 April 2020 and 10 July 2020, and  
97 data from wave 2 collected between 17 October 2020 and 31 January 2021.  
98 Briefly, the survey was available in 8 languages and anyone 18 years and above  
99 with access to the survey link through several social media channels (website -  
100 [www.GlobalCOVIDStudy.com](http://www.GlobalCOVIDStudy.com) -, email, LinkedIn, Whatsapp, Instagram,  
101 Facebook, and Reddit) was able to take part in the study. Participants received a  
102 randomized presentation of 13 standardized questionnaires assessing mental



103 health including self-perceived loneliness, anxiety, depression, aggression,  
 104 physical health, social relationships (empathy), living conditions, and background  
 105 variables. For this study 12 indices derived from the previous questionnaires were  
 106 included in the analytic sample (see Table 1). This study received ethical approval  
 107 from the University College London Institute of Education Research Ethics  
 108 Committee (REC 1331; April 2020).

## 109 2.2. Participants

### 110 *Participants from the first wave of lockdown*

111 During the first period of lockdown, a total of 2,276 adults from 66 different  
 112 countries participated in the study. As in Carollo et al. [19], we excluded  
 113 participants who: i) dissented to take part (n = 32), had incomplete (n = 712) or  
 114 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.	<i>International Physical Activity Questionnaire – Short Form</i> (IPAQ-SF, 6-items) [25]	Physical Activity	Not applicable
Mild Activity Difference	Time Difference between minutes of mild physical activity post- and pre- COVID-19 lockdown.	<i>International Physical Activity Questionnaire – Short Form</i> (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.	<i>International Physical Activity Questionnaire – Short Form</i> (IPAQ-SF, 6-items) [25]	Physical Activity	Not applicable
Sleep Quality	Self-reported sleep quality and quantity, where higher scores reflect better sleep quality.	<i>Pittsburgh Sleep Quality Index</i> (2-items) [26], <i>Epworth Sleepiness Scale</i> [27], <i>Subjective and Objective Sleepiness Scale</i> [28]	Sleep Quality	0.73 (0.7-0.77)
Empathy	Self-reported affective, cognitive, and somatic empathy, where higher scores reflect higher empathy.	<i>Cognitive, Affective, Somatic Empathy Scale</i> (CASES, 30-items) [29]	Empathy	0.87 (0.85-0.88)
Anxiety	Higher scores reflect higher anxiety.	<i>General Anxiety Disorder-7</i> (GAD-7) [30]	Anxiety	0.89 (0.88-0.91)
Depression	Higher scores reflect higher depression.	<i>Patient Health Questionnaire-9</i> (PHQ-9, 9-items) [31]	Depression	0.87 (0.86-0.89)
Perceived Loneliness	Higher scores reflect higher perceived loneliness.	<i>Loneliness Questionnaire</i> (LQ, 20-items) [32]	Perceived Loneliness	0.94 (0.93-0.95)
Living Conditions/Environment	Higher scores reflect more chaotic home environments.	<i>Chaos, Hubbub, and Order Scale and Health Risk Behaviors</i> (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)

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

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

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

133 In contrast to Carollo et al. [19], the current study examined UK participants  
134 only. After also excluding the participants who completed the survey after week  
135 9 of lockdown ( $n = 40$ ), the analytic sample ( $N = 435$ ) had the following  
136 demographic features: female = 345 (79.31%), male = 81 (18.62%), non-binary =  
137 4 (0.92%), prefer not to say = 2 (0.46%), self-identified = 3 (0.69%); age: Mean  
138 = 37.62, SD = 13.83 (missing = 1) (see Table 2).

139

140

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

168 al. [19] depended on the chosen machine learning model, we used wave 1 data  
169 and we adopted a data-drive machine learning approach with a different model to  
170 identify the most influential health variable (out of the 12 indices included). This  
171 was followed by a statistical approach with significance tests corrected for  
172 multiple comparisons. Conversely, *b*) to test whether the patterns of self-perceived  
173 loneliness found in Carollo et al. [19] were unique to wave 1 of lockdown, we  
174 used wave 2 data and applied the same statistical method to try to replicate the U-  
175 shaped pattern found in wave 1.

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

177 The current paper first adopted a machine learning approach to test whether  
178 the results in Carollo et al. [19] were specific to the RandomForest model or  
179 whether we would replicate the result using a new model, Support Vector  
180 Regressor (SVR) [36]. Data from 12 variables of interest (outlined in Table 1)  
181 were included in the SVR model to predict weeks in lockdown. First, we applied  
182 a standardized 10x5fold cross-validation scheme [37] to train the SVR model on  
183 75% of the data. Once the model was established, we then applied the SVR model  
184 to the remaining 25% of data, the 'testing set' data, to test its accuracy by  
185 comparing real and predicted values. The SVR model's performances were  
186 evaluated by Mean Squared Error (MSE), where a lower MSE value corresponds  
187 to a higher overlap between the real and predicted data. For every training  
188 iteration, the variables were ranked by their absolute coefficient value to reflect  
189 their influence on the model's built. On all the training' rankings, we computed a  
190 Borda count [38] to determine the most important variable for the model's  
191 prediction of the Weeks in lockdown - the most informative variable in the  
192 model's training process. By comparing the several training-evaluation iterations,  
193 we derived the optimal hyper-parameter C to set in the final SVR model,

194 specifically  $C = 0.01$ . This final model was then trained by using all the data from  
195 the training set and its performance was evaluated on the testing set data.

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

203

#### 204 *Statistical replication of the results in wave 2*

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

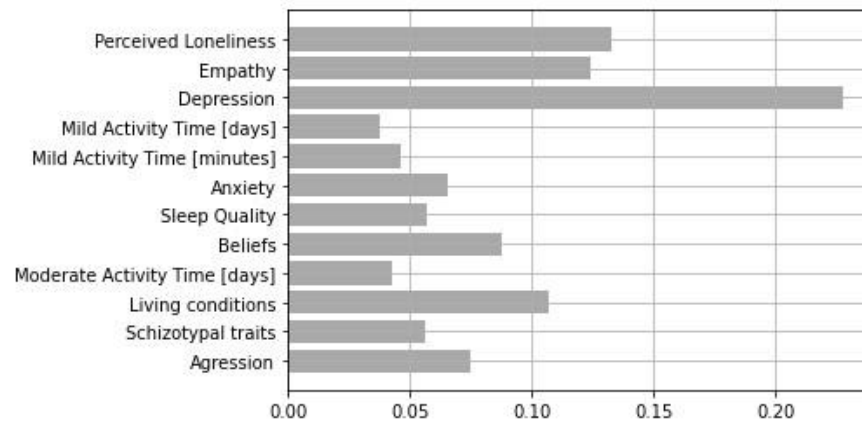
### 213 **3. Results**

#### 214 *3.1. Replication of the results in wave 1*

215 The MSEs for the SVR performances were 2.04 and 2.29 for the training and  
216 test data, respectively. While the performance on the training set is slightly worse  
217 than in Carollo et al. [19], the performance on the test is in line with the previous  
218 paper. Furthermore, depression scores were found to be the most informative for

219 the model's training, above and beyond the other variables in the model (see  
220 Figure 1).

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



223

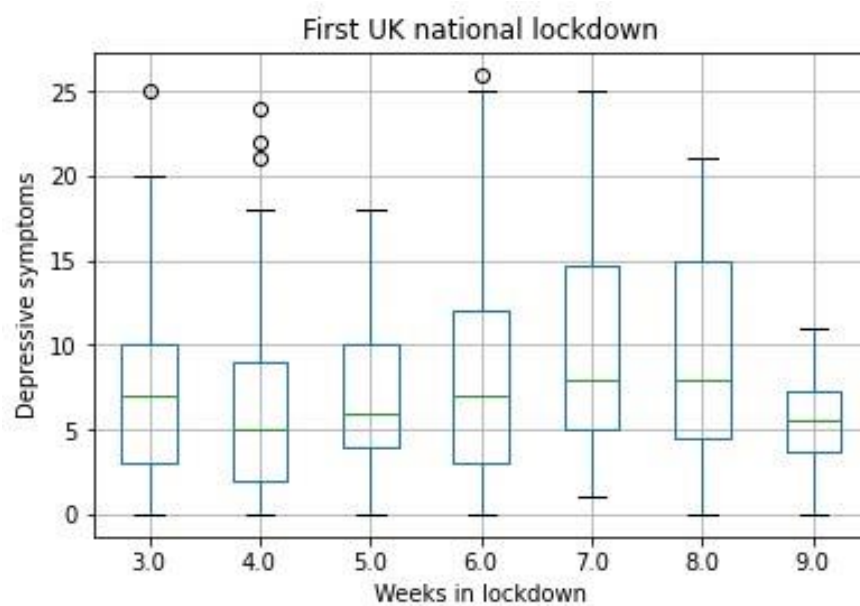
224 Figure 1: Average importance of the selected variables when training a Support Vector Regressor  
225 model on data from the first lockdown period.

226 depression during weeks 4 and 5 were lower compared to weeks 3 and 7 of wave  
227 2 lockdown (see Figure 2).

228 A Kruskal-Wallis test confirmed that at least one week (in the period from the  
229 3rd to the 7th week of lockdown) differed significantly from the others in terms  
230 of depressive symptoms ( $H=22.03, p < 0.001$ ). Specifically, symptoms from week  
231 4 to week 7 ( $H=22.52, p < 0.001$ ), and week 5 to week 7 ( $H=9.69, p=0.002$ ) were  
232 statistically different. Conversely, the comparisons between week 3 to week 7  
233 ( $H=4.64, p=0.031$ ), and week 6 to week 7 ( $H=4.02, p=0.045$ ) were not significant  
234 after applying the Bonferroni bias-correction.

235 3.2. Statistical replication of the results in wave 2

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



240

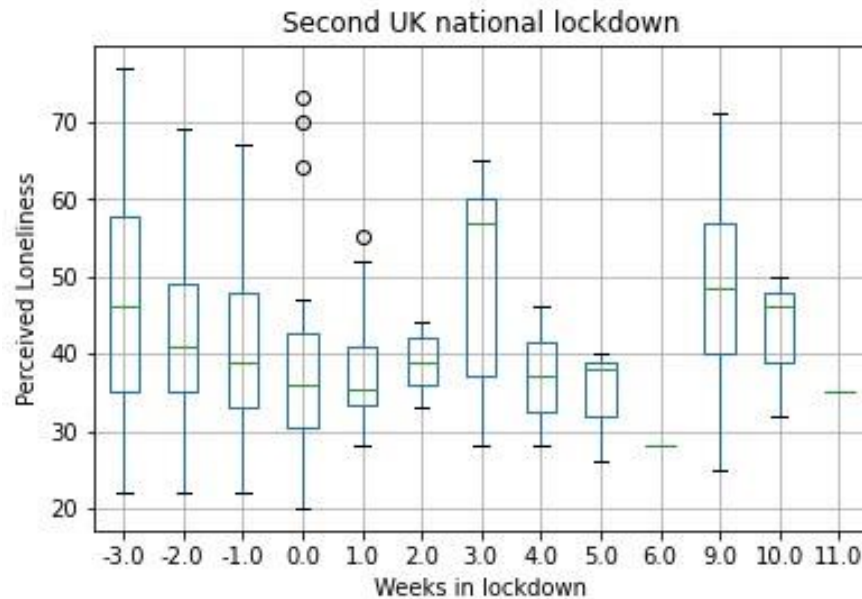
241 Figure 2: Symptoms of Depression reported by week during the first UK national lockdown.

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

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

248 **4. Discussion**

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



251

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

253 2020 to 31 January 2021) of the UCL-Penn Global COVID Study [24] identifies  
254 the mental health variable(s) most influential in predicting UK lockdown duration,  
255 and how the variable varies by week. With the aim of replicating and extending  
256 the results from our previous paper, Carollo et al. [19], we applied a Support  
257 Vector Regressor (SVR) model instead of a RandomForest model to predict  
258 participant's weeks in lockdown. We found that depressive symptoms, over and  
259 above the other 11 health indices in the model, were the most important variable  
260 for the SVR model when determining the model best-fit to the data and was the  
261 best at predicting lockdown duration in weeks. Specifically, depressive symptoms



262 reported across the 9 lockdown weeks resulted in a U-shaped pattern where  
263 symptoms were lowest during weeks 4 and 5 compared to week 7.

264 Variation in the population's depressive symptoms during lockdown has been  
265 reported by past studies as depressive symptoms have been a key mental health  
266 issue during the COVID-19 pandemic [39, 40, 41, 42]. Specifically, Ammar et al.  
267 [43] compared the scores pre- and post-lockdown symptoms of depression and  
268 found higher depressive symptoms as a result of home confinement. Notably, this  
269 study relied on self-report ratings of depression from participants internationally  
270 (e.g., Asia, Europe, and Africa), thus further substantiating the reliability of our  
271 finding. This is not surprising, given that social isolation is a common precursor  
272 of poorer mental and physical health [44], with increased risk for depression [45,  
273 46, 47]. In another study by Delmastro and Zamariola [48] of lockdown in Italy,  
274 people living alone, or not being allowed to leave the house to go to work, tended  
275 to have higher depressive symptoms. Like self-perceived loneliness, symptoms of  
276 depression have varied during the first UK lockdown. Self-report data from the  
277 US during their first three-months of lockdown also showed that self-perceived  
278 loneliness was positively correlated with depression and suicide ideation at  
279 various time-points [49]. In fact, during the COVID-19 pandemic, self-perceived  
280 loneliness - a discrepancy between desired and perceived social connection -  
281 seemed to be one of the most important risk-factors for depression (and anxiety)  
282 [50], and social trust [18]. Specifically, higher perceived social support during  
283 lockdown - in other words, lower self-perceived loneliness - was associated with  
284 lower depressive symptoms [51]. After such periods, instead, self-perceived  
285 loneliness appeared to act as a moderator between stress and depression [52].

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

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

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

313 **Author contribution**

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

318 **Conflicts of interest**

319 The authors declare no conflict of interest.

320 **Ethics**

321 This study was pre-registered (<https://osf.io/4nj3g/>) on 17 April 2021 and  
322 ethical approval for the COVID-19 Social Study was granted by the University  
323 College London Institute of Education Ethics and Review Committee in April  
324 2020 (REC 1331; [24]). The study is GDPR compliant.

325 **References**

- 326 [1] F. Wu, S. Zhao, B. Yu, Y.-M. Chen, W. Wang, Z.-G. Song, Y. Hu, Z.-W.  
327 Tao, J.-H. Tian, Y.-Y. Pei, et al., A new coronavirus associated with human  
328 respiratory disease in china, *Nature* 579 (2020) 265–269.
- 329 [2] T. Zhang, Q. Wu, Z. Zhang, Probable pangolin origin of sars-cov-2  
330 associated with the covid-19 outbreak, *Current biology* 30 (2020) 1346–  
331 1351.
- 332 [3] P. Zhou, X.-L. Yang, X.-G. Wang, B. Hu, L. Zhang, W. Zhang, H.-R.  
333 Si, Y. Zhu, B. Li, C.-L. Huang, et al., A pneumonia outbreak associated  
334 with a new coronavirus of probable bat origin, *nature* 579 (2020) 270– 273.

- 335 [4] T. T. Nguyen, P. N. Pathirana, T. Nguyen, Q. V. H. Nguyen, A. Bhatti, D.  
336 C. Nguyen, D. T. Nguyen, N. D. Nguyen, D. Creighton, M. Abdelrazek,  
337 Genomic mutations and changes in protein secondary structure and solvent  
338 accessibility of sars-cov-2 (covid-19 virus), *Scientific Reports* 11 (2021) 1–  
339 16.
- 340 [5] W. H. Organization, Coronavirus Disease 2019 - Situation Report  
341 – 51, [https://www.who.int/docs/default-source/coronaviruse/situation-](https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200311-sitrep-51-covid-19.pdf)  
342 [reports/20200311-sitrep-51-covid-19.pdf](https://www.who.int/docs/default-source/coronaviruse/situation-reports/20200311-sitrep-51-covid-19.pdf), 2020.
- 343 [6] W. H. Organization, Weekly epidemiological update on covid-19 14  
344 september 2021, [https://www.who.int/publications/m/item/ weekly-](https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19---14-september-2021)  
345 [epidemiological-update-on-covid-19---14-september-2021](https://www.who.int/publications/m/item/weekly-epidemiological-update-on-covid-19---14-september-2021), 2021.
- 346 [7] G. Iacobucci, Covid-19: Uk lockdown is “crucial” to saving lives, say  
347 doctors and scientists, 2020.
- 348 [8] R. S. Ogden, The passage of time during the uk covid-19 lockdown, *Plos one*  
349 15 (2020) e0235871.
- 350 [9] M. Qian, J. Jiang, Covid-19 and social distancing, *Journal of Public Health*  
351 (2020) 1–3.
- 352 [10] J. S. Kuiper, M. Zuidersma, R. C. O. Voshaar, S. U. Zuidema, E. R. van den  
353 Heuvel, R. P. Stolk, N. Smidt, Social relationships and risk of dementia: A  
354 systematic review and meta-analysis of longitudinal cohort studies, *Ageing*  
355 *research reviews* 22 (2015) 39–57.

- 356 [11] J. Holt-Lunstad, T. B. Smith, M. Baker, T. Harris, D. Stephenson, Loneliness  
357 and social isolation as risk factors for mortality: a metaanalytic review,  
358 *Perspectives on psychological science* 10 (2015) 227–237.
- 359 [12] N. K. Valtorta, M. Kanaan, S. Gilbody, S. Ronzi, B. Hanratty, Loneliness  
360 and social isolation as risk factors for coronary heart disease and stroke:  
361 systematic review and meta-analysis of longitudinal observational studies,  
362 *Heart* 102 (2016) 1009–1016.
- 363 [13] N. Cotterell, T. Buffel, C. Phillipson, Preventing social isolation in older  
364 people, *Maturitas* 113 (2018) 80–84.
- 365 [14] T. Elmer, K. Mepham, C. Stadtfeld, Students under lockdown: Comparisons  
366 of students’ social networks and mental health before and during the covid-  
367 19 crisis in switzerland, *Plos one* 15 (2020) e0236337.
- 368 [15] A. J. Idrissi, A. Lamkaddem, A. Benouajjit, M. B. El Bouaazzaoui, F. El  
369 Houari, M. Alami, S. Labyad, A. Chahidi, M. Benjelloun, S. Rabhi, et al.,  
370 Sleep quality and mental health in the context of covid-19 pandemic and  
371 lockdown in morocco, *Sleep medicine* 74 (2020) 248–253.
- 372 [16] R. Rossi, V. Socci, D. Talevi, S. Mensi, C. Niolu, F. Pacitti, A. Di Marco, A.  
373 Rossi, A. Siracusano, G. Di Lorenzo, Covid-19 pandemic and lockdown  
374 measures impact on mental health among the general population in italy,  
375 *Frontiers in psychiatry* 11 (2020) 790.
- 376 [17] C. Pieh, S. Budimir, J. Delgadillo, M. Barkham, J. R. Fontaine, T. Probst,  
377 Mental health during covid-19 lockdown in the united kingdom,  
378 *Psychosomatic medicine* 83 (2021) 328–337.

- 379 [18] K. K.-Y. Wong, Y. Wang, G. Esposito, A. Raine, A three-wave network  
380 analysis of covid-19's impact on schizotypal traits, paranoia and mental  
381 health through loneliness., UCL Open: Environment Preprint (2021).
- 382 [19] A. Carollo, A. Bizzego, G. Gabrieli, K. K.-Y. Wong, A. Raine, G. Esposito,  
383 I'm alone but not lonely. u-shaped pattern of perceived loneliness during the  
384 covid-19 pandemic in the uk and greece, medRxiv (2020).
- 385 [20] J. M. Groarke, E. Berry, L. Graham-Wisener, P. E. McKenna-Plumley,  
386 E. McGlinchey, C. Armour, Loneliness in the uk during the covid19  
387 pandemic: Cross-sectional results from the covid-19 psychological  
388 wellbeing study, PloS one 15 (2020) e0239698.
- 389 [21] W. D. Killgore, S. A. Cloonan, E. C. Taylor, N. S. Dailey, Loneliness: A  
390 signature mental health concern in the era of covid-19, Psychiatry research  
391 290 (2020) 113117.
- 392 [22] S. G. S. Shah, D. Nogueras, H. C. van Woerden, V. Kiparoglou, The covid-  
393 19 pandemic: A pandemic of lockdown loneliness and the role of digital  
394 technology, Journal of Medical Internet Research 22 (2020) e22287.
- 395 [23] M. T. Tull, K. A. Edmonds, K. M. Scamaldo, J. R. Richmond, J. P. Rose, K.  
396 L. Gratz, Psychological outcomes associated with stay-at-home orders and  
397 the perceived impact of covid-19 on daily life, Psychiatry research 289  
398 (2020) 113098.
- 399 [24] K. K. Wong, A. Raine, Covid-19: Global social trust and mental health study,  
400 <https://doi.org/10.17605/OSF.IO/FE8Q7>, 2020.
- 401 [25] P. H. Lee, D. J. Macfarlane, T. H. Lam, S. M. Stewart, Validity of

- 402 the international physical activity questionnaire short form (ipaq-sf): A  
403 systematic review, *International Journal of Behavioral Nutrition and*  
404 *Physical Activity* 8 (2011) 115.
- 405 [26] D. J. Buysse, C. F. Reynolds III, T. H. Monk, S. R. Berman, D. J. Kupfer,  
406 The pittsburgh sleep quality index: a new instrument for psychiatric practice  
407 and research, *Psychiatry research* 28 (1989) 193–213.
- 408 [27] M. W. Johns, A new method for measuring daytime sleepiness: the epworth  
409 sleepiness scale, *sleep* 14 (1991) 540–545.
- 410 [28] T. Åkerstedt, M. Gillberg, Subjective and objective sleepiness in the active  
411 individual, *International Journal of Neuroscience* 52 (1990) 29– 37.
- 412 [29] A. Raine, F. R. Chen, The cognitive, affective, and somatic empathy scales  
413 (cases) for children, *Journal of Clinical Child & Adolescent Psychology* 47  
414 (2018) 24–37.
- 415 [30] R. L. Spitzer, K. Kroenke, J. B. Williams, B. Löwe, A brief measure for  
416 assessing generalized anxiety disorder: the gad-7, *Archives of internal*  
417 *medicine* 166 (2006) 1092–1097.
- 418 [31] K. Kroenke, R. L. Spitzer, J. B. Williams, The phq-9: validity of a brief  
419 depression severity measure, *Journal of general internal medicine* 16 (2001)  
420 606–613.
- 421 [32] D. W. Russell, Ucla loneliness scale (version 3): Reliability, validity, and  
422 factor structure, *Journal of personality assessment* 66 (1996) 20–40.

- 423 [33] A. P. Matheny Jr, T. D. Wachs, J. L. Ludwig, K. Phillips, Bringing order out  
424 of chaos: Psychometric characteristics of the confusion, hubbub, and order  
425 scale, *Journal of applied developmental psychology* 16 (1995) 429– 444.
- 426 [34] A. Raine, D. Benishay, The spq-b: A brief screening instrument for  
427 schizotypal personality disorder, *Journal of Personality Disorders* 9 (1995)  
428 346–355.
- 429 [35] A. Raine, K. Dodge, R. Loeber, L. Gatzke-Kopp, D. Lynam,  
430 C. Reynolds, M. Stouthamer-Loeber, J. Liu, The reactive–proactive  
431 aggression questionnaire: Differential correlates of reactive and proactive  
432 aggression in adolescent boys, *Aggressive Behavior: Official Journal of the*  
433 *International Society for Research on Aggression* 32 (2006) 159–171.
- 434 [36] V. Vapnik, *The nature of statistical learning theory*, Springer science &  
435 business media, 2013.
- 436 [37] A. Bizzego, G. Gabrieli, M. H. Bornstein, K. Deater-Deckard, J. E. Lansford,  
437 R. H. Bradley, M. Costa, G. Esposito, Predictors of contemporary under-5  
438 child mortality in low-and middle-income countries: a machine learning  
439 approach, *International journal of environmental research and public health*  
440 18 (2021) 1315.
- 441 [38] G. Jurman, S. Riccadonna, R. Visintainer, C. Furlanello, Algebraic  
442 comparison of partial lists in bioinformatics, *PloS one* 7 (2012) e36540.
- 443 [39] C. Pieh, S. Budimir, T. Probst, The effect of age, gender, income, work, and  
444 physical activity on mental health during coronavirus disease (covid-19)  
445 lockdown in austria, *Journal of psychosomatic research* 136 (2020) 110186.



- 446 [40] D. A. Antiporta, Y. L. Cutip'e, M. Mendoza, D. D. Celentano, E. A. Stuart,  
447 A. Bruni, Depressive symptoms among peruvian adult residents amidst a  
448 national lockdown during the covid-19 pandemic, *BMC psychiatry* 21 (2021)  
449 1–12.
- 450 [41] J. A. Cecchini, A. Carriedo, J. Ferná'ndez-R'io, A. M'endez-Gim'enez, C.  
451 Gonza'lez, B. Sa'nchez-Mart'inez, P. Rodr'iguez-Gonz'alez, A longitudinal  
452 study on depressive symptoms and physical activity during the spanish  
453 lockdown, *International Journal of Clinical and Health Psychology* 21 (2021)  
454 100200.
- 455 [42] M. Daly, A. R. Sutin, E. Robinson, Depression reported by us adults in  
456 2017–2018 and march and april 2020, *Journal of affective disorders* 278  
457 (2021) 131–135.
- 458 [43] A. Ammar, P. Mueller, K. Trabelsi, H. Chtourou, O. Boukhris, L. Masmoudi,  
459 B. Bouaziz, M. Brach, M. Schmicker, E. Bentlage, et al., Psychological  
460 consequences of covid-19 home confinement: The eclb-covid19 multicenter  
461 study, *PloS one* 15 (2020) e0240204.
- 462 [44] N. Leigh-Hunt, D. Bagguley, K. Bash, V. Turner, S. Turnbull, N. Valtorta,  
463 W. Caan, An overview of systematic reviews on the public health  
464 consequences of social isolation and loneliness, *Public health* 152 (2017)  
465 157–171.
- 466 [45] X. Wang, L. Cai, J. Qian, J. Peng, Social support moderates stress effects on  
467 depression, *International journal of mental health systems* 8 (2014) 1–5.

- 468 [46] R. T. Han, Y.-B. Kim, E.-H. Park, J. Y. Kim, C. Ryu, H. Y. Kim, J. Lee, K.  
469 Pahk, C. Shanyu, H. Kim, et al., Long-term isolation elicits depression and  
470 anxiety-related behaviors by reducing oxytocin-induced gabaergic  
471 transmission in central amygdala, *Frontiers in molecular neuroscience* 11  
472 (2018) 246.
- 473 [47] L. Pancani, M. Marinucci, N. Aureli, P. Riva, Forced social isolation and  
474 mental health: A study on 1,006 italians under covid-19 lockdown, *Frontiers*  
475 *in Psychology* 12 (2021) 1540.
- 476 [48] M. Delmastro, G. Zamariola, Depressive symptoms in response to covid19  
477 and lockdown: a cross-sectional study on the italian population, *Scientific*  
478 *reports* 10 (2020) 1–10.
- 479 [49] W. D. Killgore, S. A. Cloonan, E. C. Taylor, M. A. Miller, N. S. Dailey,  
480 Three months of loneliness during the covid-19 lockdown, *Psychiatry*  
481 *Research* 293 (2020) 113392.
- 482 [50] Y. Palgi, A. Shrira, L. Ring, E. Bodner, S. Avidor, Y. Bergman, S. Cohen-  
483 Fridel, S. Keisari, Y. Hoffman, The loneliness pandemic: Loneliness and  
484 other concomitants of depression, anxiety and their comorbidity during the  
485 covid-19 outbreak, *Journal of affective disorders* 275 (2020) 109.
- 486 [51] A. Sommerlad, L. Marston, J. Huntley, G. Livingston, G. Lewis, A. Steptoe,  
487 D. Fancourt, Social relationships and depression during the covid-19  
488 lockdown: longitudinal analysis of the covid-19 social study, *Psychological*  
489 *medicine* (2021) 1–10.

490 [52] T. Probst, S. Budimir, C. Pieh, Depression in and after covid-19 lockdown  
491 in austria and the role of stress and loneliness in lockdown: a longitudinal  
492 study, *Journal of Affective Disorders* 277 (2020) 962.