Trait resilience protects against depression caused by loneliness during the COVID pandemic

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Abstract

Trait resilience has emerged as an important and widely used construct to explain how people cope with adversity, but studies often lack strong stressors in large samples. Capitalizing on a unique longitudinal dataset of 447 healthy American adults acquired during the COVID pandemic, we used well established self-report instruments to find that resilience at time 1 buffered individuals against the effects of loneliness at time 2 causing depression at time 3. Effects were further associated with the Big Five personality factors which provides important insight into the discriminative validity of trait resilience as a construct. However, our results were relatively specific to depression as the outcome, and did not generalize to other adverse outcomes, such as stress and anxiety. The findings document the important role of resilience and personality factors in responding to a major national stressor: loneliness in the COVID pandemic. Future studies can use the open dataset on which our study is based to further test the interventional potential of our findings.

Keywords

COVID pandemic, depression, loneliness, resilience, personality

Introduction

Resilience (Latin: *resilire*, to spring back) refers to an individual's or community's ability to maintain or recover mental health despite challenges from adverse events, a feature most clearly highlighted in theories of resilience that focus on stress and trauma (Yates et al., 2015). Resilience has been construed as a trait (e.g., possibly corresponding to a particular polygenic profile), a dynamic process (e.g., the active coping process itself), or even an outcome (e.g., a better outcome in the face of a stressor is sometimes simply defined as resilience) (Smith & Hayslip Jr, 2012). These three construals are typically closely related (indeed, on some treatments, resilience subsumes all three of the above definitions (Laird et al., 2019). Some studies incorporate resilience into the dynamics of an effect — that is, resilience is conceptualized as a state variable, for instance causally influenced by loneliness (Gerino et al., 2017).

Here we specifically treat resilience as a latent trait variable: it predisposes individuals to cope better and to have better mental health outcomes, but it is causally distinct from either of these. The COVID-19 pandemic has been a unique and global stressor, offering a natural test-bed for the protective effects of resilience (Vinkers et al., 2020). We capitalized on a longitudinal dataset acquired during the COVID pandemic (Rusch et al., 2021) in order to test a specific causal model: that resilience protects against the deleterious effects of loneliness in causing depression. In addition to testing the validity of trait resilience, our study provides important insight into how loneliness during the COVID pandemic results in individual differences in negative health-relevant outcomes.

A widely used, psychometrically very extensively validated instrument to assess such a resilience construct is the Connor-Davidson resilience scale (CD-RISC), whose original 25-item self-report instrument (Connor & Davidson, 2003) is well correlated with the shorter 10-item version that we used here (Campbell-Sills et al., 2009) (please see Methods for a discussion of other scales used to measure trait resilience). The CD-RISC provides high reliability and validity

across a very large number of studies and across cultures (Connor & Davidson, 2014). Our use of the CD-RISC here as measuring a trait-like variable is further supported by the high test-retest reliability of this instrument, which ranges from 0.7-0.9 (Baek et al., 2010; Connor & Davidson, 2003; Giesbrecht et al., 2009; Wang et al., 2010; Ye et al., 2017). Given that it is a self-report instrument, validity is borne out by relations to many other measures. For instance, CD-RISC scores have been shown to protect against depression and PTSD following specific disasters such as earthquakes (Ahmad et al., 2010; Ying et al., 2014), tsunamis (Irmansyah et al., 2010), and oil spills (Grattan et al., 2011).

Across studies, resilience has been found to be associated with personality factors from the Big Five: it is positively correlated with extraversion and conscientiousness, and negatively correlated with neuroticism (Oshio et al., 2018) (see Table 1). Some studies have reported that resilience contributes unique variance to outcomes that are not fully accounted for by the Big Five alone. For instance, (Campbell-Sills et al., 2006) found that a full regression model to predict coping explained more variance when resilience was included as a regressor together with these personality traits than when only the Big Five traits were included. A similar finding was obtained more recently in the context of the COVID pandemic: (Kocjan et al., 2021) found that in a sample of over 2000 Slovenian adults the CD-RISC fully or partly mediated the effects of the Big Five on perceived stress and wellbeing. Also in the context of the COVID pandemic, however, a longitudinal study with a sample of 80 German adults found that both neuroticism and extraversion predicted higher biological stress load while resilience showed no effects (Engert et al., 2021). With most previous studies restricted to correlational analysis, the discriminative validity of resilience as a construct with respect to the Big Five remains unclear.

The COVID pandemic clearly provided an acute change in social isolation, with loneliness prominently increased (Killgore et al., 2020; Wickens et al., 2021). Loneliness is usually conceptualized as a discrepancy between a person's actual social interactions and their desired

ideal, resulting in a negatively valenced emotional experience: the number and/or quality of social interactions are insufficient, for that person (Peplau, 1982). While there are enormous individual differences here, with some people needing intense social interaction while others prefer solitude, the need for some social interaction is thought to be a fundamental aspect of human nature (Cacioppo & Patrick, 2008). Loneliness appears to be surprisingly impervious to interventions, with generally small-moderate effect sizes across studies (Masi et al., 2011). Importantly, loneliness and depression are distinct, with loneliness as a separable risk factor for depression (the core causal model whose moderation by resilience we tested in the present study) (Cacioppo et al., 2006; Heinrich & Gullone, 2006).

A protective role for resilience in the effects of a stressor on depression has been studied in a number of studies; for instance, the effect childhood adversity on later depression in adulthood is influenced by resilience (Poole et al., 2017). Polygenic risk scores for depression are mediated by both resilience and neuroticism (as separately measured variables) (Navrady et al., 2018), perhaps one of the clearest role for resilience in protecting against depression within a causal model.

Of studies specifically during the COVID pandemic, one examined loneliness and resilience using separate instruments (Marchini et al., 2021). However, a single cross-sectional data collection was undertaken and no causal model was tested. Another study found an association between resilience and depression — but was again entirely cross-sectional (Ran et al., 2020). A few other studies have also probed resilience during the COVID pandemic (Coulombe et al., 2020; Kimhi et al., 2021) (see (Finstad et al., 2021) for a review), but all remain cross-sectional. Similarly cross-sectional are studies outside the scope of the COVID pandemic, showing that resilience protects against the effects of loneliness on mental health in the elderly (Zhao et al., 2018), in homeless people (Perron et al., 2014), and in students (Jakobsen et al.,

2020): all demonstrate the expected associations, but none permit strong causal inferences because resilience and outcome are sampled at the same time.

Our conceptualization allowed us to test a specific causal model, leveraging a unique longitudinal dataset in which resilience, loneliness, and depression could be temporally separated in epochs corresponding to the pre-registered causal model. We do note, however, that we did not analyze dynamics of change in any of the variables, in part because we did not have pre-COVID baselines available in our dataset. Instead, in each case, we aimed to have the variable in question be temporally stable over the specific time window of interest; this also permitted a more precise estimation of the latent variable from the average of its sampled measures. Our study thus had three aims. First, given the COVID pandemic as an experiment of nature, can we capitalize on the longitudinal data of the COVID-Dynamic dataset to test a specific, pre-registered hypothesis, that trait resilience buffers against the depression and stress caused by loneliness experienced during the pandemic. Second, are there differentiable effects on the outcomes of depression and stress? And third, to what extent are the effects of resilience redundant or distinct from those of the Big Five personality traits? These questions have typically been addressed in separate studies; probing them here in an exceptionally well characterized sample of healthy American adults provides strong additional tests of the predictive and discriminative validity of trait resilience.

Methods

Data

Data used in this study were acquired in the COVID-Dynamic longitudinal dataset, which was pre-registered before data collection began (<https://osf.io/sb6qx>). Details about the entire dataset can be found in the data release paper (Rusch et al., 2021), and a pre-registered data-request provides the broad aims and variables requested for the present study (<https://osf.io/3tfnh/>). Here,

we provide brief descriptions of the subject recruitment and psychological measures used in this study. We also report the internal consistency for each of the measures as evaluated by Cronbach's alpha.

The recruitment was done through Prolific (www.prolific.co) and subjects were required to be adults 18 or older, fluent in English and reside in the United States. In addition, they had to have a Prolific approval rating of 98% or higher, and a minimum of 5 Prolific studies completed. In total, 1797 subjects completed Wave 1 of the COVID-Dynamic study (see Fig. 1 for a timeline of the wave administrations).

The Connor-Davidson Resilience Scale - 10 Item (CD-RISC) (Connor & Davidson, 2003) is a self-report questionnaire of coping responses in the past month that is the most common measure of psychological resilience (internal consistency: 0.94). The NEO Five-Factor Inventory (NEO) (Costa & McCrae, 1992) is a 60-item self-report questionnaire that assesses an individual on five dimensions of personality (the so-called Big Five personality traits): openness, conscientiousness, extraversion, agreeableness, and neuroticism (internal consistency: O: 0.78, C:0.9, E: 0.89, A: 0.82, and N: 0.93). The NIH toolbox: Loneliness scale (NIH-Loneliness) (Gershon et al., 2013) is a 5-item self-report questionnaire of how often an individual felt lonely or alone in the past month (internal consistency: 0.94). Beck Depression Inventory – II (BDI) (Beck et al., 1996) is a 21-item self-report questionnaire that examines depressive symptomatology over the past two weeks (internal consistency: 0.95). The State Trait Anxiety Inventory (STAI) (Spielberger, 1983) is a 20-item self-report questionnaire that we used to measure current (state) anxiety (internal consistency: 0.96). The Perceived Stress Scale (PSS) (Cohen et al., 1983) is a 10-item self-report questionnaire that measures the extent to which a participant perceives personal life events in the past month as stressful (internal consistency: 0.92).

A comparison of 19 resilience scales showed that three of them had the best psychometric properties: the Resilience Scale for Adults, the Brief Resilience Scale, and the CD-RISC (Windle

et al., 2011). Of these, the CD-RISC is the most widely used and has the largest associated literature; it is also designed for adults and has extensive test-retest reliability. This together with the availability of validated relatively brief versions of the CD-RISC, such as the 10-item version we used here, led to our choice of this instrument in our study. Other resilience scales may be better when testing specific populations such as children (Sun & Stewart, 2007) or international samples (Ungar et al., 2008), but our study was restricted to American adults. We also note that the CD-RISC is correlated with the Big Five personality traits, as shown in Table 1 (see also Introduction).

Exclusion criteria

We applied the following a priori exclusion criteria to ensure data quality. Subjects were excluded if they failed one or more attention checks per data collection wave (on average, three attention questions were included for each wave) across a total of three or more waves. Subjects were also excluded if they self-reported that they were diagnosed with any of the following mental health conditions not related to our hypothesis: schizophrenia, bipolar disorder, or posttraumatic stress disorder; or multiple comorbid psychiatric conditions other than depression and anxiety. After exclusion, the total number of unique subjects was reduced from 1797 (which we refer to as the 'initial' sample) to 1580 (which we refer to as the 'quality' sample).

Further subject selection

The longitudinal nature of the COVID Dynamic study allowed us to select specific time windows (Fig. 1) to establish baseline resilience and personality trait measures at time 1 (CD-RISC: waves 5, 7; NEO: wave 1), loneliness at time 2 (waves 8,11,13), and subsequent depression, anxiety, and stress at time 3 (BDI: waves 14,16; STAI: waves 14,15,16; PSS: waves 14,15,16) out of all available waves. Since we consider resilience and NEO personality to be temporally stable traits, all six available waves of data for these two measures were used in this further selection step (however, only the initial waves were used in regression analyses to ensure clean temporal separation).

We first selected only subjects who had at least two waves of data for each measure to ensure relatively complete data from each subject (there were additional requirements specifically for CD-RISC: at least one wave of valid data was available for waves 5,7 and for NEO: wave 1 data must be complete, to avoid missing values for regression analyses). This step resulted in a total number of 634 subjects (which we refer to as the 'dense' sample) with relatively complete data across all waves of interest (note that because of attrition, the total number of subjects completing wave 16 was 876; subject attrition across the longitudinal waves was the main factor in reduction of our final sample size).

We restricted the scope of our study to resilience and personality as temporally stable traits. While we conceive of loneliness, depression, anxiety, and stress as state variables that vary within an individual over time, we nonetheless also aimed to have these variables be relatively stable within our specific time windows (since we would not be able to distinguish rapid variability from one wave to the next from measurement error – that is, within our time window, we required good test-retest reliability even for these state variables). We therefore assessed the within-subject temporal stability in the relevant time windows for each set of variables. Specifically, we calculated the difference between the maximum and minimum values of a measure across the selected windows of waves for each subject and normalized the difference by the total points range possible for each measure (for example, STAI raw scores range from 20 to 80, so we divided the temporal variation by 60) for easier comparison across measures (see Fig.S1 in the Supplementary Material for distributions of the normalized differences for all measures). We consequently selected subjects whose normalized differences were no more than 0.3 for all measures; i.e., for any of the measures, the within-subject temporal variation was no more than 30% of the range of the measure. These further selection restrictions resulted in a final sample of 447 subjects (which we refer to as the 'final' sample, see Table S1 in the Supplementary Material for characterization of the final sample).

Final variables: We used the raw (untransformed) scores produced by the CD-RISC, NEO, NIH-Loneliness, BDI, STAI and PSS. To obtain the smallest measurement error, we averaged the scores for each individual across the multiple valid longitudinal measure collections (CD-RISC: waves 5, 7; NEO: wave 1; Loneliness: waves 8,11,13; BDI: waves 14,16; STAI: waves 14,15,16; PSS: waves 14,15,16). Note that from the distributions of normalized differences (Fig.S1 in the Supplementary Material), the scores for CD-RISC and NEO were indeed empirically stable across six waves (the majority of normalized differences fell within 0.3), justifying our operationalization of resilience as a trait variable for the purposes of the present study.

Regression analysis

We carried out multiple linear regression models (lm function in R) to test the associations between the selected variables. For our main hypothesis, we first quantified the associations of loneliness and resilience (as independent variable) with depression (as outcome variable) in separate models. We then further tested the moderating effect of resilience by incorporating loneliness, resilience, and their interaction term in the same model. We also included demographic variables in all of the regression models. Age was a continuous variable while dummy variables were used to encode gender (female: 1, male: 0) and education level (low: 1, high: 0; high education is defined as bachelor's degree or above). All variables (with the exception of demographic variables) were standardized to help alleviate multicollinearity (Iacobucci et al., 2016). We repeated the same analysis scheme for different outcome variables (anxiety and stress), and for different moderators (the Big Five personality traits) in separate models and reported the results in Table 2.

The analysis scheme described above where each regression model only included one moderator allowed us to examine the overall effect of each moderator. In addition, we tested the incremental validity of each moderator. First, a full model was built that included all Big Five traits, resilience and all the respective interactions. Then, we built six additional models where each one of the six

moderators and its interaction term were taken out from the full model. We compared model performance of each of these models with the full model to see if there's a substantial change.

Statistical treatment

We report effect sizes (standardized regression coefficients) and confidence intervals, as well as exact p-values for the main hypotheses. We interpret p-values < 0.05 in combination with effect sizes with the adjective “substantial” and avoid use of the word “significant,” so as to avoid dichotomous interpretation.

By standardizing the variables, the coefficient of an independent variable can be interpreted as the effect of that variable on the outcome variable at the mean level of the other independent variables. Larger coefficients indicate greater effects, but there is no established cut point for judging the magnitude of effects for standardized regression coefficients. As our moderator variables are all continuous, the coefficients of the interaction terms reflect the change in the slope of the regression lines at different values of the moderator. To interpret the moderating effect more intuitively, simple slopes are generally plotted for three values of the moderator: the mean, one standard deviation above the mean and one standard deviation below the mean.

Results

Resilience protects against depression caused by loneliness.

To test our primary model, we first examined the associations between each pair of our main variables of interest: resilience, loneliness, and depression (Fig. 2). As expected, resilience was negatively correlated with both loneliness ($r = -0.52$, $p < 0.001$) and depression ($r = -0.59$, $p < 0.001$), while loneliness and depression were positively correlated ($r = 0.67$, $p < 0.001$). Linear regression models (Table 2), confirmed that while both loneliness ($b = 0.49$, 95% CI = [0.41, 0.56], $p < .001$) and resilience ($b = -0.30$, 95% CI = [-0.38, -0.22], $p < .001$) predicted depression (positively and negatively, respectively), these two variables also interacted ($b = -0.12$, 95% CI =

[-0.18, -0.07], $p < .001$): more resilient individuals were less depressed following loneliness compared to less resilient individuals (Fig. 3). We didn't find substantial effects for gender, age, or education (gender: $b = 0.06$, 95% CI = [-0.07, 0.18], $p = 0.396$; education: $b = 0.06$, 95% CI = [-0.07, 0.19], $p = 0.379$; age: $b = 0.00$, 95% CI = [-0.00, 0.01], $p = 0.707$).

We further tested whether our finding would replicate in samples at different stages of exclusion and selection (see Table S2 for a comparison across samples) and found qualitatively the same conclusion across samples (Table S3). As the impact of the pandemic varied across locations in the United States (see Fig.S2 for a state level map of each of our measures), we also tested the geographic specificity of our finding. To ensure sufficient sample sizes, subjects were split into four samples, corresponding to the four Census bureau-designated regions (the West, Midwest, South and Northeast). The moderating effect of resilience varied across regions with the most notable difference in the South (Table S4, West: $b = -0.18$, 95% CI = [-0.29, -0.06], $p = 0.002$; Midwest: $b = -0.16$, 95% CI = [-0.33, -0.02], $p = 0.078$; South: $b = -0.02$, 95% CI = [-0.12, 0.08], $p = 0.696$; Northeast: $b = -0.14$, 95% CI = [-0.25, -0.04], $p = 0.007$).

Generalizability to other mental health variables.

In addition to depression, we queried anxiety and stress. Anxiety was correlated with both loneliness ($r = 0.56$, $p < 0.001$) and resilience ($r = -0.67$, $p < 0.001$). Similarly, stress was correlated with both loneliness ($r = 0.64$, $p < 0.001$) and resilience ($r = -0.73$, $p < 0.001$). To test whether our findings extend beyond depression to other mental health variables, we carried out identical regression analyses as above, using anxiety or stress as outcome variables (Table 2).

While both loneliness ($b = 0.28$, 95% CI = [0.21, 0.36], $p < .001$) and resilience ($b = -0.51$, 95% CI = [-0.59, -0.43], $p < .001$) predicted anxiety (positively and negatively, respectively), they didn't interact substantially ($b = 0.00$, 95% CI = [-0.06, 0.06], $p = 0.943$). We didn't find substantial effects for gender, age, or education either.

Similar results were found for stress (Table 2), where both loneliness ($b = 0.37$, 95% CI = [0.30, 0.43], $p < .001$) and resilience ($b = -0.55$, 95% CI = [-0.61, -0.48], $p < .001$) predicted stress, but no moderating effect was found ($b = 0.04$, 95% CI = [-0.01, 0.09], $p = 0.125$). Females were more stressed than males ($b = 0.17$, 95% CI = [0.06, 0.29], $p = 0.003$), while no substantial effects were associated with education or age.

Exploring trait-resilience as a construct.

Our theoretical focus was on individual resilience as a trait, ensured by the way in which we selected subjects with temporally stable CD-RISC scores. Since we also collected personality measures (from the NEO-FFI), we expected empirically that CD-RISC scores would be correlated with at least some personality trait scores, as has been shown in prior studies (see Introduction). We tested correlations with all five personality traits (Fig. 2) and found three that correlated substantially with resilience scores: conscientiousness ($r = 0.58$, $p < 0.001$), extraversion ($r = 0.62$, $p < 0.001$), and neuroticism ($r = -0.74$, $p < 0.001$). These three personality traits were also tested separately in the same set of regression models as carried out with resilience above (Table 2). Being more conscientious, more extraverted, or less neurotic protected against depression but not anxiety or stress caused by loneliness, a pattern of results for these personality factors that was qualitatively the same as what we found with resilience.

One theoretical possibility is that the effect of resilience is redundant from those of the Big Five personality traits, at least in the context of our study. We therefore sought further insight into this by evaluating the incremental validity of each measure and found that resilience had minimal unique contribution beyond the Big Five personality traits in predicting depression while neuroticism had the most substantial incremental validity among all measures (Table 3).

Discussion

A unique longitudinal dataset in 447 American subjects exceptionally well assessed during the course of the COVID pandemic provided us with a strong test of a specific causal model, according to which resilience protects against the effects of loneliness on depression. The strong shared environmental intervention of social isolation, experienced across the country during lockdowns, gathering restrictions, and quarantine measures resulted in an increase in both loneliness and depression across our sample, and, as expected, these two variables were correlated: the key question we tested was whether preceding trait-resilience moderated this association. Regression results conformed to the causal model as we hypothesized (although not a formal test for causality themselves), restricted the effect specifically to depression (but not anxiety or stress), and extended it to encompass personality traits as protective factors as well. While we interpret resilience as mostly redundant with the Big Five personality factors in predicting depression, it remains possible that other outcomes, other populations, or other instruments for measuring resilience could yield distinct effects of resilience above and beyond what is explained by the Big Five.

While the supposition of temporal stability in resilience was our theoretical interest, and while empirically valid in the context of our study and over our time window, this in no way argues against resilience as a dynamic process. It is well established that resilience emerges throughout development and adolescence (Hart et al., 2007), and that it can change even during adulthood (Ong et al., 2006; Ong et al., 2009). The dynamic nature of resilience plays out in a complex psychosocial context, through relationships, attachments, and social support networks (Herrman et al., 2011). There is good evidence that, at least for some people, exposure to adverse events can build resilience over time (Seery, 2011). All interventions targeted at resilience itself require such a dynamic view — but it is not within the scope of the present study.

An important aspect of our study was the intervening variable of loneliness, a particularly salient feature during the COVID pandemic. This particular stressor differs from others in that social relations are widely acknowledged to be a key part of the mechanism whereby resilience acts: building relationships, seeking advice, and relying on others for emotional support are critically important for resilience (Bonanno et al., 2007). Yet these may have been precisely the mechanisms intervened upon during social isolation during the COVID pandemic. This would suggest a somewhat different interpretation of our findings: rather than thinking of social isolation as one among many possible stressors that can cause negative affect, it may interfere with one of the main mechanisms of resilience itself. Plausible future tests of this hypothesis could test the prediction that social isolation predisposes people to become depressed by other adverse events even when they are otherwise resilient.

A constraint of scope in our study were the measures we used, and hence the extent of the domain of latent variables that could be studied: for our main analysis, we used only a single measure for resilience, loneliness, and depressive symptomatology. The generalizability of our findings was addressed to some extent by testing other measures of negative affect, and by testing traits other than resilience. Whereas the latter did show an interesting generalization, the former showed that our findings are specific to depression and do not generalize to anxiety or stress – again, at least as available from our measures. We want to emphasize the fact that all of the measures used in our study are self-report questionnaires, and one clearly important future direction would be to reproduce our findings with measures that do not depend on self report.

While we have established that the generalizability of our findings was not impacted by our subject selection strategy, preliminary results did suggest some geographic specificity of our findings. The moderating effect of resilience was most substantial in the West and the Northeast (possibly limited by sample size for the Midwest), but not in the South despite having the largest sample size among all regions (Table S4). We didn't observe noticeable patterns from the state-

level maps of our measures (Fig. S2), larger-scale future studies ideally with more comprehensive characterization of the demographics and COVID-related situational factors are needed to further address and explore the regional heterogeneity.

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Author Contributions

Y.H. participated in collecting the data and conducted all analyses; both authors conceived the study and wrote the paper. Data were acquired as part of the COVID-Dynamic study, with contributions by specific individuals as shown in Table S5.

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Conflicts of Interest

The authors declare no competing interests.

Informed Consent

All participants consented to the research before beginning the study.

Ethics Approval

The study was reviewed and granted exemption by the Institutional Review Board of the California Institute of Technology.

Data Availability

All data used in this study were part of the COVID-Dynamic longitudinal dataset, which is publicly available on our website (<https://covidynamic.caltech.edu/data-sharing>).

Fig. 1 Timeline of the wave administrations and our selection of time windows. Orange triangles denote each wave administration (black tick marks depict weekly intervals). The gray curve indicates the daily 7-day average of new, confirmed COVID-19 cases in the U.S., black encircled X's on top of the curve mark grim U.S. COVID-19-related death milestones (100,000 to 400,000 dead). The green line shows the monthly unemployment rate. The upper gradient (yellow-red) indicates the daily count of states with active stay-at-home restrictions (peak=41). The lower gradient (blue-purple) shows the daily count of U.S. anti-racism crowd events. Colored triangles below the gradients indicate local maxima for the various measures. Events of interest are indicated with vertical blue lines. Selection of time windows for measures of interest are indicated by vertical dashed lines at the bottom. Note that we only indicated the subset of waves selected for this study, total number of waves available for each measure are CD-RISC: $n = 6$; NEO: $n = 6$; NIH-Loneliness: $n = 8$; BDI: $n = 7$; STAI: $n = 16$; and PSS: $n = 15$. Figure adapted From:(Rusch et al., 2021).

Fig. 2 Associations between measures. **a** Histograms on the diagonal show the distributions of each measure. Off-diagonal scatterplots show associations between each pair of measures (with fitted regression lines). **b** Pearson correlation coefficients between each pair of measures.

Fig. 3 Regression results testing the effect of loneliness and/or resilience on depression. **a** Regression result showing the influence of loneliness on depression: higher loneliness predicted higher depression. **b** Regression result showing the influence of resilience on depression: higher resilience predicted lower depression. **c** Simple slopes for the association between loneliness and depression were tested for low (-1 SD below the mean), moderate (mean), and high (+1 SD above the mean) levels of resilience, showing the effect of loneliness on depression was moderated by resilience. All variables were standardized. Males and females are indicated using blue and pink circles respectively.

Table 1 Correlation coefficients between the Big Five personality traits and CD-RISC as reported in previous studies. Adapted from (Oshio et al., 2018).

N	E	O	A	C	Study
-0.65	0.61	0.2	0.15	0.46	Campbell-Sils et al.,2006
-0.27	0.39				Zhang et al., 2011
-0.49	0.55				Peng et al., 2012
-0.32	0.29				Baldwin-Kirchoff & Ansborg, 2013
-0.49	0.47	0.15	0.2	0.55	Rudow et al., 2014
-0.39	0.4				Lü et al., 2014
-0.38	0.37	0.42	0.18	0.28	Di Fabio & Saklofske, 2014
-0.24	0.2	0.18		0.11	Foumani et al., 2015
-0.48	0.55				Sarubin et al.,2015
-0.42	0.44	0.34	0.27	0.42	Mansouri et al., 2015

Table 2 Results of multiple regression models testing whether the association between loneliness and an outcome variable depends on a moderator variable. Results are divided into three sections of different outcome variables: depression (BDI), anxiety (STAI), and stress (PSS). For a given outcome variable, six moderators were tested in separate models: resilience (R), openness (NEO_O), conscientiousness (NEO_C), extraversion (NEO_E), agreeableness (NEO_A), and neuroticism (NEO_N).

Outcome (Y), Moderator (M)	Gender	Education	Age	Loneliness (X)	Moderator (M)	Interaction term (X*M)	R-squared
BDI, R	0.06	0.06	0.00	0.49***	-0.30***	-0.12***	0.55
BDI, NEO_O	0.13	0.11	0.00	0.67***	0.00	-0.07*	0.46
BDI, NEO_C	0.14*	0.07	0.00	0.57***	-0.18***	-0.10**	0.50
BDI, NEO_E	0.12	0.03	0.00	0.52***	-0.24***	-0.16***	0.52
BDI, NEO_A	0.14*	0.11	0.00	0.63***	-0.08*	-0.05	0.47
BDI, NEO_N	0.02	0.04	0.00	0.30***	0.48***	0.17***	0.60
STAI, R	0.04	-0.01	0.00	0.28***	-0.51***	0.00	0.51
STAI, NEO_O	0.14	0.07	-0.01**	0.53***	-0.02	-0.03	0.33
STAI, NEO_C	0.14	0.02	-0.01*	0.42***	-0.26***	-0.02	0.39
STAI, NEO_E	0.10	-0.04	-0.01*	0.41***	-0.31***	0.04	0.40
STAI, NEO_A	0.17*	0.06	-0.01*	0.49***	-0.14**	0.04	0.35
STAI, NEO_N	0.02	0.00	0.00	0.20***	0.55***	-0.03	0.49
PSS, R	0.17**	0.02	0.00	0.37***	-0.55***	0.04	0.64
PSS, NEO_O	0.26***	0.11	-0.01	0.63***	0.00	-0.06	0.44
PSS, NEO_C	0.27***	0.06	0.00	0.51***	-0.28***	0.04	0.49
PSS, NEO_E	0.23***	0.01	0.00	0.51***	-0.28***	0.03	0.49
PSS, NEO_A	0.31***	0.10	0.00	0.57***	-0.19***	0.08*	0.47
PSS, NEO_N	0.13*	0.03	0.00	0.25***	0.63***	-0.04	0.64

Note: *p < .05. **p < .01. ***p < .001. This table only reported estimates, for confidence intervals and exact p values, please see supplementary materials.

Table 3 Results of hierarchical regression analysis. The full model included resilience (R) and all five NEO personality traits (NEO_O, NEO_C, NEO_E, NEO_A, NEO_N) and the respective interactions (with depression as outcome), and the subsequent models took each variable and its interaction out from the full model.

Different Models	R^2	ΔR^2	F statistic	P
Full model	0.6215			
Full model without R	0.6194	0.0021	1.2201	0.2962
Full model without NEO_O	0.6171	0.0044	2.4902	0.08409
Full model without NEO_C	0.6213	0.0002	0.1278	0.8801
Full model without NEO_E	0.6159	0.0056	3.1774	0.04267 *
Full model without NEO_A	0.6212	0.0003	0.2001	0.8187
Full model without NEO_N	0.5700	0.0515	29.237	1.243e-12 ***

Note: *p < .05. **p < .01. ***p < .001.

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Supplementary Material

Trait resilience protects against depression caused by loneliness during the COVID pandemic

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Fig. S1 Distribution of normalized within-subject difference (maximum – minimum, divided by the total points range possible for each measure) across waves for all selected measure: **(a)** Stress, **(b)** Anxiety, **(c)** Depression, **(d)** Loneliness, **(e)** Resilience, **(f)** Openness, **(g)** Conscientiousness, **(h)** Extraversion, **(i)** Agreeableness and **(j)** Neuroticism. Red traces indicate the cumulative probability.

Fig. S2 State-level maps of different measures. Each state is color coded using the average across subjects from that state, note that states with less than 5 subjects are omitted.

Table S1 Demographic characteristics, means and standard deviations of all measures used for the final sample.

	All (N = 447)	Female (N=227)	Male (N=220)
Age (in years) (mean; sd)	43.21 (14.03)	44.49 (13.83)	41.89 (14.15)
Education: below Bachelor (n; %)	169 (37.81%)	78 (34.36%)	91 (41.36%)
Education: Bachelor and above (n; %)	278 (62.19%)	149 (65.64%)	129 (58.64%)
CD-RISC 10 (mean; sd)	26.89 (7.9)	26.34 (8.02)	27.46 (7.75)
NEO Openness (mean; sd)	30.8 (6.81)	31.9 (6.81)	29.66 (6.64)
NEO Conscientiousness (mean; sd)	34.88 (7.74)	35.06 (7.34)	34.69 (8.15)
NEO Extraversion (mean; sd)	23.11 (8.85)	22.78 (8.36)	23.45 (9.34)
NEO Agreeableness (mean; sd)	33.33 (6.54)	34.14 (6.45)	32.5 (6.55)
NEO Neuroticism (mean; sd)	18.62 (10.72)	19.51 (10.86)	17.7 (10.52)
NIH Loneliness (mean; sd)	10.88 (5.01)	10.88 (5.08)	10.87 (4.95)
BDI (mean; sd)	9.15 (10.02)	9.74 (10.25)	8.55 (9.76)
STAI (mean; sd)	35.46 (11.86)	36.1 (12.64)	34.8 (10.99)
PSS (mean; sd)	13.83 (7.55)	14.73 (7.75)	12.89 (7.23)

Table S2 Characteristics (means of all measures) of samples at different stages of exclusion and selection.

	Initial (N = 1797)	Quality (N = 1580)	Dense (N = 634)	Final (N = 447)
CD-RISC 10	26.02	26.35	26.57	26.89
NEO Openness	30.67	30.33	30.6	30.8
NEO Conscientiousness	32.26	32.65	34.42	34.88
NEO Extraversion	22.92	23.21	22.51	23.11
NEO Agreeableness	31.82	31.93	33.2	33.33
NEO Neuroticism	22.43	21.65	19.76	18.62
NIH Loneliness	11.78	11.57	11.13	10.88
BDI	11.48	10.56	10.01	9.15
STAI	38.43	37.58	36.72	35.46
PSS	15.74	15.16	14.54	13.83

Table S3 Results of the main regression model (depression as outcome, and resilience as moderator) using samples at different stages of exclusion and selection.

Different samples	Gender	Education	Age	Loneliness	Resilience	Loneliness *Resilience	R- squared
Initial (N = 1797)	0.11*	0.15**	-0.00	0.49***	-0.28***	-0.06**	0.50
Quality (N = 1580)	0.09	0.11*	-0.00	0.53***	-0.25***	-0.07**	0.51
Dense (N = 634)	0.04	0.12*	0.00	0.51***	-0.27***	-0.10***	0.53
Final (N = 447)	0.06	0.06	0.00	0.49***	-0.30***	-0.12***	0.55

Note: *p < .05. **p < .01. ***p < .001.

Table S4 Results of the main regression model (depression as outcome, and resilience as moderator) using samples of different Census Bureau-designated regions.

Different regions	Gender	Education	Age	Loneliness	Resilience	Loneliness *Resilience	R- squared
West (N = 135)	0.05	-0.11	0.01	0.50***	-0.32***	-0.18**	0.56
Midwest (N = 97)	0.04	0.09	-0.00	0.51***	-0.28**	-0.16	0.50
South (N = 145)	0.10	0.11	0.00	0.48***	-0.22**	-0.02	0.53
Northeast (N = 70)	0.08	0.26	-0.00	0.49***	-0.39***	-0.14**	0.72

Note: *p < .05. **p < .01. ***p < .001.

Table S5 Contributions by the COVID-Dynamic team. 0: no contribution, 1: minimal contribution, 2: substantial contribution, 3: lead contribution.

	Yanting Han	Ralph Adolphs	Dehua Liang	Amber Hopkins	Uri Maoz	Lynn Paul	Damian Stanley	Teresa Lopez-Castro	Marie-Christine Nizzi	Tessa Rusch
Conceptualization: Initial Inception of paper	3	3	0	0	0	0	0	0	1	0
Conceptualization: Composition and Scope of Article	3	2	0	0	0	0	0	0	0	0
Data Acquisition	3	0	0	2	1	3	3	0	0	3
Data Curation, Q/A, Sharing	0	0	2	0	1	3	2	0	0	2
Data analysis	3	0	0	0	0	0	0	0	0	0
Funding Acquisition	0	3	0	0	3	0	1	1	0	0
Methodology: Questionnaire and Task Selection/ Development	2	0	0	0	1	3	3	1	0	0
Supervision	0	3	0	0	0	0	1	0	0	0
Writing: Original draft	3	3	0	0	0	0	0	0	0	0
Writing: Review & Editing	2	2	0	0	0	0	1	2	2	0

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