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A global longitudinal study of social-ecological factors affecting depression and anxiety during COVID-19

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ABSTRACT

Background: This study models depression and anxiety over time and the effect of individual, relational, community and societal-level predictors during the initial COVID-19 outbreak, to explore important factors for research or clinical practice.

Methods: Pre-registered analysis was conducted on longitudinal survey data from The Global Social Trust and Mental Health Study conducted between April 2020 and July 2021. There were 2345 respondents with data available for analysis across 6 continents (70.6 % female, 24.7 % male, mean age 36.4 years). Anxiety and depression symptoms were stable and low (below clinical cut-offs) on average. Random Intercept Cross-lagged Panel Models and Latent Transition Analysis estimated the effects of parental status, household chaos, household crowding, outdoor access, demographic variables, and lockdown stringency on depression and anxiety symptoms.

Conclusions: In line with the Social Ecological Model, multi-level factors were associated with anxiety and depression. Female gender, younger age, non-marginalised ethnicity, lower socioeconomic status, not being a parent, higher household chaos, less outdoor access and lower lockdown stringency were associated with the greater levels of depression and anxiety across the study.

Introduction

The COVID-19 outbreak and subsequent infection control policies disrupted lives and psychological health [1]. In line with the Social Ecological Model (SEM),[2] risk factors for negative psychological outcomes were at individual (younger age, fear of infection), relational (lack of social support, caregiving) and community/societal levels (lockdown policies, financial strain) [3]. Subsequently, research was needed to elucidate predictors of distress to inform policy and health interventions.

Parental status (i.e. caring for dependent children) intersects individual and relational levels and according to a rapid review, was associated with higher rates of depression and anxiety during the pandemic versus pre-pandemic [4]. However, the review also highlighted the lack of studies directly comparing parents and non-parents and subsequent literature reported both positive [5] and negative [6] effects of parenting, with differences potentially explained by socio-ecological factors such as socio-economic status and infection control policies.

The protracted nature of COVID-19 meant mental health covariates could be time-variant. Longitudinal studies demonstrated time variability in the relational factor of household chaos, defined as the degree of disorganisation, confusion, and noise in the home environment [7]. Parents in Chile [8] and Israel [9] reported initial increases in household chaos with later fluctuations positively correlating with lockdown stringency. Only, Gordon-Hacker [9] reported a corresponding maternal depression pattern. The current study will extend these findings in cross-country sample.

Community and societal factors became salient as COVID-19 infection control policies across countries limited environmental interactions. In Denmark, the UK and France, living in a crowded home (defined by Eurostat criteria) was associated with greater loneliness and anxiety over time [10]. Access to outdoor spaces was associated with better psychological outcomes longitudinally in the UK,[11] Europe, Asia and Australia [12]. Longitudinal relationships between outdoor access and mental health relative to other environmental factors have been underexplored.

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Objective

This study explored the relative individual effects of parental status, household chaos, household crowding and outdoor access on depression and anxiety across the first 15 months of the pandemic. These variables were selected as they indicate possible clinical groups of interest or intervention targets for clinical practice, public health interventions and policy, but current research has not elucidated if any factors are more pertinent for resource allocation. It extends previous research with its longitudinal design, use of validated mental health measures, and application of structural equation modelling to explore patterns of anxiety and depression, and complex effects of socio-ecological variables over three timepoints in non-clinical adults. The study aims to answer the following questions: (1) Is household chaos stable over time between April 2020 to July 2021? (2) What are the relative contributions of the individual, relational, community and societal factors of parental status, household chaos, household crowding and outdoor access on anxiety and depression symptoms during the COVID-19 pandemic?

Methods

This study is a secondary analysis of a prospective, longitudinal data from the Global Social Trust and Mental Health Study (UCL-Penn Global Covid-19 Study),[13] designed to explore the effects of COVID-19 on mental and physical health, and social trust. The UCL-Penn Study received ethical approval from University College London's Institute of Education Research Committee on 8th April 2020 (REC 1331). Research questions and analyses were pre-registered before data access: https://doi.org/10.17605/OSF.IO/GSNH8.

Participants and Procedures

Adult volunteers were invited by convenience sampling to complete an Qualtrics survey (available in English, Italian, Greek, Chinese traditional, Chinese simplified, German, and Spanish) at three timepoints: 17th April-14th July 2020 (wave 1), 17th October 2020-31st January 2021 (wave 2), and 17th April-31st July 2021 (wave 3). Qualtrics is a widely-used, password protected, cloud-based survey research platform, requiring institutional login, used by organisations to collect and analyse user experiences [14]. The study link was distributed locally and abroad by the research team through social media channels, charities and networks affiliated with the research department (i.e. email, LinkedIn, Whatsapp, Meta and Reddit). The survey consisted of a series of standardised questionnaires measuring physical activity, sleep, psychiatric symptoms, aggression, loneliness, demographic details, parenting style and custom questionnaires examining COVID-19-related worries, beliefs and behaviours developed based on prior on-going studies of the time and the research team's expertise in developing psychometric instruments. Participants provided necessarily personal identifiable information (date of birth, ethnicity, email address), which were linked to a unique ID number so data across three waves was linked and analysed in a pseudonymised fashion. This is compliant with GDPR regulations. All participation was voluntary and weekly follow-up reminder emails from the Qualtrics platform were sent at each wave to increase compliance during data collection, up to a maximum follow-up of 5 emails. All participants provided informed consent and data were anonymised for analysis.

In accordance with current study objectives, authors had access to demographic data alongside measures of anxiety, depression, household-related variables and outdoor access. Secondary data were used from respondents who completed the survey at least twice, providing data for the independent and dependent variables ($n = 2345$).

Patient and Public Involvement

Patients and members of the public were not involved in study design and dissemination.

Outcomes

Anxiety and depression were measured using the Generalized Anxiety Disorder scale (GAD-7) and Patient Health Questionnaire (PHQ-9). Both are validated measures of anxiety and depression symptoms with clinical cut-off scores of 10 + for moderate cases and 15 + for moderate-to-severe cases, and reported to have good reliability and internal consistency in general population samples ($\alpha = 0.89$ (GAD-7); 0.89 (PHQ-9)) [15,16]. A variable (coded as 0 vs 1) was computed to represent chronic anxiety and depression (scores 15 +) across all study waves.

Independent variables

Socioeconomic status (SES).

The operationalisation of SES was informed by health research guidance that SES variables should reflect the life course position of participants [17], and existing research indicating the impact of employment and educational socio-economic factors on mental health during the COVID-19 pandemic [18]. SES was therefore a composite variable, summing scores from binary variables of: Income (above (0)/below-income £30 k per annum (1)), Education (above (0)/below A-level equivalent education (1)), and Employment (employed or student (0) vs unemployed (1)). Higher scores indicated lower SES.

Lockdown stringency.

Lockdown stringency scores were derived from The Oxford Covid-19 Government Response Tracker [19] ranging from 0 to 100 with higher scores indicating more restrictive country-wide policies. For each participant, stringency scores were imputed according to their country of residence on the date corresponding to the start of each study wave (e.g. Wave 1 UK score = 79.63, Wave 1 Hong Kong score = 66.67).

Ethnicity.

Participants self-identified their ethnicity, providing a categorical variable. Based on the majority (82.9 %) of the sample residing in historically Euro- and Western-centric countries, a binary variable grouped White English, Irish, Scottish, Welsh, any other white background into a non-marginalised ethnic identity group (0), and Black, Asian, Latin American, Hispanic, Arab, Irish gypsy traveller and any mixed ethnic identities were grouped as historically marginalised ethnic identities (1).

Parental status.

Parents were defined as respondents who self-reported currently living with children $\leq$ 18 years. Parents not living with their children were not classed as 'actively' parenting.

Household Environment.

Household chaos was measured with the 6-item Confusion, Hubbub and Order Scale six-item version (CHAOS) [7]. Higher scores indicated higher levels of household chaos (range 0–30). The short-form version reduces respondent burden and has demonstrated some cross-cultural validity and internal reliability when completed by mothers or fathers ($\alpha = 0.62$–.79) [20], so was deemed adequate for population analyses.

Household crowding.

Respondents provided information on the number of co-habitants they had and number of bedrooms in their home. Informed by World Health Organisation guidelines, [21], using the available data, household crowding was based on the American Crowding Index [22]. Scores are calculated according to the number of people per room in the house (including kitchen and excluding bathrooms) to create a binary variable (0 = no crowding (scores < 1) versus 1 = crowding (scores 1 ≤)).

Outdoor access.

Participants reported the number of gardens, balconies, or public green spaces (within 20 a minute walk) they had access to. Responses were summed into a composite continuous variable, with higher scores indicating greater outdoor access (maximum score 15). Outdoor access was mostly accounted for by local public spaces (reported by 82 % of the sample). A smaller proportion of respondents had access to a garden (55 %) or balcony (43 %). The rationale for this operationalisation was that all three variables conceptually reflect opportunity for extended exposure to outdoor environment, and the construct also aligns with prior pandemic-related mental health research which has operationalised outdoor access similarly [23].

Statistical analysis

Analyses were conducted in R 4.2.1, SPSS 28.0, and Mplus 8.

Research Question One: Stability of household chaos.

Changes in household chaos were examined with repeated measures analysis.

Research Question Two: Impact of socio-ecological variables on anxiety and depression over time.

Reflecting the evolving nature of the pandemic, a primary Random Intercept Cross-lagged Panel Model (RI-CLPM) was conducted to test changes in anxiety and depression scores across time before predictors of these outcomes were added into analysis. RI-CLPMs also allow for the addition of time-varying and time-invariant covariates (independent variables) and estimate their effect over multiple (2 <) timepoints, which less complex models do not. A 'random intercept' represented across-person variation in outcomes accounted for by unobserved confounders [24]. Covariates were regressed onto random intercepts to explain between-person variance and estimate the relative contribution of the independent variables. State-like latent factors estimated correlations between depression and anxiety at each timepoint and cross-lag coefficients estimated correlations over time. Models used the MLR estimator to account for non-normality and missing data [25]. Model fit indices were comparative fit index (CFI > 0·95), Tucker-Lewis Index (TLI > 0·95), root mean square error of approximation (RMSEA < 0·05), and standardized root mean square residual (SRMR < 0·08) [26]. Chi-square statistics should be interpreted cautiously for large samples and non-normal distributions.

Research Question Two: Impact of socio-ecological variables on chronic anxiety and depression.

To identify potential predictors of a clinically relevant and important sub-group, separate binary logistic regression analyses were conducted to model the socio-ecological predictors of chronic depression and anxiety (sustained scores 15 + on PHQ-9 and GAD-7). The significance of each predictor was assessed using an alpha value of 0.05.

Additional analyses for research Question Two: Classes of anxiety and depression and association with socio-ecological variables.

As standard clinical cut-offs were not validated in pandemic contexts when studies indicated higher than usual levels, Random Intercept Latent Transition Analysis models (RI-LTA) modelled classes of anxiety and depression across time,[27], and the relationship between these classes and independent variables. RI-LTA additionally reported movement between classes. Depression and anxiety scores were indicators of latent classes within each study wave, with random intercept factors constrained to equal loading over time. LTA analyses increased class numbers from an initial two-class model to find the best fit assessed using lower Bayesian information criterion (BIC) and sample-corrected BIC, and higher log-likelihood values. Chi-square difference tests compared models using log-likelihood values and MLR scaling correction factors (p < 0.05).

Missing data

Of 2,345 respondents to at least one study variable, 514 (22.52 %) had complete data across waves. M*plus* applies full information maximum likelihood (FIML) via the MLR estimator command, providing maximum likelihood estimates and robust standard errors relatively robust to non-normality and missing data [28]. Cases with missing data on conditional variables were excluded by M*plus*, reducing the analysed sample. As such, attrition on depression and anxiety, and covariates in later models reduced the analysed sample. Missing data analysis examined predictors of missingness in outcomes. Multiple imputation was not used, as FIML performs well with three timepoints and samples < 500 [25].

Results

Appendices A and B detail descriptive statistics, proportion of missing values and correlation matrix for main study variables. Table 1 presents means and proportions of time-variant variables and the proportion of respondents meeting clinical cut-off criteria for outcomes at each time-point, which did not differ significantly across time. These were included as time-invariant covariates in subsequent analyses. Parental status was considered a stable factor.

Highest levels of missing data were observed in the anxiety and depression at waves two (58.3 % missing) and three (67.7 % missing). Regression analyses associated missingness in measures of depression

Table 1
Descriptive statistics within the whole sample (n = 2345) and mean and proportion comparison tests of time-variant variables.

	Wave 1	Wave 2	Wave 3	Equality test
	M (SD)	M (SD)	M (SD)	
Depression	7·2 (5·6)	7·1 (5·9)	7·0 (6·0)	**·039**[a]*
Anxiety	5·5 (4·9)	5·5 (5·0)	5·5 (5·2)	0.126[a]
Household chaos	12·6 (4·2)	12·5 (4·0)	12·2 (4·1)	·647[a]
Lockdown Stringency	66·5 (12·4)	65·5 (11·4)	64·7 (10·6)	·29[b]
	n (%)	n(%)	n(%)	
Moderate Depression	512 (21·8)	257 (11·0)	194 (8·3)	·53[c]
Moderate-Severe Depression	214 (9·1)	126 (5·4)	98 (4·2)	·67[c]
Moderate Anxiety	349 (14·9)	190 (8·1)	150 (6·4)	·77[c]
Moderate-Severe Anxiety	131 (5·6)	80 (3·4)	61 (2·6)	·76[c]
Parental status (children at home)	413 (17·6)	195 (8·3)	109 (4·6)	**·002**[c]**

[a]Friedman Test; [b]Repeated measures ANOVA; [c]Cochran q test
*$p < 0.05$, **$p < 0.001$

and anxiety at wave two with younger age, male gender identity, being a parent, greater outdoor access, higher lockdown stringency, and to a lesser extent, higher anxiety scores at wave one ($p = 0.039$ for wave two depression, $p = 0.037$ for wave two anxiety). Missingness was associated with younger age at wave three.

Research Question One: Stability of household chaos

According to Friedman test, household chaos demonstrated stability ($\chi^2(2) = 0.871$, $p = 0.647$) and was considered a time-invariant covariate.

Research Question Two: Random Intercept Cross-lagged Panel model (RI-CLPM)

Depression and anxiety showed moderate-to-large positive correlations within and between waves, stronger within waves. Standardized and unstandardized estimates indicated stable intercepts with small standard errors (Appendices C and E). Indices for the baseline RI-CLPM model indicated a good fit (CFI = 1.00, TLI = 1.00, RMSEA = 0.00 (90 % CI: 0.00-0.02), SRMR = 0.00, AIC = 38759.23) (Appendix D). Together with intercept estimates, this suggests mean-level stability in depression and anxiety across time.

A strong correlation between random intercepts (0.852 [.081, 0.894], $p < 0.001$) indicated high depression levels co-occurred with high anxiety. The strongest within-wave association was at wave two (0.706 [.622-0.790], $p < 0.001$). A significant carry-over effect (0.225 [.030-0.421], $p < 0.05$) suggested wave two depression predicted wave three depression. A cross-lag effect (0.185 [-0.010-0.380], $p < 0.05$) indicated higher-than-expected wave one depression was linked to higher wave two anxiety. Other cross-lag effects were not significant (Appendix H).

RI-CLPM with covariates.

Independent variables (gender, age, ethnicity, SES, lockdown stringency, parental status, household chaos, household crowding and outdoor access) were regressed onto random intercepts to explain between-person variability in outcomes across time. Model indices suggested a good fit (CFI = 0.99, TLI = 0.99, RMSEA = 0.03 (90 % CI: 0.02-0.04), SRMR = 0.04, AIC = 32563.09). Higher levels of depression and anxiety were associated with younger age, lower socio-economic status, lower lockdown stringency, higher household chaos and lower outdoor access (Table 2), identifying as a woman, being from a non-marginalised ethnic group and not being a parent. Fig. 1 shows standardised estimates of outcome variables when covariates are added.

Impact of socio-ecological variables on chronic anxiety and depression

Separate logistic regression analyses were conducted for chronic depression and anxiety, with all independent variables (IV) as covariates. Regression analysis for chronic depression was statistically significant ($\chi^2(9) = 74{\cdot}18$, $p < 0.001$, $R^2 = 24{\cdot}1\%$). Increased odds of chronic depression were associated with younger age (Wald statistic = 4·87, $p = 0.027$, OR = 0.976, 95 % CIs: 0.95, 0.99), lower SES (Wald statistic = 23·70, $p < 0.001$, OR = 2·82, 95 % CIs: 1·86, 4·28) and higher household chaos scores (Wald statistic = 27·37, $p < 0.001$, OR = 1·19, 95 % CIs: 1·12, 1·27). There was a weak association between higher household crowding and lower odds of chronic depression but confidence intervals were wide (Wald statistic = 3·91, $p = 0.048$, OR = 0.28, 95 % CIs: 0.08, 0.99).

Regression analysis for chronic anxiety was statistically significant ($\chi^2(9) = 37{\cdot}86$, $p < 0.001$, $R^2 = 16{\cdot}6\%$). Odds of reporting chronic anxiety were associated with lower SES (Wald statistic = 7·46, $p = 0.006$, OR = 1·94, 95 % CIs: 1·21, 3·12) and higher household chaos (Wald statistic = 21·58, $p < 0.001$, OR = 1·19, 95 % CIs: 1·11, 1·29).

Classes of anxiety and depression and association with socio-ecological variables

Given their covariance and comorbidity, depression and anxiety scores were combined as indicators of latent classes of 'symptoms of psychological distress'. Independent variables were regressed onto class membership of the five-class model based on model fit indices (Appendix F) and chi-square difference testing against the baseline two-class model ($\chi^2(64) = 796{\cdot}398$, $p < 0.001$). Although the six-class model had good fit, class similarities lacked clinical relevance, and four of the six classes contained less than 10 % of the sample.

The identified classes presented in Table 3 can be interpreted as:

- Class 1 – high overall distress (7·09 % sample at wave 1)
- Class 2 – higher levels of anxiety than depression (5·60 % sample at wave 1)
- Class 3 – higher levels of depression than anxiety (8·32 % sample at wave 1)
- Class 4 – moderate overall distress (19·20 % sample at wave 1)
- Class 5 – low overall distress (59·80 % sample at wave 1)

The largest class had the lowest depression and anxiety, while the smallest had higher anxiety with moderate depression. Mean distress scores were ~ 8.5 for depression and ~ 8 for anxiety, below the clinical cut-off of 10. Depression scores were generally higher than anxiety across classes.

In Fig. 2, values on the diagonal represent the probability of class stability. The lowest distress class (class five) was most stable, with ≥ 85 % remaining across waves The higher anxiety class (class two) was least stable, with most transitioning to lower distress (class four or five), while a subset moved to higher distress between each wave. Stability in the high overall distress class indicates a potential group of clinical interest.

Odds ratios (Appendix G) indicated that high distress (class one) in wave one was predicted by female gender, younger age, lower SES, less outdoor access, lower lockdown stringency, and higher household chaos. Younger age and household chaos also predicted higher anxiety, higher depression, and moderate distress classes. Female gender was predictive of higher anxiety and moderate overall distress classes. Lower

Table 2
Standardised estimates and 95% confidence intervals of the effects of covariates on within-person variance of depression and anxiety over time.

	Random Intercept Depression				Random Intercept Anxiety			
	Standardised estimate	Lower 95 % CI	Upper 95 % CI	*p*	Standardised estimate	Lower 95 % CI	Upper 95 % CI	*p*
Gender	·13	·08	·18	<·001	·19	·14	·24	<·001
Age	−·18	−·23	−·12	<·001	−·20	−·26	−·14	<·001
Ethnicity	−·08	−·13	−·02	·005	−·10	−·16	−·05	<·001
SES	·21	·15	·27	<·001	·14	·07	·20	<·001
Lockdown stringency	−·18	−·24	−·12	<·001	−·11	−·17	−·05	<·001
Parental status	−·10	−·15	−·05	<·001	−·06	−·11	−·00	·041
Household Chaos	·37	·30	·43	<·001	·35	·28	·41	<·001
Household Crowding	−·01	−·07	·05	·679	·00	−·06	·06	·982
Outdoor access	−·07	−·12	−·01	·013	−·07	−·13	−·01	·033

Note. Gender (0 = male, 1 = female); Ethnicity (0 = non-marginalised, 1 = marginalised ethnicity); Socio-economic status (SES) = Higher scores indicate lower socio-economic status; Parental status (0 = not a parent, 1 = parent).

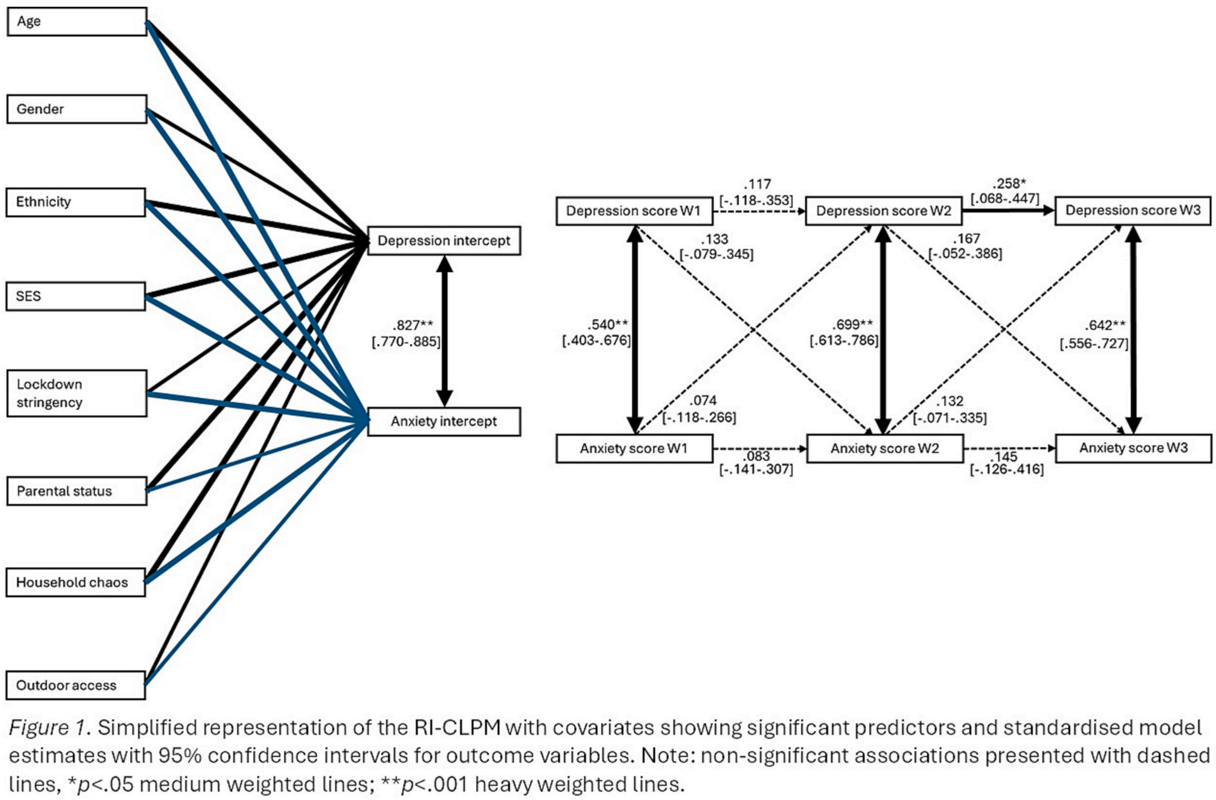

Fig. 1. Simplified representation of the RI-CLPM withcovariates showing significant predicators and standardished model estimates with 95 % confidence intervals for outcome variables. Note: non-significant associations presented with dashed lines, *$p < 0.05$ medium weighted lines;**$p < 0.001$ heavy weighted lines.

Table 3
Estimated class proportions and mean values of PHQ-9 and GAD-7 in the 5 class LTA model with covariates.

Wave	Class	n sample	% sample	Depression mean value estimates	Anxiety mean value estimates
1	1	113	7·1	18·6	15·4
	2	89	5·6	11·0	15·4
	3	132	8·3	13·6	5·8
	4	305	19·2	8·5	8·1
	5	951	59·8	4·3	2·7
2	1	149	9·3	18·6	15·4
	2	71	4·4	9·2	14·2
	3	141	8·9	13·6	5·8
	4	244	15·4	8·5	8·1
	5	987	62·0	4·3	2·7
3	1	124	7·8	18·6	15·4
	2	94	5·9	11·0	15·4
	3	119	7·5	13·6	5·8
	4	259	16·3	8·5	8·1
	5	995	62·5	4·3	2·7

SES predicted higher depression (class three). Lower lockdown stringency predicted higher depression (class three) and moderate distress (class four). These effects were absent in later waves, except for lower SES predicting high distress in wave two.

Discussion

This study examined socio-ecological factors linked to depression and anxiety during COVID-19 in non-clinical adults. RI-CLPM and RI-LTA showed that *individual* (female gender, younger age, non-marginalized ethnicity, lower SES), *relational* (not being a parent, higher household chaos), and *community/societal* factors (less outdoor access, lower lockdown stringency) were associated with greater severity of anxiety and depression, supporting multi-level interventions to improve public health.

Findings align with research on sex, age, SES, parental status, and outdoor access [3,6,9], but contrast with studies exploring marginalised ethnicity and household crowding [10,29]. Collectivist coping strategies during the pandemic-era may boost resilience in underserved groups [30]. Exploring community resilience and ways to facilitate such social processes is an important future direction for public health research. While Vescovi et al [4] report parents to have increased risk of mental health difficulties during COVID-19, low rates of crowding and good outdoor-access could mitigate parenting burden in the current study, meaning parents were less vulnerable to loneliness, unstructured time, and reduced sense of purpose. Moreover, discrepancies may be attributable to high SES ameliorating the effects of risk factors [6]. The consistent negative impact of low SES highlights how pandemics worsen health disparities, reinforcing the need for public health interventions.

At the societal level, higher lockdown stringency correlated with anxiety and depression symptoms, corresponding with a *meta*-analysis reporting lower depression symptoms where stringent policies were rapidly initiated [31]. The Health Belief Model (HBM) [32] would suggest that COVID-19 was perceived as a severe threat and lockdown policies offered reassuring containment, underscoring the role of public health psychology in health policy, media and government communications.

Strengths

A key strength is in the theoretical underpinning of the study, applying the Social Ecological Model [2] to explore variables at multiple levels. Structural equation modelling allowed simultaneous estimation of patterns in anxiety and depression and socio-ecological associations over time. The large global sample enabled complex modelling and improved generalisability. Standardised measures of crowding and

Wave 1-2 transitions

		Classes wave 2				
		1	2	3	4	5
Classes wave 1	1	·57	·04	·10	·16	·13
	2	·27	·17	·00	·47	·09
	3	·15	·00	·44	·10	·32
	4	·10	·12	·05	·48	·26
	5	·01	·01	·06	·03	·89

Wave 2-3 transitions

		Classes wave 3				
		1	2	3	4	5
Classes wave 2	1	·41	·22	·16	·15	·06
	2	·19	·21	·00	·18	·42
	3	·00	·02	·41	·05	·52
	4	·04	·15	·05	·56	·20
	5	·03	·02	·02	·08	·85

Figure 2. Estimated probabilities of transition between classes between waves of data collection.
Note: Lighter shading indicates lower probability of transition, darker shading indicates higher probability of transition.

Fig. 2. Estimated probabilities of transition between waves of data collection. Note: Lighter shading indicates higher probability of transition.

psychological outcomes enhanced validity and comparability across studies. As clinical cut-offs may overlook psychological diversity, LTA was conducted to capture distinct classes reflecting both anxiety and depression symptoms.

Limitations

Findings have limited generalizability to lower-income populations, which could be improved with stratified or random sampling compared to the convenience sampling deployed in the UCL-Penn Study. Having four or more data points would enable latent growth curve modelling for a more parsimonious analysis of trajectories [26]. The composite outdoor access measure did not distinguish between private and public spaces, with the high public space access (82 %) likely influencing results.

There were challenges when operationlising demographic variables for a global sample. For instance, a 30 k income cut-off was used as part of the SES composite variable based on this being the median salary in the UK where 39 % of participants were residing. This may not reflect economic status in other regions. Similarly, the ethnicity status was constructed through a eurocentric lens due to 82.9 % of the sample residing in Europe, North America or Australasia, but this categorisation may not reflect experiences of minoritisation across the global sample, and may account for the unexpected direction of findings with this variable. While the short-form CHAOS scale shows acceptable consistency across parent-raters, Larsen et al (2023) [20], report measurement invariance, indicating the long-form version would increase construct validity.

Missing data analysis indicated some bias in attrition. Younger participants and those under stricter lockdowns were less likely to complete follow-ups; it is possible the mental health of these respondents was worse, leaving less capacity to respond, and meaning the results of this study underestimate the impact of the pandemic on the mental health of this sub-group. There is some evidence to support this hypothesis as higher anxiety scores at wave two were linked to missingness suggesting mean anxiety estimates at this wave are likely to under-estimate the true value and stable estimates across waves may reflect selective retention. However, when looking more closely at the data, mean differences were minimal (∼.25), had higher p-values, and associations between anxiety and wave three missingness were not observed. The loss of male participants and parents may have reduced power for these variables, leading to an underestimation of the effect of these independent variables on anxiety and depression symptoms. Overall loss in sample size decreases statistical power meaning wider confidence intervals and non-significant findings at these waves should be interpreted with more caution. In future, multiple imputation or sensitivity analyses could address attrition.

Clinical Implications

Compared to *meta*-analyses,[1] depression severity levels were similar only at wave one and anxiety was lower throughout. This is possibly attributable to the relatively high SES (89·2%) sample from higher-income countries (96·3%), and earlier *meta*-analysis drawing mostly from earlier pandemic data. However, ∼60 % of individuals maintained moderate-to-high symptoms between timepoints, potentially warranting 'watchful waiting' or early interventions for groups defined by relational and societal-level as well as individual level factors. This would require investment in cross-functional systems allowing aggregation of data on environmental factors (i.e. outdoor access and housing quality) with individual-level, demographic information.

Study findings reinforce the importance of addressing health inequalities and considering the differential impact of public health events on a population across socio-ecological levels as social inequalities lead to poorer psychological and physical health which compound disparities, negatively impact quality of life and increase healthcare costs. Alongside recognition of individual factors, investment is needed at more macro levels. For example, established family, systemic interventions could target the relational factor of household chaos [33]. At social and community levels, in line with the UN Sustainable

Development Goals, promoting social cohesion through community engagement and civic participation and facilitating safe and inclusive access to outdoor spaces could harbour resilience to the psychological impact of the pandemic [34,35]. This could include implementation of short- and long-term recommendations such as open streets, outdoor-focused public health initiatives and urban planning.

Conclusion

This study explored patterns of depression and anxiety and the impact of socio-ecological variables on these dependent variables over the first 15 months of the COVID-19 pandemic. Depression and anxiety symptoms were relatively stable. Higher levels of anxiety and depression were associated with identifying as female, being from a non-marginalised ethnic group, not being a parent, younger age, lower SES, less outdoor access, lower lockdown stringency and higher household chaos. These findings inform clinical practice, healthy policy and public health initiatives that address health outcomes and pervasive health inequalities.

Ethics Statement

The UCL-Penn Study received ethical approval from University College London's Institute of Education Research Committee on 8th April 2020 (REC 1331). All participants consented to participation in this study. An amendment to undertake secondary analysis for this paper was approved on 7th December 2022.

CRediT authorship contribution statement

Abbeygail Jones: Writing – original draft, Visualization, Validation, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Vaughan Bell:** Writing – review & editing, Supervision. **Keri Ka-Yee Wong:** Writing – review & editing, Validation, Supervision, Software, Methodology, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.pmip.2025.100168.

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