Who Got Lonelier during the Covid-19 Pandemic? Evidence from the English Longitudinal Study of Ageing

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Introduction

Loneliness is a public health concern that was acknowledged before the onset of the COVID-19 pandemic. Its negative impacts on people's mental and physical health are well-documented in the literature. Loneliness is hypothesised to increase during the COVID-19 (SARS-CoV-2) pandemic because disease control measures restrict in-person social contacts. This research aims to investigate whether people got lonelier during the pandemic through the longitudinal analysis of the English Longitudinal Study of Ageing data. The COVID-19 pandemic also sheds a light on the social and health inequality: not all people experience the pandemic with the equal sets of advantages and resources. Therefore, this research also identifies heterogeneous trajectories of loneliness changes before and during the pandemic and seek to explain such heterogeneity through investigating three pillars of factors, namely vulnerability - general risk factors for loneliness, exposure - pandemic related risk factors, and capacity of response - protective factors.

Research Questions

The current study aims to answer the following research questions:

RQ1: Did the prevalence of loneliness among older adults in England increase during the COVID-19 pandemic compared to pre-pandemic time?
RQ2: What are the different trajectories of loneliness changes among these older adults?
RQ3: Which older subpopulations were more prone to increased loneliness during the pandemic?
RQ4: What are the general risk factors, pandemic factors and protective factors associated with the various observed loneliness trajectories among older adults in England during the pandemic?

Method

Study Design and Participants

This study draws upon data from the English Longitudinal Study of Ageing (ELSA), a nationally representative panel study comprising individuals aged 50 and over living in England (Banks et al. 2021). Our longitudinal analysis encompasses data from the two most recent pre-pandemic waves, Wave 8 (2016-2017) and Wave 9 (2018-2019), and the two peri-pandemic waves from COVID-19 Substudy, waves 1 and 2. Our analysis includes individuals aged 50 and over who participated in all four waves and responded to questions related to loneliness, yielding a final sample of 4,492 persons.

Measurements

Loneliness was assessed across all four waves using the three-item UCLA (University of California, Los Angeles) loneliness scale. Respondents were asked how often they felt 'lack companionship', 'left out', and 'isolated'. Responses include hardly ever or never (scored as 1), some of the time (scored as 2) and often (scored as 3). The sum of these scores yielded a loneliness scale ranging from 3 to 9. Loneliness was then dichotomized, with scores of 3-5 indicating no loneliness and 6-9 indicating loneliness.

Demographic variables, including *age* (categorized as young-old: 50-64 years old, middle-old: 65-74 years old, and old-old: 75 and older), *sex* (female VS male), *ethnicity* (White VS non-White), were extracted from Wave 8. *Place of residence* (rural VS urban) was extracted from the COVID Substudy, which sourced from the 2011 Census archive.

General risk factors include 1) *Wealth*, was measured in Wave 9 using total (non-pension) wealth at benefit unit level (ELSA 2022). For analytical purposes, participants were divided into three categories by dividing the wealth distribution into equal thirds, with the bottom 33% categorized as 'poorest', the middle 33% as 'middle', and the upper 33% as 'richest'. 2) *Employment status*, extracted from COVID Wave 1, was categorized into three groups: 'retired', 'employed' (encompassing those in employment, on paid/unpaid leave from employment, self-employed and those currently working/not working), and 'unemployed' (including those unemployed, permanently sick or disabled, or looking after home or family). 3) *Self-rated general health*, assessed in COVID Wave 1, was grouped into 'good' (comprising responses of excellent, very good and good) and 'poor' (comprising responses of fair and poor). 4) *Depression symptoms* were measured in COVID Wave 1 using the 8-item Centre for Epidemiologic Studies Depression Scale (CES-D), with a total score of 3 or greater indicating the presence of depression symptoms (White et al. 2016).

Pandemic factors include 1) *COVID worries*, measured in COVID Wave 1, included reporting worries about future financial situation, enough food and other essential items. 2) Experiencing two or more COVID symptoms in COVID Wave 1 was coded as '*having COVID symptoms*'. 3) *Lifestyle change* was assessed in COVID Wave 1 based on participants reporting changes (including both less and more than usual) in three or more of the following items: physical activity, sitting down, eating, sleeping, and watching TV. 4) *Self-isolation* information was extracted from COVID Wave 2 including self-isolation in either April or October/November.

Protective factors include 1) Whether *pray/meditate daily*. 2) *Partner support*, categorized as 'higher support', 'lower support', or 'no partner'. 3) *Positive mindset*, measured in COVID Wave 1 using the Control, Autonomy, Self-realization, and Pleasure (CASP)-12 scale. 4) *Social contact changes* were the changes of social contacts with children, family and friends between COVID Wave 1 and Wave 9. These changes were further distinguished into changes in oral communication with contacts (video/phone call) and written communication with contacts (email, text).

Statistical Analysis

We initially viewed the sample as a whole and conducted multilevel binary logistic analysis to assess whether there was a statistically significant increase in the prevalence of loneliness among the older population in England during the pandemic, in comparison to pre-pandemic period. Subsequently, we conducted latent class growth (LCG) analysis using Latent GOLD Version 6.0 to identify distinct loneliness trajectories within the older population in England. LCG model is a variant of latent class regression modelling, aiming to uncover latent classes for which the intercept and the predictor effects in the regression model differ (Vermunt 2010). The first step is to build a clustering model, in which we estimated models with up to six latent classes. The determination of the number of classes was based on both statistical indices and substantive grounds. In the second step, we assigned individuals to the class for which the posterior class membership probability was highest.

The third step in our LCG analysis is to investigate the association between classification and demographic variables and the three pillars of variables. We employ the BCH Bia-adjusted step-3 approach (Bolck, Croon and Hagenaars 2004; Vermunt 2010). This approach, integrated within the LatentGOLD software, corrects for classification errors, thereby preventing biased downwards. Model 0 includes solely demographic variables. Model 1 expands upon the baseline model by including general risk factors and Model 2 integrates pandemic factors. Model 3 encompasses all variables from previous models and introduces protective factors.

Results

Increased Loneliness Prevalence during the Pandemic

Loneliness prevalence exhibited an upward trend across all four waves. However, the result of the multilevel binary logistic analysis indicates that a statistically significant increase in loneliness prevalence was observed only between COVID Wave 1 and Wave 9 (OR=1.344, p<0.001, 95% CI: 1.187,1.523). The increase between two pre-pandemic waves, Wave 9 and Wave 8 (OR=1.104, p=0.136, 95% CI: 0.969,1.257), and between two peri-pandemic waves, COVID Wave 2 and COVID Wave 1 (OR=1.071, p=0.259, 95% CI: 0.951,1.208), did not reach statistical significance. These findings demonstrate that the loneliness prevalence of older population in England did not increase linearly with years but rather suggesting that the pandemic played a substantial role in this trend.

Four Loneliness Trajectories within the Older Population

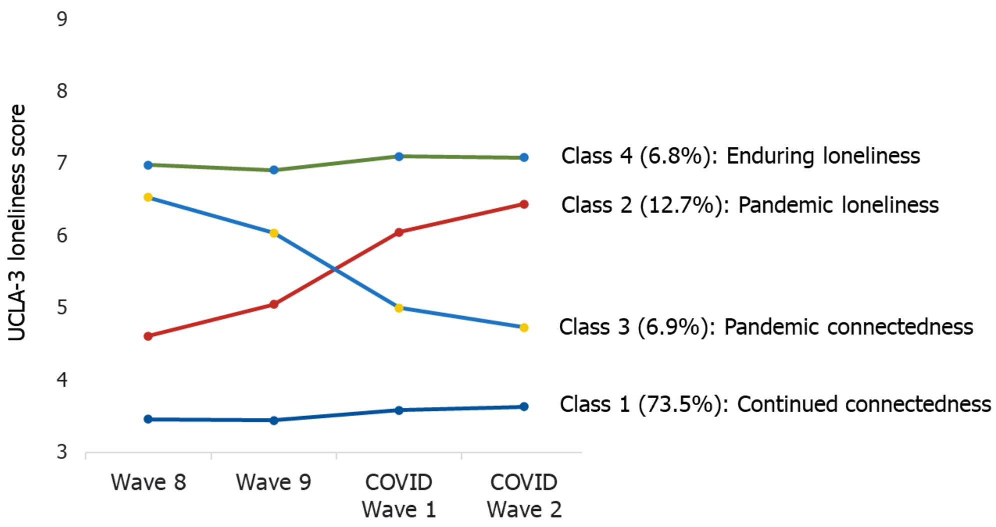
In LCG analysis, we run up to six latent classes models and found the 4-class solution to provide the best trade-off between model fit and interpretability. Table 1 presents the model fit indices.

Table 1 Model selection criteria for the six latent class growth models

Class	Log-likelihood	BIC(LL)	AIC(LL)	VLMRT (p-value)	Entropy R^2	Smallest class proportion
1	-8455.53	16927.88	16915.06	<0.001	1.00	1.00
2	-6798.42	13638.89	13606.84	<0.001	0.80	0.21
3	-6741.05	13549.38	13498.10	<0.001	0.64	0.08
4	**-6703.19**	**13498.89**	**13428.38**	**<0.001**	**0.67**	**0.07**
5	-6695.659	13509.04	13419.30	0.0005	0.64	0.02
6	-6695.599	13534.16	13425.18	0.0206	0.41	0.02

Notes. BIC=Bayesian Information Criterion; AIC=Akaike Information Criterion; VLMRT=Vuong-Lo-Mendell-Rubin Likelihood Ratio Test. VLMART compare an n class model with an n-1 class model.

Figure 1 Growth trajectories of loneliness for each class based on estimated means



Most older adults (73.5%) belong to the Continued Connectedness class, representing individuals who were not lonely both before and during the pandemic. The second largest class (12.7%) is referred to as the Pandemic Loneliness class and individuals in this class were not lonely pre-pandemic but became lonely during the pandemic. In contrast, the Pandemic Connectedness class (6.9%) was lonely pre-pandemic but transitioned to a non-lonely state during the pandemic. Finally, the Enduring Loneliness class (6.8%) is characterized with loneliness both before and during the pandemic.

Subpopulations at Risk of Adverse Loneliness Outcomes

In Model 3, the full model incorporating all groups of variables, individuals belonging to the Pandemic Loneliness class were more likely to be women (OR=1.51, $p<0.001$) and non-White participants (OR=2.02, $p<0.001$) compared to those in the Continued Connectedness class. Non-White participants were also more likely than White participants to be in the Enduring Loneliness class (OR=4.36, $p<0.001$) compared to the Continued Connectedness class. Paired comparison indicates that, in the Model 0, the baseline model including sole demographic variables, age did not merge as a significant predictor for membership in the Continued Connectedness class or the Pandemic Loneliness class. However, in Model 3, age became a significant predictor, with old-old participants showing a lower likelihood than young-old participants of belonging to the Pandemic Loneliness class. Regarding rural/urban residence, it was a significant predictor of class membership in Model 0 with, rural residents having a lower likelihood of belonging to both the Pandemic Loneliness class (OR=0.72, $p<0.001$) and the Enduring Loneliness class (OR=0.73, $p<0.001$) compared to the Continued Connectedness class. However, in Model 3, rural/urban residence no longer significantly predicted class membership overall, although the distinction between the Pandemic Loneliness and Continued Connectedness classes remained significant ($p=0.02$).

Vulnerability: General Risk Factors of Loneliness

Wealth, employment status, self-rated general health and depression symptoms all merged as significant predictors of class membership overall. Among the three wealth groups and employment statuses, participants categorized as the poorest and unemployed had the highest probability of belonging to the Pandemic Loneliness, Pandemic Connectedness and Enduring Loneliness classes, while having the lowest probability to be in the Continued Connectedness class. Participants reporting poor health and those experiencing depression symptoms had a greater probability of membership in the Pandemic Loneliness, Pandemic Connectedness and Enduring Loneliness classes in comparison to their counterparts with good health and without depression symptoms, while having a lower probability of belonging to the Continued Connectedness class.

Exposure: Pandemic Factors

In Model 2, without having the protective factors, participants who reported COVID worries (OR: 2.5, $p<0.001$), substantial lifestyle changes (OR: 1.76, $p<0.001$), and self-isolation (OR: 1.32, $p<0.001$) had a higher risk of belonging to the Pandemic Loneliness class instead of the Continued Connectedness class. Having two or more COVID symptoms did not significantly predict class memberships. However, in Model 3, when protective factors were included, the differences associated with lifestyle change and self-isolation were no longer statistically significant. Although having COVID worries remained a significant predictor of membership overall, paired comparisons show that the differences between Pandemic Loneliness and Continued Connectedness classes were also no longer significant. Meanwhile, participants with COVID symptoms were more likely to belong to the Enduring Loneliness class rather than the Continued Connectedness class.

Capacity: Protective Factors

Positive mindset, measured with CASP-12 (range from 3 to 36), are significant protective factors. The mean CASP-12 scores for the four classes, ranked from low to high, are as follows: Enduring Loneliness class (17.84), Pandemic Loneliness class (21.48), Pandemic Connectedness class (23.42), and Continued Connectedness class (28.51). Paired comparisons reveal statistically significant differences between the Enduring Loneliness and Pandemic Connectedness classes, as well as between the Pandemic Loneliness and Continued Connectedness classes. These differences suggest that a higher level of control, autonomy, pleasure, and self-realization helps protect older adults from experiencing loneliness during the pandemic and aids those who were lonely pre-pandemic in overcoming their loneliness in the pandemic. Older participants with greater partner support were more likely to belong to the Continued Connectedness class than to the other three classes. Notably, participants with lower partner support, similar to having no partner, were less likely to belong to the Continued Connectedness class and more likely to belong to the other three classes. Among the four classes, older participants with increased written communication were relatively over-presented in the Enduring Loneliness (44%) and Pandemic Connectedness (42%) classes than the average (41%). Paired comparisons indicate significant differences in terms of oral social contact changes between the Continued Connectedness and Pandemic Loneliness classes but no significant differences between the Enduring Loneliness and Pandemic Connectedness classes. This suggests that increased oral communication with contacts protect older participants who were not lonely pre-pandemic from becoming lonely during the pandemic but do not alleviate the loneliness of those who were lonely before the pandemic. According to paired comparisons, increased written communication with contacts only predict differences between the Continued Connectedness and Enduring Loneliness classes, with the latter class having a higher proportion of participants with increased written communication (41%) than the former class (33%). Finally, participants who pray or meditate daily were significant more likely to belong to the Enduring Loneliness class than the other three classes.