

RESEARCH

Open Access



Trajectories of depressive symptom and its association with air pollution: evidence from the Mr. OS and Ms. OS Hong Kong cohort study

Yinan Zhao¹, Qingcai Liu¹, Yifei Chen¹, Timothy C. Y. Kwok^{2*}, Jason C. S. Leung², Hui Feng^{1,3*} and Samuel Yeung Shan Wong^{4,5}

Abstract

Background Depression is a global health priority. Maintaining and delaying depressive symptoms in older adults is a key to healthy aging. This study aimed to identify depressive symptom trajectories, predictors and mortality, while also exploring the relationship between air quality and depressive symptoms in older adults in the Hong Kong community over 14 years.

Methods This study is a longitudinal study in Hong Kong. The target population was community-dwelling older adults over age 65. Depressive symptoms were measured by the Geriatric Depression Scale (GDS-15). Group-based trajectory model was used to identify heterogeneity in longitudinal changes over 14 years and examine the associations between baseline variables and trajectories for different cohort members using multinomial logistic regression. The Kaplan–Meier method was employed to conduct survival analysis and explore the variations in survival probabilities over time among different trajectory group. Linear mixed model was used to explore the relationship between air quality and depressive symptoms.

Results A total of 2828 older adults were included. Three different trajectories of depressive symptoms in older people were identified: relatively stable (15.4%), late increase (67.1%) and increase (17.5%). Female, more number of chronic diseases, poor cognitive function, and poor health-related quality of life (HRQOL) were significantly associated with other less favorable trajectories compared with participants with stable levels of depressive symptoms. The late increase group had a lower mortality rate than the relatively stable and increased groups. Lower baseline ambient air pollutant exposure to NO₂ over 14 years was significantly associated with fewer depressive symptoms.

Conclusions In this study, we found that a late increase in depressive symptoms was the predominant trend in older Chinese people in Hong Kong. Poorer HRQOL was predictive of less favorable trajectories of depressive symptoms. Ambient air pollution was associated with depressive symptoms. This novel observation strengthens the epidemiological evidence of longitudinal changes in depressive symptoms and associations with late-life exposure to air pollution.

*Correspondence:

Timothy C. Y. Kwok
tkwok@cuhk.edu.hk
Hui Feng
feng.hui@csu.edu.cn

Full list of author information is available at the end of the article



© The Author(s) 2024. **Open Access** This article is licensed under a Creative Commons Attribution 4.0 International License, which permits use, sharing, adaptation, distribution and reproduction in any medium or format, as long as you give appropriate credit to the original author(s) and the source, provide a link to the Creative Commons licence, and indicate if changes were made. The images or other third party material in this article are included in the article's Creative Commons licence, unless indicated otherwise in a credit line to the material. If material is not included in the article's Creative Commons licence and your intended use is not permitted by statutory regulation or exceeds the permitted use, you will need to obtain permission directly from the copyright holder. To view a copy of this licence, visit <http://creativecommons.org/licenses/by/4.0/>. The Creative Commons Public Domain Dedication waiver (<http://creativecommons.org/publicdomain/zero/1.0/>) applies to the data made available in this article, unless otherwise stated in a credit line to the data.

Key points

- This study was intended to capture the trajectories of depressive symptoms and the associated with air quality.
- Three different trajectories of depressive symptoms in older people were identified: relatively stable, late increase and increase trajectories.
- Female, poor cognitive function, and poorer health-related quality of life were significantly associated with other less favorable trajectories.
- After 14 years, the late increase group exhibited a lower mortality rate compared to the relatively stable and increased groups.
- Long-term exposure to NO₂ over 14 years was significantly associated with more depressive symptoms.

Keywords Depressive symptoms, Longitudinal trajectory, Air pollutants, Older adults

Background

Depression is one of the highest disease burdens worldwide [1]. Globally, more than 20% of adults aged 60 and older have a mental or neurological disorder (excluding headache disorders), and 6.6% of all disabilities occurring among persons aged 60 and older are attributable to neurological and psychiatric disorders [2]. In China, the estimated loss of disability-adjusted life years (DALYs) due to depression was more than 10 million in 2013, with this figure expected to rise by 10% by 2025 [3, 4]. As the population ages, the adverse effects of depression will become more severe. A deeper understanding of the nature of depression in older populations and how to minimize it is critical to reduce this global burden. Depression is best viewed as a continuum category [5, 6]. Because the long-term trajectory of depressive symptoms varies widely across the population, some individuals have few or no symptoms, others experience transient symptoms, and others suffer from chronic depression [7]. Therefore, it is vital to determine the time point of onset and decline of depressive symptoms with strategies to delay their development and to intervene on time. Trajectory analysis of longitudinal data provides an opportunity to understand how different levels of depression appear to behave differently over time and the factors that influence them [8].

The trajectory of depressive symptoms has been used in the maternal population [9, 10], young adults [11–13], people in enforced isolation [14], recurrently depressed adults [15], and widowed elderly individuals [16]. The categorization of these trajectories varies depending on the study population and can range from 2 to 6 distinct patterns. In addition, the statistical analysis models used in each study also vary; of these, the group-based trajectory model (GBTM) is one example that allows for investigating depressive symptom trajectories [17, 18]. Despite extensive research, the trajectory of depressive symptoms among community-dwelling older adults has primarily been explored through short-term cohort studies. Therefore, more longitudinal studies on the natural courses of

depression are needed, especially in older adults, where limited studies have been conducted.

Another issue is determining how different risk factors are associated with varying depression symptom patterns, which may be necessary for understanding the etiology of depression and improving treatment. Recent studies have explored the impact of a range of risk factors on depression, which can be broadly categorized into biological, psychological, and social factors. These include the number of chronic diseases [19–21], vascular factors [22, 23], health status [19, 24], disability and habits [21, 25], low self-esteem [20], low contact frequency [19], smaller network size [26], and marital status [19, 27]. With the increasing urbanization of the world's population, there is a growing interest in studying the role of physical and social environmental factors in the development of depression [28].

In recent years, there has been a growing concern about the influence of environmental factors on depression. According to the report, air pollution caused 4.9 million deaths in 2017 and was associated with a loss of 1.47 billion Disability-Adjusted Life Years (DALYs) [29]. Indicators of poor air quality include fine particulate matter with an aerodynamic diameter of 2.5 μm or less (PM_{2.5}), nitrogen dioxide (NO₂), tropospheric ozone (O₃), sulfur dioxide (SO₂), and carbon monoxide (CO) [30]. The exposure to air pollutants has the potential to cause detrimental effects on the neurological system, resulting in a wide range of consequences such as alterations in behavior and the development of neurodegenerative illnesses [31, 32]. Due to widespread exposure to environmental pollutants, there is increasing evidence indicated that short-term exposure to air pollution is significantly related to residents' depression and anxiety, was associated with increased risk of hospitalization [33–35]. However, the evidence of long-term effects of air pollution has emerged with conflicting findings [36–39]. Meanwhile, due to economic disparities, most air quality studies have been conducted in developed countries, the existence of

such a relationship in developing countries is very limited [40, 41]. In addition, considering the vulnerability of older adults, they tend to have more prevalent comorbidities that may lead to broader consequences [42].

Therefore, this study aims to identify trajectories of depressive symptoms over 14 years, predictors of trajectories, and associations of different trajectories with mortality, as well as to explore the relationship between air quality and depressive symptoms among older adults in the Hong Kong community.

Methods

Design and study sample

All data from the Mr. OS and Ms. OS Hong Kong cohort study. The Mr. OS and Ms. OS study is the first large-scale osteoporosis study in Hong Kong and was initiated in 2001 with 2,000 men and 2,000 women [43]. After a baseline survey in 2001, the survey project conducted four waves of follow-up surveys in 2003, 2005, 2007, and 2014 [44]. From 2015 to 2017, participants were invited for a 14-year follow-up visit that included repeat questionnaire interviews and physical measurements [45]. In the current study, participants aged 65 years and older at baseline and still alive after 14 years of follow-up were included. Written informed consent was obtained from all participants, and the study was approved by the Clinical Research Ethics Committees of the Chinese University of Hong Kong.

We excluded participants who experienced mortality within 7 years of the start of the study and those who had missing data for more than 2 waves, as the limited observation time would have prevented them from developing any meaningful engagement trajectories [46]. Therefore, all participants in our analysis had at least 7 years to form trajectories before being censored. Moreover, during the process of investigating the association between air pollutants and the trajectories of depressive symptoms, participants who did not have baseline air pollutants data were excluded from the analysis. This report follows the Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) reporting guidelines [47].

Measurement

Depressive symptoms

Depressive symptoms were measured by the Geriatric Depression Scale (GDS-15), which is an instrument to measure depressive complaints specifically in an older population. Covinsky also used it to screen for caregiver depression [48]. The GDS-15 correlates highly with clinical depression [49, 50]. We used the short version, consisting of 15 yes or no questions. The scores were summed and ranged from 0 to 15, and the participant was categorized as having depressive complaints with

a score of 5 or higher [51–53]. When evaluated against diagnostic criteria of clinical depression (AGECAT and several DSM versions), the GDS-15 appeared to have 64–98% specificity and 69–92% sensitivity [54].

Air pollution concentration monitoring data

Long-term hourly air pollution data with high temporal resolution recorded by the Hong Kong Environmental Protection Department (HKEPD) Local Air Quality Monitoring Network (AQMN) in the last 14 years (2001 to 2014) were collected to develop land-use regression (LUR) models for different air pollutants, as described elsewhere [55]. The gaseous air pollutants CO (carbon monoxide), NO_x (nitrogen oxides), SO₂ (sulfur dioxide), and particulate air pollutants PM_{2.5} [material μm with a particle aerodynamic diameter less than or equal to 2.5, also known as fine particulate matter (FSP)] and PM₁₀ [particulate matter with an aerodynamic diameter less than or equal to 10 μm, also known as respirable particulate matter (RSP)] were collected from 15 air quality monitoring stations (AQMS) of AQMN.

Covariates

Age, gender, chronic illness, cognitive impairment, functional impairment, social support, personality traits, and a history of depression were shown to be predictors of clinically relevant depressive symptoms [56, 57]. Based on this evidence, we selected the following covariates available in the dataset: age, sex, educational attainment, marital status, subjective social status, quality of life, cognitive function and physical function. The physical function includes body mass index (BMI), self-reported physical activity, self-reported health, fall history within the past 12 months, health behaviors and cognitive function. Additional information regarding the measures of the covariate can be found in Additional file 5.

Statistical analyses

The sociodemographic and clinical characteristics of the sample are presented using means and standard deviations for continuous variables and frequencies for categorical variables. Participants' depressive symptom trajectories were modeled using a group-based trajectory model (GBTM). Trajectories were derived by modeling depressive symptoms as a function of change over time. The GBTM was used to identify potential clusters of similar trajectories by analyzing the dynamics of seven-wave data, and the best-fit model was based on a Bayesian information criterion and the presence of at least 5% of participants for each trajectory to ensure stable estimation of each trajectory [17, 18]. The posterior probability of assigning each participant to a trajectory group was greater than 0.9, indicating a good model fit. A Wald test

was performed to determine if the slopes of the trajectories were significantly different. The STATA Traj plug-in (Stata Corp., College Station, TX) was used to model the physical trajectories with a censored normal distribution [58].

To determine sociodemographic, clinical and the air quality predictive factors of the different trajectories of depressive symptoms, we used the LASSO algorithm (LASSO) based on the available data at baseline. A criterion of $p < 0.05$ was used to select the relevant variables to include in a multivariate model. A stepwise multinomial logistic regression model was performed to solve for the membership of the depression trajectory according to the selected relevant factors as well as baseline air quality. Additionally, The Kaplan-Meier method was employed to conduct survival analysis and explore the variations in survival probabilities over time among different trajectory group.

The third step of the analysis aimed to determine whether the air quality index, such as PM₁₀ and NO₂, were associated with depressive symptoms scores during follow-up. A linear mixed model was realized with the concentration of PM₁₀ and the concentration of NO₂ evaluated at each visit as the dependent variable and the depressive symptom scores as the primary independent variable. The more details showed in Additional file 6.

Additionally, we conducted a sensitivity analysis to enhance the robustness of our research findings. Initially, in order to mitigate any potential impacts of multiple imputation on the observed outcomes, participants with missing depressive symptoms data were excluded. Subsequently, a comprehensive reanalysis was performed on the resultant trajectories. Recognizing the pronounced causal relationship between disease conditions and depressive symptoms, participants with a history of pre-existing chronic conditions at baseline were subsequently excluded, including but not limited to cardiovascular diseases, stroke, and cancer.

All statistical analyses regarding associations between class membership and other variables were also performed using R statistical software, version 4.0.0 (R Project for Statistical Computing).

Results

Sample characteristics

According to the selection criteria, a total of 2828 samples were included in the study (Fig. 1). Overview of the study design showed in Fig. 2. Table 1 shows the baseline characteristics of the total sample and the sample by the different trajectory groups. Compared with the excluded participants, the included people were younger, more female, higher educational level, better quality of life in the physical component, lower quality of life in

mental component, higher BMI index, fewer smokers, less depressive symptoms and better cognitive function (Additional file 1). At baseline, the ages of the participants varied from 65 to 86, with a mean age of 71.65 years and a standard deviation of 4.72. The majority of participants in the study were female, with a significant proportion (69.5%) having attained a high school degree or below. A significant proportion of the participants were in a marital relationship. Initially, the median exposure to PM₁₀ was recorded at 52.00 µg/m³, while the median exposure to NO₂ was measured at 62.95 µg/m³.

The trajectories of depressive symptoms

In each trajectory, less than 5% of the proportions in the groups were excluded, which might indicate inadequately populated classes [59]. After several data processing sessions (Additional file 2), we found that among the models in Groups 1–4, the absolute BIC values of the models in Group 3 were lower than those of the other models, and the Ave PP values were high, all being greater than 0.70. Table 2 compares the models found by GBTM for trajectory classes 1 to 4.

Three distinct trajectories were identified over the 14-year follow-up (Fig. 3). The first trajectory consisted of 17.5% of cohort members with low depressive symptom scores at baseline who were relatively stable over time (marked as “relatively stable”). The second trajectory consisted of 15.4% of cohort members who had a slow rate of growth over 14 years (labeled “increase”). Finally, the third trajectory consisted of 67.1% of cohort members whose depressive symptom scores declined slowly in the first 7 years but increased significantly from years 7 to 14 (labeled “late increase”).

Baseline predictors of the trajectories

To identify sociodemographic and clinical predictors of the various depressive symptom trajectories, it is essential to include the most significant subset of predictors from the dataset. The LASSO regression was used to filter variables based on the available data at baseline, and more details are shown in Additional file 3. A total of 10 variables were included in the next step of the analysis. We choose “relatively stable” as the reference category because it has a relatively smooth trend in the baseline and subsequent development compared with the other three trajectories. Full results from the multivariate analysis of risk factors with varying trajectories are presented in Fig. 4 and Table 2.

The quality of life in the physical component (increase: OR, 0.93; 95% CI, 0.90–0.95; late increase: OR, 0.94; 95% CI, 0.92–0.96) and in mental component (increase: OR, 0.91; 95% CI, 0.87–0.95; late increase: OR, 0.95; 95% CI, 0.92–0.99) and the score of depressive

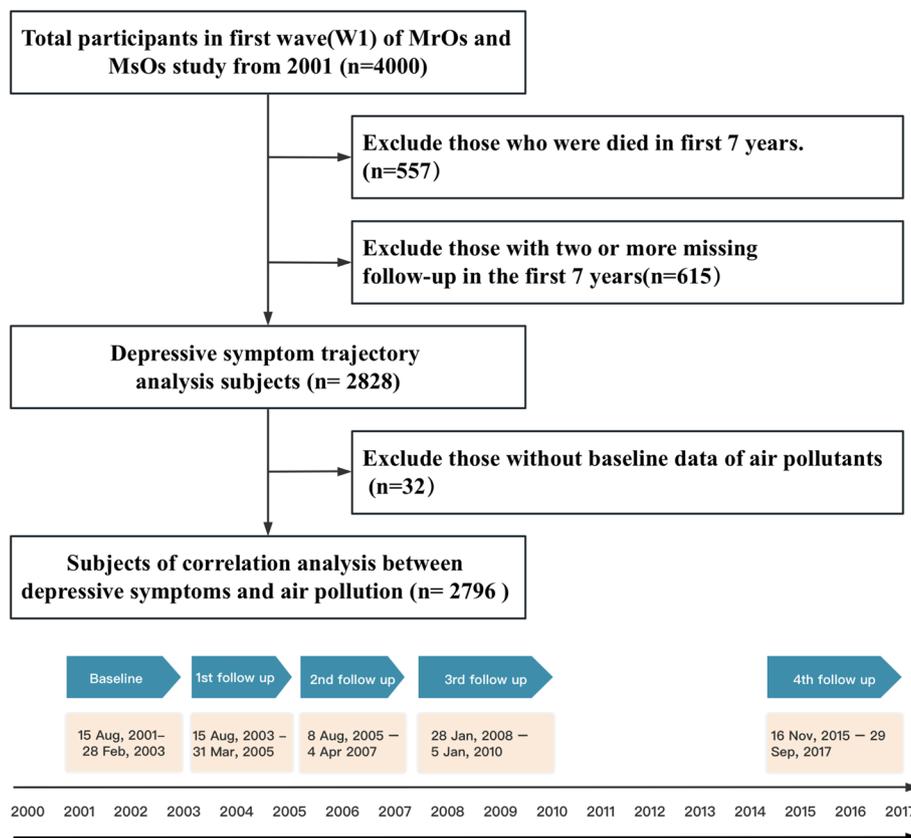


Fig. 1 Flowchart of study population and demonstration of study timeline

symptoms (increase: OR,19.37; 95% CI, 14.81–25.32; late increase: OR,11.50; 95% CI, 8.85–14.93) were associated with all trajectories. Compared to the relatively stable group, the female sex (OR, 1.61; 95% CI, 1.00–2.56) and the number of chronic diseases (OR, 0.91; 95% CI, 0.85–0.98) were associated with the increased group, but they were not associated with the increased group. Separate older adults (OR, 0.91; 95% CI, 0.85–0.98) were associated with the late increase group, but they were not associated with the increase group.

The mortality by trajectory group

There were markedly different risks of mortality based on trajectory group membership. We obtained stratified estimates of the cumulative incidence of mortality by trajectory group using the Kaplan–Meier method. Time 0 is the baseline date, and patients were administratively reviewed at the time of death. The late-increase group had a lower death rate after 14 years, which was significantly different from the other two groups ($p=0.008$) (Fig. 5).

The relationship between air quality and depressive symptoms

The results found no significant associations between baseline ambient air pollutant exposure and either depressive symptoms at baseline or the occurrence of less favorable trajectories (Table 3). This observation remained not statistically significant after adjustment for confounding factors such as sex, marital status, quality of life (including mental and physical components), number of chronic illnesses, and cognitive function.

Next, we explored whether there was a correlation between depressive symptoms and air pollution over 14 years. The results of a linear mixed model exploring the link between the change in depressive symptoms and air quality. Based on fully adjusted models (Table 4, Model V), residing in locations with better ambient air quality (NO_2 : $\beta=0.170/\text{year}$, 95% CI: 0.106–0.234) was associated with fewer depressive symptoms (Table 4).

Sensitivity analysis

To avoid the influence of multiple imputations and selection bias on the results, we removed populations with

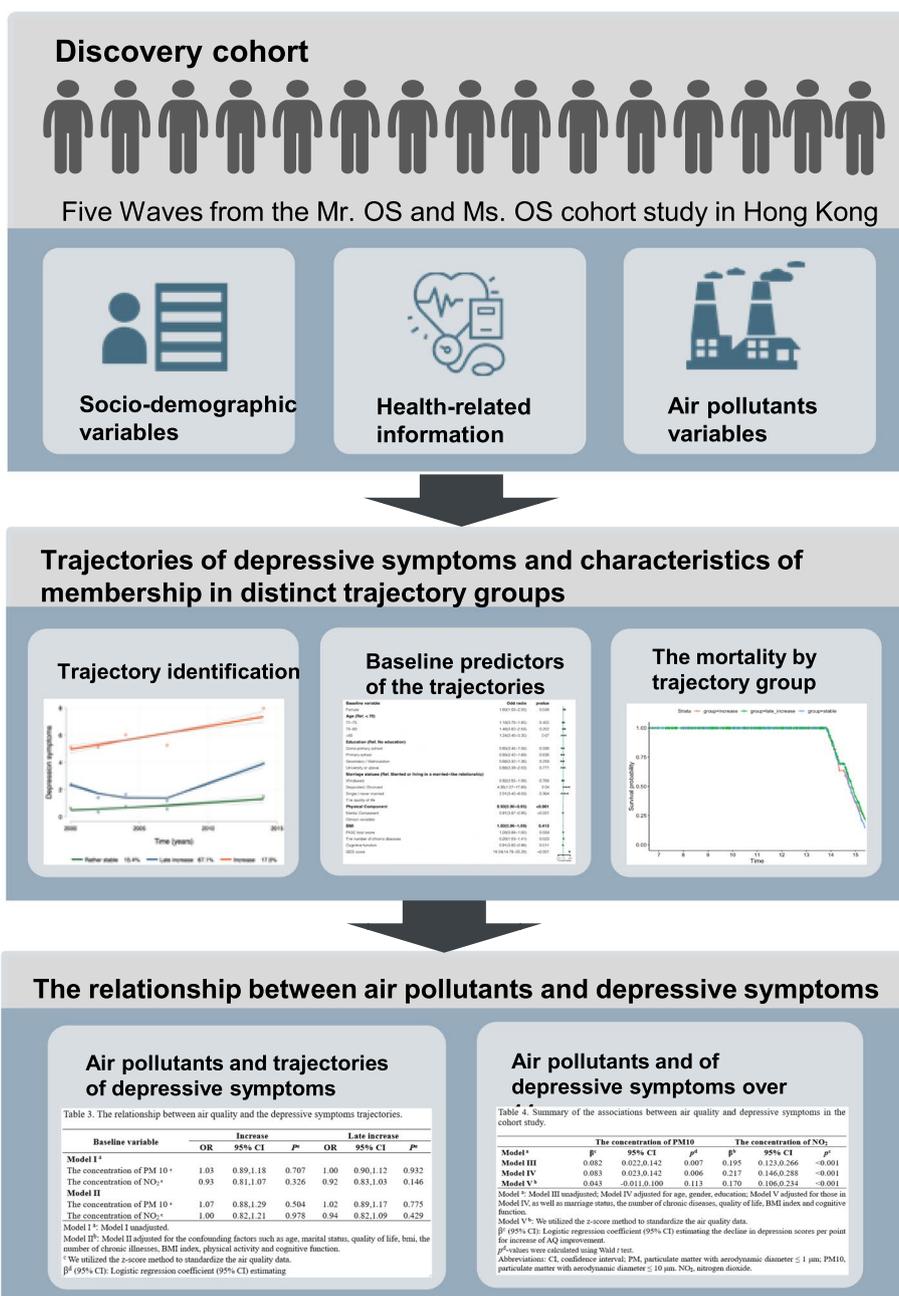


Fig. 2 Overview of the study design

missing data in any wave during follow-up ($n=2018$). The proportions of the three groups and the appearance of the trajectories were similar to those in the full cohort (Additional file 4).

Discussion

This was the first study to capturing depressive symptom trajectories in older Chinese people over 14 years. A late increase after several years of stability appeared to be

the predominant trend. Only a small percentage of participants maintained a low level of depressive symptoms with a small increase over the years. Both physical and mental health-related quality of life (HRQOL) at baseline was most consistently and significantly associated with the less favorable trajectories. Females, those with more chronic diseases, and those with poorer cognitive function were more likely to have rising depressive symptoms over the next 14 years. The identified groups

Table 1 Baseline characteristics of the total sample and the sample by the different trajectory groups

Variable	Total	Groups		
		Increase (N = 414)	Late increase (N = 2023)	Relatively stable (N = 391)
Socio-demographic variables^a				
Age, M (SD)	71.65 (4.72)	72.17 (4.96)	71.63 (4.70)	71.24 (4.55)
Gender, (n, %)				
Male	1380 (48.8)	141 (34.1)	1026 (50.7)	213 (54.5)
Female	1448 (51.2)	273 (65.9)	997 (49.3)	178 (45.5)
Education, (n, %)				
No education	557 (19.7)	122 (29.5)	383 (18.9)	52 (13.3)
Some primary school	913 (32.3)	132 (31.9)	681 (33.7)	100 (25.6)
Primary school	495 (17.5)	68 (16.4)	347 (17.2)	80 (20.5)
Secondary / Matriculation	558 (19.7)	63 (15.2)	399 (19.7)	96 (24.6)
University or above	305 (10.8)	29 (7.0)	213 (10.5)	63 (16.1)
Marriage statuses, (n, %)				
Married or living in a married-like relationship	2063 (72.9)	269 (65.0)	1489 (73.6)	305 (78.0)
Windowed	646 (22.8)	121 (29.2)	447 (22.1)	78 (19.9)
Separated	44 (1.6)	7 (1.7)	35 (1.7)	2 (0.5)
Divorced	25 (0.9)	6 (1.4)	17 (0.8)	2 (0.5)
Single, never married	50 (1.8)	11 (2.7)	35 (1.7)	4 (1.0)
The quality of life				
Physical Component, M (SD)	49.19 (8.05)	45.91 (9.33)	49.22 (7.85)	52.48 (5.98)
Mental Component, M (SD)	56.09 (6.48)	51.51 (8.86)	56.67 (5.84)	57.99 (4.15)
Health-related information				
BMI, M (SD)	23.79 (3.18)	23.93 (3.25)	23.79 (3.22)	23.65 (2.91)
Self-reported health status, (n, %)				
Poor/ very poor/ fair	2662 (94.1)	357 (86.2)	1920 (94.9)	385 (98.5)
Good / excellent	162 (5.7)	57 (13.8)	103 (5.1)	6 (1.5)
The number of chronic diseases, M (SD)	1.54 (1.28)	1.80 (1.33)	1.54 (1.29)	1.28 (1.07)
PASE, M (SD)	94.31 (43.45)	88.63 (39.74)	94.73 (43.89)	98.14 (44.43)
Smoke, (n, %)				
No smoke	2666 (94.3)	395 (95.4)	1897 (93.8)	374 (95.7)
Current smoker	162 (5.7)	19 (4.6)	126 (6.2)	17 (4.3)
Drink, (n, %)				
No	2446 (86.5)	382 (92.3)	1742 (86.1)	323 (82.6)
Yes	381 (13.5)	32 (7.7)	281 (13.9)	68 (17.4)
Depression symptom, M (SD)	2.47 (2.24)	5.21 (2.42)	2.34 (1.79)	0.22 (0.57)
Cognitive function, M (SD)	25.98 (3.39)	24.72 (3.92)	26.03 (3.32)	27.04 (2.64)
Air quality variables^b				
The concentration of PM ₁₀ , M (SD)	52.00 (2.89)	52.05 (2.91)	51.99 (2.87)	51.98 (2.94)
The concentration of NO ₂ , M (SD)	62.95 (12.98)	62.93 (12.22)	62.78 (13.03)	63.83 (13.50)

PASE Physical Activity Scale for the Elderly

^a N = 2828

^b N = 2796

showed large differences in survival: after adjustment, the late increase group had a lower mortality rate than the relatively stable and increased groups. Furthermore, we found that ambient air NO₂ exposure over 14 years was

significantly associated with depressive symptoms after adjusting for several confounding variables.

Previous studies have identified 3 to 5 different trajectory categories for trajectory patterns, with

Table 2 Risk factors of depressive symptoms trajectories (relative risk ratios and 95% confidence interval)

Baseline variable	Group	
	Increase	Late increase
Socio-demographic variables		
Female	1.60* (1.00–2.55)	0.87 (0.61–1.24)
Age (Ref. < 70)		
71–75	1.18 (0.76–1.85)	0.97 (0.69–1.36)
76–80	1.46 (0.82–2.59)	1.17 (0.75–1.81)
> 80	1.24 (0.46–3.35)	1.07 (0.48–2.38)
Education (Ref. No education)		
Some primary school	0.85 (0.46–1.56)	1.03 (0.64–1.72)
Primary school	0.85 (0.42–1.69)	0.78 (0.47–1.40)
Secondary / Matriculation	0.66 (0.32–1.36)	0.65 (0.40–1.23)
University or above	0.88 (0.39–2.03)	0.74 (0.43–1.37)
Marriage statuses (Ref. Married or living in a married-like relationship)		
Windowed/ Separated	0.92 (0.55–1.56)	0.91 (0.60–1.37)
Divorced	4.35* (1.07–17.68)	4.13* (1.25–13.66)
Single, never married	2.01 (0.45–9.03)	1.68 (0.47–6.01)
The quality of life		
Physical Component	0.93*** (0.90–0.95)	0.94*** (0.92–0.96)
Mental Component	0.91*** (0.87–0.95)	0.95* (0.92–0.99)
Health-related information		
BMI	1.03 (0.96–1.09)	1.02 (0.97–1.07)
PASE	1.00 (0.99–1.00)	1.00 (0.99–1.00)
The number of chronic diseases	1.20* (1.03–1.41)	1.10 (0.97–1.25)
Cognitive function	0.91* (0.85–0.98)	0.94 (0.89–1.00)

BMI Body mass index, GDS Geriatric Depression Scale, PASE Physical activity scale for the elderly

* $p < 0.05$, *** $p < 0.001$

approximately 10% of individuals falling into the persistent high-risk group [7, 60–62]. These variations may be due to differences in study populations, sample sizes, methodologies for identifying trajectories, and evaluation schedules [7, 60, 61, 63–70]. Two significant findings differed from previous trajectories. First, the predominant trend in the development of depressive symptoms over the 14 years was to increase in the later years, some of them are directly rising, and some of them are showing a trend of decreasing first and then rising. Only a few people maintain a low level of depressive symptoms. This highlights the increasing propensity for depression with age. This may be due to retirement, physical and cognitive decline, bereavement, reduced social networks and loss of social roles [71, 72]. Furthermore, the study revealed that elderly individuals exhibiting symptoms of depression at baseline exhibited a significant reduction in depressive symptoms over 14 years. It is plausible this is due to the inclusion of individuals who survived the first 7-year period and those who demonstrated substantial

improvement in depressive symptoms and, consequently, were more likely to participate in the follow-up assessments. This finding also suggests that individuals with higher may possess better-coping mechanisms to manage the aftermath of depression, leading to an enhanced probability of reducing their depressive symptoms [73].

Understanding the underlying trajectory of health and the driver of health is critical to guiding long-term investments and policy implementation [74]. The significant predictors of depressive trajectories identified in our study were generally consistent with those in previously cited studies, such as gender and cognitive function [75, 76]. Our study also revealed a robust association between quality of life and the manifestation of depressive symptoms. Previous cross-sectional studies have identified a significant association between depression and quality of life in older adults [77]. This study also adds to the evidence from longitudinal studies that found that older people with lower quality of life at baseline had a subsequent worsening of depressive conditions, even among those without previous depressive conditions. This underscores the importance of not only addressing the needs of older individuals with preexisting disease conditions but also promoting the well-being of those who are healthy. However, our study also observed similar findings in the decline group, which may be because these older individuals were already exhibiting symptoms of depression at baseline and had experienced a decline in their quality of life.

The WHO estimates that globally, ambient air pollution caused 4.2 million deaths in 2016 [78]. Several previous epidemiological studies have investigated the association between short-term exposure to ambient air pollution and the risk of depression [32, 34, 79–81]; two used inpatient data [79, 81]; four used community setting data [37, 82–84], and only one used community-dwelling older adults [37]. A cross-sectional study in China found higher levels of PM_{2.5}, SO₂ and TSP emission intensity were consistently associated with higher prevalence of depression [85]. Altug enrolled 821 older women from the German SALIA cohort and found that an increase of one interquartile range in PM₁₀, PM_{2.5}, NO₂ and NO_x was associated with depressive symptoms assessed with the CESD-R score [86]. This article adds evidence that long-term exposure of NO₂ is significantly associated with depressive symptom decline in elderly individuals after adjusting for several confounding variables, such as age, gender, and education level over a 14-year period. This is similar to findings from a study focused on older adults in the United States [87]. Consensus has not been reached on the pathophysiological mechanisms underlying the association between NO₂ and depression; however, numerous paths may show that inhaling air

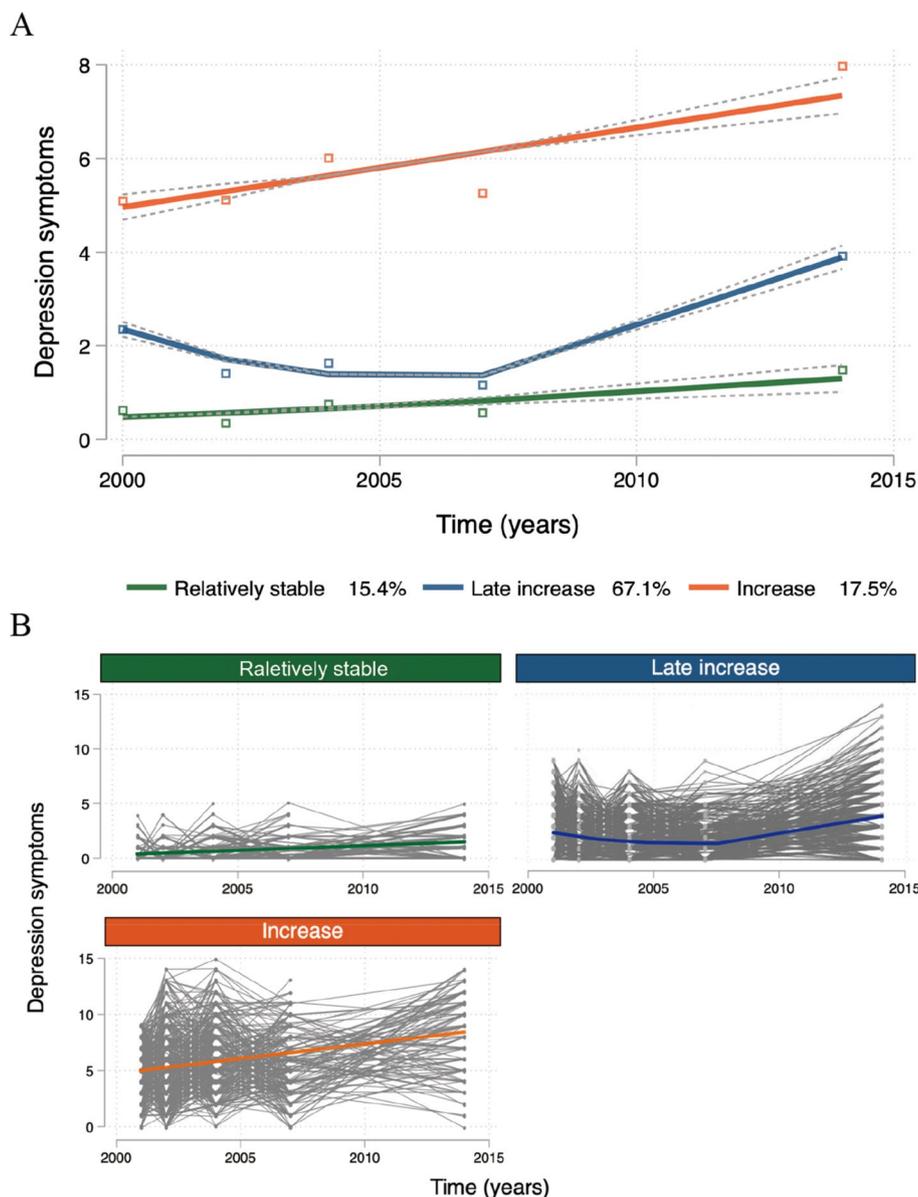


Fig. 3 Trajectories of the depression symptom scores. **(A)** Each color represents a depressive symptom trajectory. The solid lines (blue: late increase; green: relatively stable; yellow: late increase) represent estimated values. **(B)** Individual trajectories observed in different groups.)

pollutants causes oxidative stress and systemic inflammation and induces dopaminergic neurotoxicity, which leads to depressive symptoms [88–90].

The strengths of our study include the following. First, the large sample size provided by Hong Kong allowed sufficient power to identify trajectories and look for differences between trajectories. Second, we used GBTM, which can identify clusters of individuals who follow similar developmental trajectories on a given outcome by fitting a semiparametric mixture model to longitudinal data to maximize the data quality. Third, to find

baseline characteristics strongly correlated with trajectory group membership, high-dimensional holdout data are incorporated into the model using machine learning algorithms. This modern robust statistical technique minimizes multicollinearity between variables. Finally, our study explored the correlation between air pollution and depressive symptoms over time-based on temporal factors.

The results of this study should be interpreted with some caution. First, the variables we used were derived from self-report surveys, which may lead to

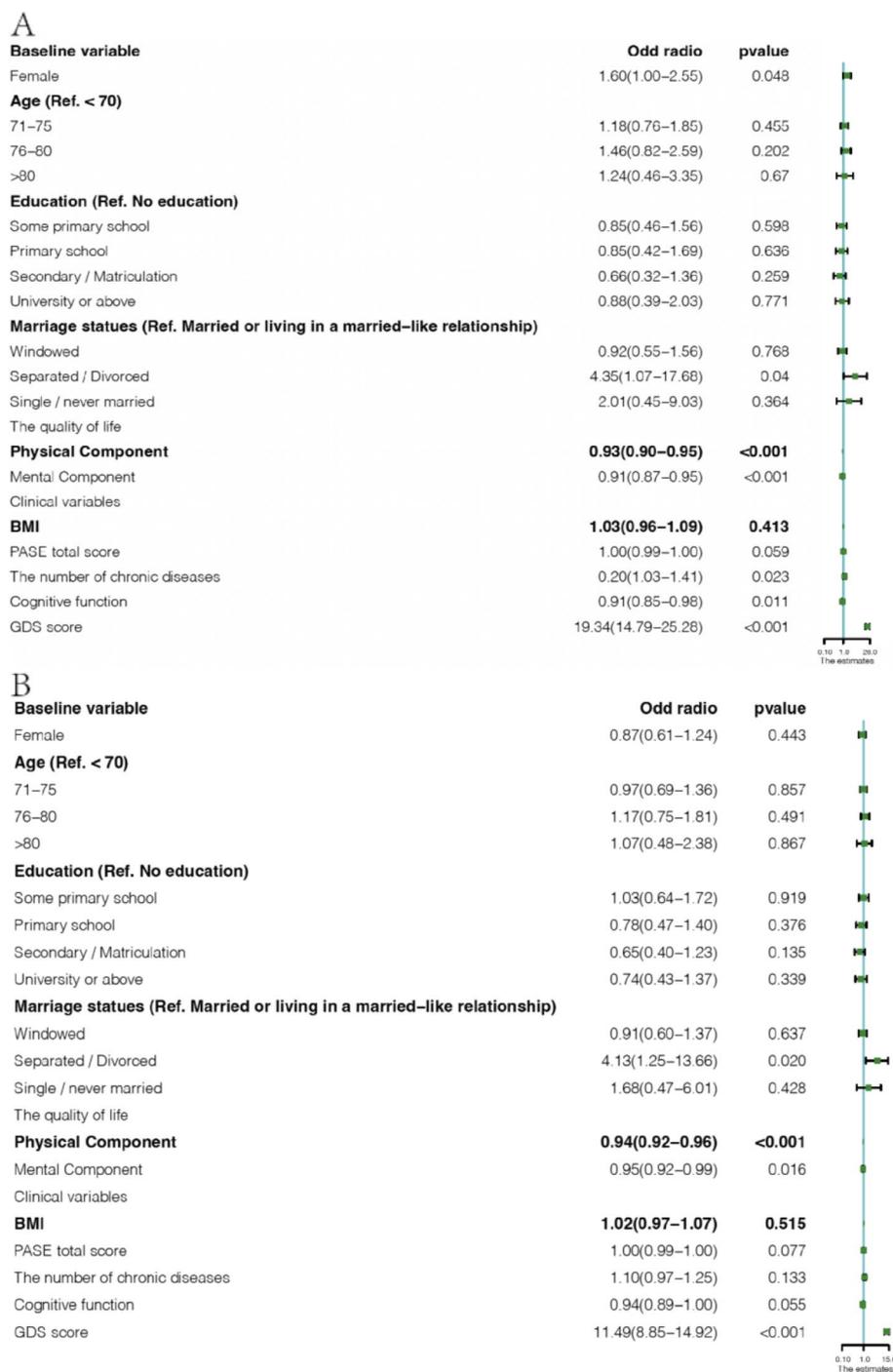


Fig. 4 Forest plot of risk factors for depressive symptom trajectories (relative risk ratios and 95% confidence intervals). **A** group1 (stable vs increase); **B** group2 (stable vs late increase)

bias. However, self-reported data are commonly used in depressive symptom studies of older adults, which can accurately reflect the status of individuals interacting with the real world. Second, the ambient air pollution data in this study are based on home addresses

at baseline. Participants may have moved houses, and indoor air pollution is influenced by other factors, such as building characteristics, occupant behaviors and levels of outdoor air pollution [91–93]. In addition, the decline in depressive symptoms is a long-term process. Although

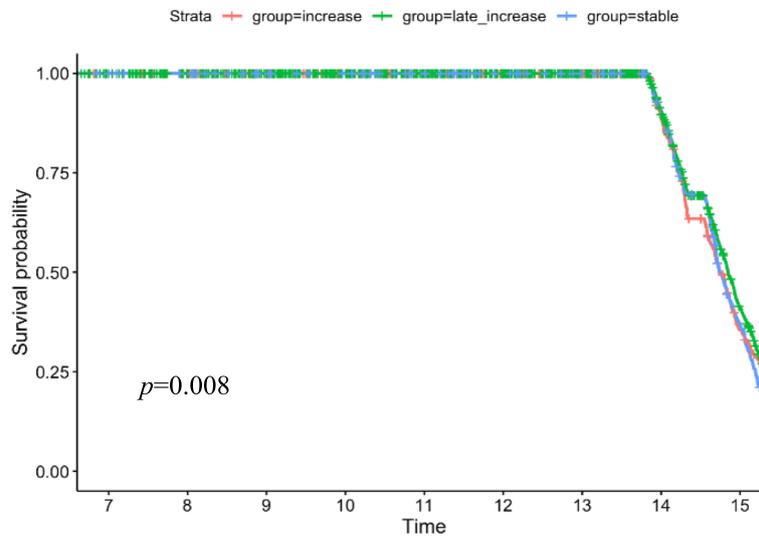


Fig. 5 Kaplan-Meier estimate of the survival probability of mortality by trajectory group

Table 3 The relationship between air quality and the depressive symptoms trajectories

Baseline variable	Increase			Late increase		
	OR	95% CI	<i>p</i> ^a	OR	95% CI	<i>p</i> ^a
Model I^a						
The concentration of PM ₁₀ ^c	1.03	0.89,1.18	0.707	1.00	0.90,1.12	0.932
The concentration of NO ₂ ^c	0.93	0.81,1.07	0.326	0.92	0.83,1.03	0.146
Model II^b						
The concentration of PM ₁₀ ^c	1.07	0.88,1.29	0.504	1.02	0.89,1.17	0.775
The concentration of NO ₂ ^c	1.00	0.82,1.21	0.978	0.94	0.82,1.09	0.429

Model I^a: Model I unadjusted

Model II^b: Model II adjusted for the confounding factors such as age, marital status, quality of life, bmi, the number of chronic illnesses, BMI index, physical activity and cognitive function

^c We utilized the z-score method to standardize the air quality data

Table 4 Summary of the associations between air quality and depressive symptoms in the cohort study

Model ^a	The concentration of PM10			The concentration of NO ₂		
	β^c	95% CI	<i>p</i> ^d	β^b	95% CI	<i>p</i> ^c
Model III	0.082	0.022,0.142	0.007	0.195	0.123,0.266	< 0.001
Model IV	0.083	0.023,0.142	0.006	0.217	0.146,0.288	< 0.001
Model V^b	0.043	-0.011,0.100	0.113	0.170	0.106,0.234	< 0.001

Abbreviations: CI Confidence interval, PM Particulate matter with aerodynamic diameter $\leq 10 \mu\text{m}$, PM10 Particulate matter with aerodynamic diameter $\leq 10 \mu\text{m}$, NO₂ Nitrogen dioxide

Model^a: Model III unadjusted; Model IV adjusted for age, gender, education; Model V adjusted for those in Model IV, as well as marriage status, the number of chronic diseases, quality of life, BMI index and cognitive function

Model V^b: We utilized the z-score method to standardize the air quality data

β^c (95% CI): Logistic regression coefficient (95% CI) estimating the decline in depression scores per point for increase of AQ improvement

p^d-values were calculated using Wald *t* test

the 14-year cohort has been considered current, the length of the study for depressive symptom analysis is relatively long, which may result in an underestimation of the number of trajectories.

Conclusion

The decline in depressive symptoms is a multifactorial process that includes sociodemographic characteristics, psychosocial factors, lifestyle, and indoor environment. Overall, our study shows that three trajectories of depressive symptoms have been identified in a 14-year follow-up sample of community-dwelling older adults in Hong Kong, with significant associations between gender, quality of life and cognitive function, and that increased ambient air pollution (NO₂) is associated with the risk of an increase in depressive symptoms in community-dwelling older adults. Many researchers are paying attention to the early prevention and timely intervention of aging. These results highlight the importance of capturing these highly dimensional and heterogeneous patterns of depressive symptom development and using this information to guide depressive symptom treatment planning to develop more robust strategies to reduce the incidence of depression. This better understanding of depressive symptoms in late-life older adults could ultimately be used to effectively and efficiently tailor interventions to different groups. Targeted strategies such as more stringent air pollution guidelines and air quality control measures may help promote public mental health. This research could help maintain or slow the rate of decline in mental health and improve healthy aging.

Supplementary Information

The online version contains supplementary material available at <https://doi.org/10.1186/s12877-024-04731-w>.

- Additional file 1.** Baseline characteristics of the included and excluded participants.
- Additional file 2.** The GBTM fit parameter estimates ($N = 2828$).
- Additional file 3.** Details of the process of convergence path using Lasso regression.
- Additional file 4.** Details of sensitivity analyses
- Additional file 5.** Definition and Measurement Instruments for Covariates.
- Additional file 6.** Details of linear mixed model analyses.

Acknowledgements

We thank the current and past staff at Jockey Club Centre for Osteoporosis Care and Control of the Chinese University of Hong Kong for their continued supports. I would also like to express my special thanks to Anjo Lu for her care and help during my study at the Chinese University of Hong Kong.

Authors' contributions

ZYN, LQC, TCYK and JCSL made substantial contributions to conception and design, or acquisition of data, or analysis and interpretation of data. ZYN and LQC involved in drafting the manuscript or revising it critically for important intellectual content. All authors given final approval of the version to be

published. Each author should have participated sufficiently in the work to take public responsibility for appropriate portions of the content, and all authors agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Funding

This work was also supported by the National Key R&D Program of China (Grant number 2020YFC2008602), and the Natural Science Foundation of China (Grant number 72174212), Hunan Postgraduate Innovation Project (Grant number CX20220336), China Scholarship Council (Grant number 202206370163).

Availability of data and materials

The datasets used or analyzed during the current study are available from the corresponding author on reasonable request.

Declarations

Ethics approval and consent to participate

Written informed consent was obtained from all participants, and informed consent for all illiterate participants was obtained from their parents and/or their legal guardian(s). The study was approved by the Clinical Research Ethics Committees of the Chinese University of Hong Kong (CREC Ref. No. 2003.102). All the participants were given detailed information about the goals, purpose and reasons for the research. All methods were carried out in accordance with The Declaration of Helsinki.

Consent for publication

Not applicable.

Competing interests

The authors declare no competing interests.

Author details

¹Xiangya School of Nursing, Central South University, Changsha, Hunan Province, China. ²Department of Medicine & Therapeutics, Faculty of Medicine, Prince of Wales Hospital, The Chinese University of Hong Kong, Hong Kong, SAR, China. ³Xiangya-Oceanwide Health Management Research Institute, Central South University, Changsha, Hunan Province, China. ⁴Jockey Club Centre for Osteoporosis Care and Control, The Chinese University of Hong Kong, Hong Kong, SAR, China. ⁵Jockey Club School of Public Health and Primary Care, The Chinese University of Hong Kong, Hong Kong, SAR, China.

Received: 20 May 2023 Accepted: 19 January 2024

Published online: 05 April 2024

References

1. Skoog I. Psychiatric disorders in the elderly. *Can J Psychiatry*. 2011;56(7):387–97.
2. Mental health of older adults. <https://www.who.int/news-room/fact-sheets/detail/mental-health-of-older-adults>.
3. Charlson FJ, Baxter AJ, Cheng HG, Shidhaye R, Whiteford HA. The burden of mental, neurological, and substance use disorders in China and India: a systematic analysis of community representative epidemiological studies. *Lancet*. 2016;388(10042):376–89.
4. Out of the shadows: making mental health a global development priority. http://www.who.int/mental_health/advocacy/wb_background_paper.pdf?ua=1.
5. Hankin BL, Fraley RC, Lahey BB, Waldman ID. Is depression best viewed as a continuum or discrete category? A taxometric analysis of childhood and adolescent depression in a population-based sample. *J Abnorm Psychol*. 2005;114(1):96–110.
6. Wray NR, Ripke S, Mattheisen M, Trzaskowski M, Byrne EM, Abdellaoui A, Adams MJ, Agerbo E, Air TM, Andlauer TMF, et al. Genome-wide association analyses identify 44 risk variants and refine the genetic architecture of major depression. *Nat Genet*. 2018;50(5):668–81.

7. Musliner KL, Munk-Olsen T, Eaton WW, Zandi PP. Heterogeneity in long-term trajectories of depressive symptoms: patterns, predictors and outcomes. *J Affect Disord*. 2016;192:199–211.
8. Kwong ASF, López-López JA, Hammerton G, Manley D, Timpson NJ, Leckie G, Pearson RM. Genetic and environmental risk factors associated with trajectories of depression symptoms from adolescence to young adulthood. *JAMA Netw Open*. 2019;2(6):e196587.
9. Najman JM, Plotnikova M, Williams GM, et al. Trajectories of maternal depression: a 27-year population-based prospective study. *Epidemiol Psychiatr Sci*. 2017;26(1):79–88.
10. Oh Y, Joung YS, Baek JH, Yoo N. Maternal depression trajectories and child executive function over 9 years. (1573–2517 (Electronic)). *J Affect Disord*. 2020;276:646–52. <https://doi.org/10.1016/j.jad.2020.07.065>.
11. Perry BI, Stochl J, Upthegrove R, Zammit S, Wareham N, Langenberg C, Winpenny E, Dunger D, Jones PB, Khandaker GM. Longitudinal trends in childhood insulin levels and body mass index and associations with risks of psychosis and depression in young adults. (2168–6238 (Electronic)). *JAMA Psychiatry*. 2021;78(4):416–25. <https://doi.org/10.1001/jamapsychiatry.2020.4180>.
12. Scott K, Lewis CC, Marti CN. Trajectories of symptom change in the treatment for adolescents with depression study. (1527–5418 (Electronic)). *J Am Acad Child Adolesc Psychiatry*. 2019;58(3):319–28. <https://doi.org/10.1016/j.jaac.2018.07.908>.
13. Werner-Seidler A, Perry Y, Calear AL, Newby JM, Christensen H. School-based depression and anxiety prevention programs for young people: a systematic review and meta-analysis. (1873–7811 (Electronic)). *Clin Psychol Rev*. 2017;51:30–47. <https://doi.org/10.1016/j.cpr.2016.10.00>.
14. Fancourt D, Steptoe A, Bu F. Trajectories of anxiety and depressive symptoms during enforced isolation due to COVID-19 in England: a longitudinal observational study. (2215–0374 (Electronic)). *Lancet Psychiatry*. 2021;8(2):141–9. [https://doi.org/10.1016/S2215-0366\(20\)30482-X](https://doi.org/10.1016/S2215-0366(20)30482-X).
15. Ter Avest MJ, Schuling R, Greven CU, Huijbers MJ, Wilderjans TF, Spinhoven P, Speckens AEM. Interplay between self-compassion and affect during Mindfulness-Based Compassionate Living for recurrent depression: an autoregressive latent trajectory analysis. *Behav Res Ther*. 2021;146:103946.
16. Chen C, Chow AYM, Tang S. Trajectories of depression symptoms in Chinese elderly during widowhood: a secondary analysis. *Aging Ment Health*. 2020;24(8):1254–62.
17. Nagin DS, Jones BL, Passos VL, Tremblay RE. Group-based multi-trajectory modeling. *Stat Methods Med Res*. 2018;27(7):2015–23.
18. Nagin DS, Odgers CL. Group-based trajectory modeling in clinical research. *Annu Rev Clin Psychol*. 2010;6:109–38.
19. Adams KB, Sanders S, Auth E. Loneliness and depression in independent living retirement communities: risk and resilience factors. *Aging Ment Health*. 2004;8(6):475–85.
20. Bisschop MI, Kriegsman DM, Beekman AT, Deeg DJ. Chronic diseases and depression: the modifying role of psychosocial resources. *Soc Sci Med*. 2004;59(4):721–33.
21. Braam AW, Prince MJ, Beekman AT, Delepaule P, Dewey ME, Geerlings S, Kivela S-L, Lawlor B, Magnússon H, Meller I. Physical health and depressive symptoms in older Europeans: results from EURODEP. *Br J Psychiatry*. 2005;187(1):35–42.
22. Hickie I, Hickie I, Simons L, Naismith S, Simons J, Mccallum J, Pearson K. Vascular risk to late-life depression: evidence from a longitudinal community study. *Aust N Z J Psychiatry*. 2003;37(1):62–5.
23. Lyness JM, King DA, Conwell Y, Cox C, Caine ED. Cerebrovascular risk factors and 1-year depression outcome in older primary care patients. *Am J Psychiatry*. 2000;157(9):1499–501.
24. Gazmararian J, Baker D, Parker R, Blazer DG. A multivariate analysis of factors associated with depression: evaluating the role of health literacy as a potential contributor. *Arch Intern Med*. 2000;160(21):3307–14.
25. Jorm AF, Anstey KJ, Christensen H, de Plater G, Kumar R, Wen W, Sachdev P. MRI hyperintensities and depressive symptoms in a community sample of individuals 60–64 years old. *Am J Psychiatry*. 2005;162(4):699–705.
26. Jang Y, Haley WE, Small BJ, Mortimer JA. The role of mastery and social resources in the associations between disability and depression in later life. *Gerontologist*. 2002;42(6):807–13.
27. Cummings SM, Neff JA, Husaini BA. Functional impairment as a predictor of depressive symptomatology: the role of race, religiosity, and social support. *Health Soc Work*. 2003;28(1):23–32.
28. Ni MY, Yao Xi, Cheung F, Wu JT, Schooling CM, Pang H, Leung GM. Determinants of physical, mental and social well-being: a longitudinal environment-wide association study. *Int J Epidemiol*. 2020;49(2):380–9.
29. Balakrishnan K, Dey S, Gupta T, Dhaliwal R, Brauer M, Cohen AJ, Stanaway JD, Beig G, Joshi TK, Aggarwal AN. The impact of air pollution on deaths, disease burden, and life expectancy across the states of India: the Global Burden of Disease Study 2017. *Lancet Planet Health*. 2019;3(1):e26–39.
30. Organization WH. WHO global air quality guidelines: particulate matter (PM_{2.5} and PM₁₀), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. World Health Organization; 2021.
31. Chen S, Oliva P, Zhang P. Air pollution and mental health: evidence from China. National Bureau of Economic Research; 2018.
32. Szyszkwicz M, Kousha T, Kingsbury M, Colman I. Air pollution and emergency department visits for depression: a multicity case-crossover study. *Environ Health Insights*. 2016;10:155–61.
33. Szyszkwicz M, Kousha T, Kingsbury M, Colman I. Air pollution and emergency department visits for depression: a multicity case-crossover study. *Environ Health Insights*. 2016;10:EHI.540493.
34. Wang F, Liu H, Li H, Liu J, Guo X, Yuan J, Hu Y, Wang J, Lu L. Ambient concentrations of particulate matter and hospitalization for depression in 26 Chinese cities: a case-crossover study. *Environ Int*. 2018;114:115–22.
35. Gu X, Guo T, Si Y, Wang J, Zhang W, Deng F, Chen L, Wei C, Lin S, Guo X. Association between ambient air pollution and daily hospital admissions for depression in 75 Chinese cities. *Am J Psychiatry*. 2020;177(8):735–43.
36. Pun VC, Manjourides J, Suh H. Association of ambient air pollution with depressive and anxiety symptoms in older adults: results from the NSHAP study. *Environ Health Perspect*. 2017;125(3):342–8.
37. Wang Y, Eliot MN, Koutrakis P, Gryparis A, Schwartz JD, Coull BA, Mittleman MA, Milberg WP, Lipsitz LA, Wellenius GA. Ambient air pollution and depressive symptoms in older adults: results from the MOBILIZE Boston study. *Environ Health Perspect*. 2014;122(6):553–8.
38. Yang T, Wang J, Huang J, Kelly FJ, Li G. Long-term exposure to multiple ambient air pollutants and association with incident depression and anxiety. *JAMA Psychiat*. 2023;80(4):305–13.
39. Borrioni E, Pesatori AC, Bollati V, Buoli M, Carugno M. Air pollution exposure and depression: a comprehensive updated systematic review and meta-analysis. *Environ Pollut*. 2022;292:118245.
40. Wei F, Yu Z, Zhang X, Wu M, Wang J, Shui L, Lin H, Jin M, Tang M, Chen K. Long-term exposure to ambient air pollution and incidence of depression: a population-based cohort study in China. *Sci Total Environ*. 2022;804:149986.
41. Fu Z, Liu Q, Liang J, Weng Z, Li W, Xu J, Zhang X, Xu C, Huang T, Gu A. Air pollution, genetic factors and the risk of depression. *Sci Total Environ*. 2022;850:158001.
42. Ju K, Lu L, Chen T, Duan Z, Chen D, Liao W, Zhou Q, Xu Z, Wang W. Does long-term exposure to air pollution impair physical and mental health in the middle-aged and older adults? — A causal empirical analysis based on a longitudinal nationwide cohort in China. *Sci Total Environ*. 2022;827:154312.
43. Lau EM, Leung PC, Kwok T, Woo J, Lynn H, Orwoll E, Cummings S, Cauley J. The determinants of bone mineral density in Chinese men—results from Mr. OS (Hong Kong), the first cohort study on osteoporosis in Asian men. *Osteoporos Int*. 2006;17(2):297–303.
44. Kwok AW, Gong JS, Wang YX, Leung JC, Kwok T, Griffith JF, Leung PC. Prevalence and risk factors of radiographic vertebral fractures in elderly Chinese men and women: results of Mr. OS (Hong Kong) and Ms. OS (Hong Kong) studies. *Osteoporos Int*. 2013;24(3):877–85.
45. Su Y, Yeung SSY, Chen YM, Leung JCS, Kwok TCY. The associations of dietary inflammatory potential with musculoskeletal health in Chinese community-dwelling older people: the Mr. OS and Ms. OS (Hong Kong) cohort study. *J Bone Miner Res*. 2022;37(6):1179–87.
46. Guo L, An L, Luo F, Yu B. Social isolation, loneliness and functional disability in Chinese older women and men: a longitudinal study. *Age Ageing*. 2021;50(4):1222–8.
47. von Elm E, Altman DG, Egger M, Pocock SJ, Gøtzsche PC, Vandenbroucke JP. The Strengthening the Reporting of Observational Studies in Epidemiology (STROBE) statement: guidelines for reporting observational studies. *Lancet*. 2007;370(9596):1453–7.
48. Covinsky KE, Newcomer R, Fox P, Wood J, Sands L, Dane K, Yaffe K. Patient and caregiver characteristics associated with depression in caregivers of patients with dementia. *J Gen Intern Med*. 2003;18(12):1006–14.

49. Durmaz B, Soysal P, Ellidokuz H, Isik AT. Validity and reliability of geriatric depression scale-15 (short form) in Turkish older adults. *North Clin Istanbul*. 2018;5(3):216–20.
50. Zhao H, He J, Yi J, Yao S. Factor structure and measurement invariance across gender groups of the 15-item geriatric depression scale among Chinese elders. *Front Psychol*. 2019;10:1360.
51. Campbell G, Bryant C, Ellis KA, Buckley R, Ames D, GROUP AR. Comparing the performance of the HADS and the GDS-15 in the AIBL study. *Int Psychogeriatr*. 2015;27(9):1577–8.
52. Greenberg SA. How to try this: the geriatric depression scale: short form. *AJN Am J Nurs*. 2007;107(10):60–9.
53. Wancata J, Alexandrowicz R, Marquart B, Weiss M, Friedrich F. The criterion validity of the Geriatric Depression Scale: a systematic review. *Acta Psychiatr Scand*. 2006;114(6):398–410.
54. Mitchell AJ, Bird V, Rizzo M, Meader N. Diagnostic validity and added value of the Geriatric Depression Scale for depression in primary care: a meta-analysis of GDS30 and GDS15. *J Affect Disord*. 2010;125(1–3):10–7.
55. Beelen R, Hoek G, Vienneau D, Eeftens M, Dimakopoulou K, Pedeli X, Tsai M-Y, Künzli N, Schikowski T, Marcon A, et al. Development of NO₂ and NO_x land use regression models for estimating air pollution exposure in 36 study areas in Europe – the ESCAPE project. *Atmos Environ*. 2013;72:10–23.
56. Kok RM, Reynolds CF 3rd. Management of depression in older adults: a review. *JAMA*. 2017;317(20):2114–22.
57. Sjöberg L, Karlsson B, Atti A-R, Skoog I, Fratiglioni L, Wang H-X. Prevalence of depression: comparisons of different depression definitions in population-based samples of older adults. *J Affect Disord*. 2017;221:123–31.
58. Jones BL, Nagin DS. A note on a Stata plugin for estimating group-based trajectory models. *Sociol Methods Res*. 2013;42(4):608–13.
59. Warren JR, Luo L, Halpern-Manners A, Raymo JM, Palloni A. Do different methods for modeling age-graded trajectories yield consistent and valid results? *Am J Sociol*. 2015;120(6):1809–56.
60. Liang Y. Heterogeneity in the trajectories of depressive symptoms among elderly adults in rural China: the role of housing characteristics. *Health Place*. 2020;66:102449.
61. Xiang X, Cheng J. Trajectories of major depression in middle-aged and older adults: a population-based study. *Int J Geriatr Psychiatry*. 2019;34(10):1506–14.
62. Zhu Y, Li C, Xie W, Zhong B, Wu Y, Blumenthal JA. Trajectories of depressive symptoms and subsequent cognitive decline in older adults: a pooled analysis of two longitudinal cohorts. *Age Ageing*. 2021;51(1):afab191.
63. Liang J, Xu X, Quiñones AR, Bennett JM, Ye W. Multiple trajectories of depressive symptoms in middle and late life: racial/ethnic variations. *Psychol Aging*. 2011;26(4):761–77.
64. Kuo SY, Lin KM, Chen CY, Chuang YL, Chen WJ. Depression trajectories and obesity among the elderly in Taiwan. *Psychol Med*. 2011;41(8):1665–76.
65. Hsu HC. Group-based trajectories of depressive symptoms and the predictors in the older population. *Int J Geriatr Psychiatry*. 2012;27(8):854–62.
66. Byers AL, Vittinghoff E, Lui LY, Hoang T, Blazer DG, Covinsky KE, Ensrud KE, Cauley JA, Hillier TA, Fredman L, et al. Twenty-year depressive trajectories among older women. *Arch Gen Psychiatry*. 2012;69(10):1073–9.
67. Kuchibhatla MN, Fillenbaum GG, Hybels CF, Blazer DG. Trajectory classes of depressive symptoms in a community sample of older adults. *Acta Psychiatr Scand*. 2012;125(6):492–501.
68. Montagnier D, Dartigues JF, Rouillon F, Pérès K, Falissard B, Onen F. Ageing and trajectories of depressive symptoms in community-dwelling men and women. *Int J Geriatr Psychiatry*. 2014;29(7):720–9.
69. Hybels CF, Bennett JM, Landerman LR, Liang J, Plassman BL, Wu B. Trajectories of depressive symptoms and oral health outcomes in a community sample of older adults. *Int J Geriatr Psychiatry*. 2016;31(1):83–91.
70. Lu N, Xu L, Lou VW, Chi I. Intergenerational relationships and the trajectory of depressive symptoms among older Chinese adults in rural migrant families. *Aging Ment Health*. 2018;22(3):389–96.
71. Lee SL, Pearce E, Ajnakina O, Johnson S, Lewis G, Mann F, Pitman A, Solmi F, Sommerlad A, Steptoe A, et al. The association between loneliness and depressive symptoms among adults aged 50 years and older: a 12-year population-based cohort study. *Lancet Psychiatry*. 2021;8(1):48–57.
72. Victor CR, Yang K. The prevalence of loneliness among adults: a case study of the United Kingdom. *J Psychol*. 2012;146(1–2):85–104.
73. Jokela M. Why is cognitive ability associated with psychological distress and wellbeing? Exploring psychological, biological, and social mechanisms. *Personality Individ Differ*. 2022;192:111592.
74. Foreman KJ, Marquez N, Dolgert A, Fukutaki K, Fullman N, McGaughey M, Pletcher MA, Smith AE, Tang K, Yuan CW, et al. Forecasting life expectancy, years of life lost, and all-cause and cause-specific mortality for 250 causes of death: reference and alternative scenarios for 2016–40 for 195 countries and territories. *Lancet*. 2018;392(10159):2052–90.
75. Lewis AJ, Sae-Koew JH, Toumbourou JW, Rowland B. Gender differences in trajectories of depressive symptoms across childhood and adolescence: a multi-group growth mixture model. *J Affect Disord*. 2020;260:463–72.
76. Formánek T, Csajbók Z, Wolfová K, Kučera M, Tom S, Aarsland D, Cermakova P. Trajectories of depressive symptoms and associated patterns of cognitive decline. *Sci Rep*. 2020;10(1):20888.
77. Sivertsen H, Bjørkløf GH, Engedal K, Selbæk G, Helvik AS. Depression and quality of life in older persons: a review. *Dement Geriatr Cogn Disord*. 2015;40(5–6):311–39.
78. Air pollution. <https://www.who.int/airpollution/en/>.
79. Cho J, Choi YJ, Suh M, Sohn J, Kim H, Cho SK, Ha KH, Kim C, Shin DC. Air pollution as a risk factor for depressive episode in patients with cardiovascular disease, diabetes mellitus, or asthma. *J Affect Disord*. 2014;157:45–51.
80. Szyzkowicz M, Rowe BH, Colman I. Air pollution and daily emergency department visits for depression. *Int J Occup Med Environ Health*. 2009;22(4):355–62.
81. Qiu H, Zhu X, Wang L, Pan J, Pu X, Zeng X, Zhang L, Peng Z, Zhou L. Attributable risk of hospital admissions for overall and specific mental disorders due to particulate matter pollution: a time-series study in Chengdu, China. *Environ Res*. 2019;170:230–7.
82. Zock J-P, Verheij R, Helbich M, Volker B, Spreeuwenberg P, Strak M, Janssen NA, Dijkstra M, Groenewegen P. The impact of social capital, land use, air pollution and noise on individual morbidity in Dutch neighbourhoods. *Environ Int*. 2018;121:453–60.
83. Lim Y-H, Kim H, Kim JH, Bae S, Park HY, Hong Y-C. Air pollution and symptoms of depression in elderly adults. *Environ Health Perspect*. 2012;120(7):1023–8.
84. Kim J, Kim H. Demographic and environmental factors associated with mental health: a cross-sectional study. *Int J Environ Res Public Health*. 2017;14(4):431.
85. Wang R, Liu Y, Xue D, Yao Y, Liu P, Helbich M. Cross-sectional associations between long-term exposure to particulate matter and depression in China: the mediating effects of sunlight, physical activity, and neighborly reciprocity. *J Affect Disord*. 2019;249:8–14.
86. Altuğ H, Fuks KB, Hüls A, Mayer AK, Tham R, Krutmann J, Schikowski T. Air pollution is associated with depressive symptoms in elderly women with cognitive impairment. *Environ Int*. 2020;136:105448.
87. Qiu X, Shi L, Kubzansky LD, Wei Y, Castro E, Li H, Weisskopf MG, Schwartz JD. Association of long-term exposure to air pollution with late-life depression in older adults in the US. *JAMA Netw Open*. 2023;6(2):e2253668.
88. Block ML, Calderón-Garcidueñas L. Air pollution: mechanisms of neuroinflammation and CNS disease. *Trends Neurosci*. 2009;32(9):506–16.
89. Araujo JA. Particulate air pollution, systemic oxidative stress, inflammation, and atherosclerosis. *Air Qual Atmos Health*. 2011;4(1):79–93.
90. Møller P, Loft S. Oxidative damage to DNA and lipids as biomarkers of exposure to air pollution. *Environ Health Perspect*. 2010;118(8):1126–36.
91. Fabian MP, Lee SK, Underhill LJ, Vermeer K, Adamkiewicz G, Levy JI. Modeling environmental tobacco smoke (ETS) infiltration in low-income multifamily housing before and after building energy retrofits. *Int J Environ Res Public Health*. 2016;13(3):327.
92. Ferguson L, Taylor J, Davies M, Shrubsole C, Symonds P, Dimitroulopoulou S. Exposure to indoor air pollution across socio-economic groups in high-income countries: a scoping review of the literature and a modelling methodology. *Environ Int*. 2020;143:105748.
93. Taylor J, Shrubsole C, Davies M, Biddulph P, Das P, Hamilton I, Vardoulakis S, Mavrogianni A, Jones B, Oikonomou E. The modifying effect of the building envelope on population exposure to PM_{2.5} from outdoor sources. *Indoor Air*. 2014;24(6):639–51.

Publisher's Note

Springer Nature remains neutral with regard to jurisdictional claims in published maps and institutional affiliations.