Longitudinal Health Behaviour Patterns Among Chinese Adults Aged ≥ 50 Years and Their Associations With Trajectories of Depressive Symptoms Over Time: A Latent Class Analysis

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Abstract

Background Whether different longitudinal patterns of multiple health behaviours are associated with different trajectories of depressive symptoms is not well understood.

Purpose To identify distinct longitudinal patterns of multiple health behaviours and their associations with trajectories of depressive symptoms among people aged ≥ 50 years in China.

Methods We used longitudinal data from the Harmonized China Health and Retirement Longitudinal Study (three waves, 2010–2015; *n* = 8439). We performed latent class analyses to identify distinct patterns of multiple health behaviours at three timepoints. We estimated longitudinal random-effects models to predict differences in depressive symptoms trajectories by health behaviour class.

Results The best-fitting model had five latent classes, all of which showed strong behavioural stability over time: 1) socially active, moderately physically active non-smokers (29.4%); 2) socially inactive, physically active non-smokers (22.3%); 3) socially and physically inactive non-smokers (17.9%); 4) socially inactive, moderately physically active smokers (14.6%); and (5) socially active, moderately physically active smokers (14.2%). All classes characterized by low social participation (classes 2–4) were associated with significantly higher predicted depressive symptom scores compared with the other classes (1 and 5).

Conclusions Longitudinal behavioural patterns involving low probabilities of social participation were associated with more depressive symptoms. This overshadowing effect suggests that the damage caused by socially inactivity may render the effects of co-existing (un)healthy behaviours meaningless. The stability of the patterns of multiple health behaviours across survey waves suggests that interventions are needed earlier in life.

Background

Depression has become the single greatest cause of disability and a major contributor to disease burden globally, affecting 264 million people [1]. Depression is not only detrimental to individuals' well-being, but also incurs substantial medical costs [2] and affects families and society as a whole [3]. The risk of depression is greater among older adults in China than among people in other East Asian countries [4]. Depressive symptoms have been associated with modifiable unhealthy behaviours, such as physical inactivity [5]. Given that people in China tend to feel ashamed to seek help for depressive symptoms [6], strategies that involve lifestyle modification may be particularly promising in efforts to counter later-life depression in the Chinese context.

In the past two decades, researchers have begun to recognize that health behaviours do not occur in isolation; instead, they are interrelated and cluster together [7–10]. Consequently, the number of studies focusing on multiple health behaviours has increased rapidly and such research is considered to represent the future of preventive medicine [11]. The investigation of multiple health behaviours is

important for several reasons. First, clustered behaviours posing health risks may have synergistic effects on health outcomes [8, 12] that are more potent than the behaviours' individual effects [9]. Second, the phenomenon of "health behaviour overshadowing," in which the detrimental effects of certain unhealthy behaviours are so profound that they render other health behavioural dimensions largely meaningless, seems to be overlooked [13]. For example, Shaw and Agahi [13] found that the harmful effects of physical inactivity were not evident among smokers.

Although several studies have involved the combined consideration of multiple health behaviours, most researchers have used an additive approach (e.g., [14, 15]). Typically, an additive index is employed, with one point added for unhealthy behaviour in each of the dimensions considered. This approach entails the implicit assumptions 1) that every type of (un)healthy behaviour has a similar effect on the outcome considered and 2) that (un)healthy behaviours are independent of each other, i.e., that the effect of a particular unhealthy behaviour is not contingent on other health behavioural dimensions. Consequently, potential synergistic or overshadowing effects cannot be detected. Hence, an approach that considers particular patterns or clusters of health behaviours is called for. In a few studies, associations of patterns or clusters of multiple health behaviours with depression and mental health have been examined. For example, Oftedal et al. [16] used latent class analysis (LCA) to identify patterns of multiple health behaviours and found that people with high-risk behaviours in all aspects (insufficient physical activity, long daily sitting time, high-risk drinking, high-risk dietary behaviours) had the greatest odds of experiencing mental distress. However, studies of this type [16–18] have provided only snapshots of such associations because of their cross-sectional designs. Not only the influence of patterns of multiple health behaviours on depressive symptoms, but also the longitudinal effects of these patterns, needs to be examined concurrently because some behaviours show no observable health benefit unless they are maintained for certain periods of time [19]. For example, although physical exercise appears to effectively relieve depressive mood, this benefit may require long-term maintenance of this behaviour [20]. In addition, no previous study of health behaviour patterns has included the examination of social participation, which is arguably an important health behaviour because it increases community engagement and social interaction [21], in turn protecting against depressive symptoms in older adults [22, 23]. Furthermore, trajectories of health behaviour development over time may differ among ethnic groups [24]. Little is known about the longitudinal trajectories of multiple health behaviours, or the effects of different longitudinal health behaviour patterns on depressive symptoms, in middle-aged and older adult Chinese populations.

The identification of particular longitudinal combinations of health behaviours that have detrimental effects on depressive symptoms is of practical relevance. For example, policymakers can weigh the relative importance of various health behaviours and prioritize their focus on particular risky behaviour combinations, which ultimately provides valuable information to aid health professionals' development of optimal health promotion strategies. Thus, the aims of this study were to identify distinct longitudinal patterns of multiple health behaviours (smoking, physical activity, and social participation), and associations of different patterns with trajectories of depressive symptoms, in a population-based sample of people aged $\geq$ 50 years in China. We focused on smoking, physical activity, and social

participation because they are known to be associated separately with depressive symptoms [5, 25], but little is known about whether their longitudinal combinations are associated with depressive symptom trajectories. As three health behaviours were considered at three timepoints in this study, with a vast number of health behaviour combinations potentially observed, we adopted the data-reduction technique of LCA to identify the most meaningful longitudinal behaviour patterns, which best represented all possible combinations in the sample [16].

Methods

Data Source and Study Population

We used data from the Harmonized China Health and Retirement Longitudinal Study (CHARLS), a population-based survey of non-institutionalized middle-aged and older individuals in China [26]. The baseline (wave 1) survey was conducted between May 2011 and March 2012 with 17,708 participants, and follow-up surveys were conducted in 2013 (wave 2) and 2015 (wave 4) [27]. Trained interviewers conducted face-to-face interviews. The CHARLS sampling strategy has been described in detail elsewhere [27]. In this study, we analyzed Harmonized CHARLS data from waves 1, 2, and 4. As wave 3 was a special life-history survey that did not include the collection of data on health behaviour or mental health variables, wave 3 data were not included in our analysis. More detailed information can be found at www.g2aging.org.

Exclusion criteria

Respondents were excluded from the present analysis for the following reasons: age < 50 years at baseline; inconsistent age information across waves (e.g., younger reported age than in a previous wave); missing value for any covariate of interest (age, gender, residence, educational level, marital status, number of children, co-residence with a child) in at least one wave; and missing 10-item Centre for Epidemiologic Studies Depression Scale (CES-D 10) score in at least one wave. The procedure used for sample selection is summarized in Fig. 1.

We applied the age threshold of 50 years to focus on middle-aged and older adults, based on previous studies [13, 28] and in accordance with the World Health Organization's Study on Global Ageing and Adult Health [29]. The final sample comprised 25,317 observations for 8439 respondents.

Measures

Manifest items

Physical activity, social participation, and smoking served as manifest items in the LCA. The manifest items were used to identify the underlying (latent) health behaviour patterns.

Physical activity

Respondents were asked whether they performed vigorous physical activity (VPA) or moderate physical activity (MPA) for at least 10 minutes every week ("yes" or "no"). "Yes" responses prompted the interviewers to ask respondents on how many days they performed at least 10 minutes of VPA and MPA in a usual week (0–7). VPA was defined to include activities that made respondents breathe much harder than normal, such as heavy lifting, digging, plowing, aerobics, fast bicycling, and cycling with a heavy load. MPA was defined to include activities that made respondents breathe somewhat harder than normal, such as carrying a light load, bicycling at regular pace, or mopping the floor. In this study, we dichotomized the physical activity variable, classifying respondents as physically active (MPA/VPA on ≥5 days/week) and physically inactive (MPA/VPA on <5 days/week).

Social participation

In the CHARLS, the social participation variable was operationalized by asking participants whether they had done any of the following in the month prior to the survey: 1) interacted with (a) friend(s); 2) played ma-jong, chess, or cards or gone to a community club; 3) gone to a sporting event or participated in a social group or other type of club; 4) engaged in the activities of a community-related organization; 5) conducted volunteer or charity work; and 6) attended an educational or training course. The social participation variable was dichotomized, with 0 indicating that the respondent did not participate in any listed social group or activity and 1 indicating that respondent participated in any of the listed social activities in the past month [30].

Smoking

We used respondents' current smoking habits to evaluate smoking status in this study. A value of 0 was assigned to respondents who never smoked or were ex-smokers, and a value of 1 to the respondents who were current smokers. Notably, wave 2 information on smoking was missing for 2098 respondents, the majority of whom reported the same smoking status in waves 1 and 4. Thus, we coded smoking status in wave 2 as in waves 1 and 4 in these cases.

Time-varying and time-invariant covariates

Based on previous studies, the availability of CHARLS data, and known associations with health behaviours and depression [31–34], age, gender, residence, level of education, marital status, number of children, and co-residence with a child were included as potential confounders. Time-varying covariates were age (interview date – birth date), residence (urban /rural), marital status (single [separated, divorced, widowed, or never married]/not single [currently married or cohabiting]), co-residence with at least one child (no/yes), and number of living children (0/1/2/3/≥4). Time-invariant covariates were gender (male/female) and educational level (higher [upper secondary school or more]/lower [less than lower secondary school]).

Distal outcome

Depressive symptoms, assessed using the CES-D 10 [30], made up the distal outcome in this study. The respondents were asked how often they had experienced each of the following in the past week: 1) “I was bothered by things that do not usually bother me,” 2) “I had trouble keeping my mind on what I was doing,” 3) “I felt depressed,” 4) “I felt hopeful about the future,” 5) “I felt everything I did was an effort,” 6) “I felt fearful,” 7) “My sleep was restless,” 8) “I was happy,” 9) “I felt lonely,” and 10) “I could not get ‘going’.” Item responses were provided on a four-point scale ranging from 0 (“rarely or none of the time”) to 3 (“most or all of the time”). Responses to the positively worded items 4 and 8 were reverse coded before analysis. Total CES-D 10 scores range from 0 to 30, with higher scores indicating higher levels of depressive symptoms. The CES-D 10 has demonstrated sufficient reliability and validity among community-dwelling older adults in China [35], and showed good reliability for all three CHARLS waves in this study (Cronbach’s α, 0.777–0.807).

Statistical Analysis

The analysis performed for this study consisted of multiple steps. First, we performed LCA to identify distinct longitudinal health behaviour profiles. LCA identifies mutually exclusive and exhaustive unobserved classes in a population via a set of manifest items [36–38], whereby between-class variation is maximized and within-class variation is minimized [39]. Specifically, we aimed to identify latent profiles underlying manifest information about physical activity, smoking, and social participation across the three CHARLS waves. We began with a two-class solution model, and added classes until we observed no further improvement of model fit. Identification of the optimal number of classes was based on the lowest values of the Bayesian information criterion (BIC), which favors more parsimonious models, as it penalizes model complexity relatively strongly [40]. The BIC is the most widely used statistic in LCA model selection [41]. Each empty model was estimated 500 times with different initial values. We did not exclude respondents with missing information on health behaviour variables because the expectation-maximization algorithm used in LCA enables latent class model estimation even when manifest item information is missing [40]. The underlying assumption that information is missing completely at random [42] holds, as CHARLS interviewers asked only a randomly selected subsample (half of the total sample) questions about physical activity [30].

After determination of the optimal number of latent classes, the latent class with the greatest posterior probability, i.e., the class that corresponded most strongly to the observed health behaviour pattern, was stored for each respondent [43, 44]. We then estimated longitudinal random-effects models of depressive symptoms by wave, whereby we allowed the effect of wave to vary as a function of the recorded latent health behaviour class. These models, adjusted for the potential confounders, were used to examine associations between health behaviour classes and levels of depressive symptoms.

LCA was performed using the poLCA package in R version 3.6.1 (R Foundation for Statistical Computing). Random effects modeling was performed using Stata software version 15.1 (Stata Corporation, Collage Station, TX, USA).

Results

Sample Characteristics

The respondents were aged 50–100 (mean, 61.1; standard deviation, 7.3) years at baseline. More than half (50.8%) of the respondents were female at baseline. The proportion of physically inactive respondents increased and that of current smokers decreased over time. The proportion of socially inactive respondents and the mean CES-D 10 score had declined at the time of wave 2 and then increased again at the time of wave 4 (Table 1).

Identified Latent Classes

Models with two to six latent classes were estimated. A five-class solution best fit the data (BIC, 63,092.80 vs. 63192.59 [four-class solution] and 63120.32 [six-class solution]); goodness-of-fit indices are provided in Supplementary Table 1. None of the five classes identified (Fig. 2) was characterized by a pronounced change in health behavioural pattern over time.

Members of class 1 (29.4% estimated prevalence), characterized as socially active, moderately physically active non-smokers, had a very low probability of smoking, high probability of being socially active, and moderate (50%) probability of being physically active. Class 2 members (22.3% estimated prevalence), characterized as socially inactive, physically active non-smokers, had low probabilities of participation in social activities and smoking, but a high probability of being physically active. People in class 3 (17.9% estimated prevalence), characterized as socially and physically inactive non-smokers, had low probabilities of being current smokers, being physically active, and participating in social activities. Those in class 4 (14.6% estimated prevalence), characterized as socially inactive, moderately physically active smokers, had a high probability of smoking, moderate (60–70%) probability of being physically active, and low probability of being socially active. Members of class 5 (14.2% estimated prevalence), characterized as social active, moderately physically active smokers, had very high probabilities of smoking and being socially active, and a moderate probability of being physically active.

Relationships Between Classes and Depressive Symptoms

In the adjusted longitudinal random-effects models, the predicted CES-D 10 score across CHARLS waves was lowest for class 1, slightly higher for class 5, and highest for classes 2–4 (Fig. 3, Supplementary Table 2). CES-D 10 scores differed significantly between classes 2–4 and class 1 in all waves, and between classes 2–4 and class 5 in waves 1 and 4; no difference was observed among classes 2–4 in any wave (Supplementary Fig. 1).

Discussion

In this study, five distinct longitudinal patterns of (un)healthy behaviours were identified in a population-based sample of people aged ≥ 50 years in China. All of these patterns were stable over time. Three of

the behaviour patterns were associated with significantly higher CES-D 10 scores, reflecting more depressive symptoms, than were the other two patterns. These findings deepen our knowledge of the most representative longitudinal combinations of multiple health behaviours among middle-aged and older adults in China, which is an essential first step in understanding whether and how longitudinal behavioural patterns shape depressive symptom trajectories. Policymakers and health professionals may prioritize their focus on particular behaviour combinations associated with more depressive symptoms when developing optimal health promotion strategies.

In accordance with previous findings that some people engage simultaneously in risky and healthy behaviours [45, 46], all of the patterns identified in this study are combinations of risky (e.g., smoking) and healthy (e.g., being socially active) behaviours. For example, people in class 4 had a high probability of smoking and were moderately likely to be physically active, but unlikely to be socially active. Relationships among health behaviours are complex [45], involving psychological, physiological, and social factors [47]. However, explanation of the mechanisms underlying clustered health behaviours falls beyond the scope of the current study and requires deeper investigation.

Although middle-aged and older adults can benefit from positive health behaviour changes [48, 49], we observed stability of all detected health behaviour patterns across four years in this study. This result is consistent with the finding that health behaviour stability was more common than instability in a 25-year study conducted with U.S. adults aged ≥ 25 years [50]. Empirical findings indicate that many behaviours posing health risks are initiated during earlier life stages [51, 52], and that healthy and unhealthy behaviours stabilize in adolescence and adulthood [46, 50, 53]. Thus, we suggest that health behaviour interventions among adolescents and young adults are needed before unhealthy behaviours become stabilized.

Our finding that different longitudinal patterns of multiple health behaviours were associated with different depressive symptom severities is in line with Verger and colleagues' [17] cross-sectional findings. We observed that patterns entailing high probabilities of being socially inactive were associated significantly with more depressive symptoms, reflecting the overshadowing effect [13]; the harmful effects of being socially inactive might be especially detrimental to depression status in a way that overshadows the impacts of co-existing health behaviours. The vital role of social participation in the amelioration of depressive symptoms has not been documented as well as those of other health behaviours among older adults from a longitudinal perspective. Thus, our findings contribute to the bridging of this research gap and indicate the potential importance of social participation for the reduction of depressive symptoms among middle-aged and older adults in China. More research is needed to improve our understanding of the overshadowing effect of social participation relative to other (un)healthy behaviours.

Study Strengths and Limitations

Significant strengths of this study are the use of LCA to model middle-aged and older adults' multiple health behaviours and the use of a longitudinal design, which enabled the identification of distinct and

highly representative patterns of health behaviours among all possible combinations over time. In addition, the assessment of depressive symptoms in this sample using the CES-D 10 helps to diminish the well-known issue of underreporting regarding mental illness among Chinese adults [54], given the strong social stigmatism of mental illness in Chinese culture. The CES-D 10 questions are nonintrusive and easier for respondents to answer, improving the ability to detect actual depressive status [55].

The findings of this study should be viewed in light of several limitations. First, respondents' self-reporting for all health behaviour variables may have introduced bias [3]. Researchers have reported that respondents may provide socially desirable answers to questions regarding health behaviours [8]. Second, all health behaviour variables were dichotomized in this study, which may have influenced the findings to some extent [56]. More detailed measurement, such as the consideration of smoking intensity (i.e., the amount/frequency of cigarettes/tobacco smoked) or social participation intensity, might yield different patterns [13, 51]. Third, heavy smokers are known to have higher risks of earlier death [57], but our study did not include heavy smokers who had died before the age of 50 years or between CHARLS waves. Thus, our findings might underestimate the influence of heavy smoking on depressive symptoms. Finally, we could not infer the causality of the associations between longitudinal health behaviour patterns and depressive symptom trajectories; further research is needed to clarify the causality of these relationships.

Conclusions

Our empirical findings indicate that health behaviour patterns entailing high probabilities of social inactivity are associated with more depressive symptoms among middle-aged and older adults in China. Furthermore, the impacts of social inactivity may overshadow the effects of co-existing (un)healthy behaviours. Thus, social participation plays a vital role in the reduction of depressive symptoms in this population. In addition, the stability of the patterns of multiple health behaviours over time suggests that behavioural interventions are needed earlier in life. These findings should be considered when developing health promotion strategies that aim to reduce depressive symptoms among middle-aged and older adults in China.

Abbreviations

BIC: Bayesian information criterion;

CES-D 10: 10-item Centre for Epidemiologic Studies Depression Scale;

CHARLS: China Health and Retirement Longitudinal Study;

LCA: Latent Class Analysis;

MPA: Moderate Physical Activity;

VPA: Vigorous Physical Activity.

Declarations

Ethics approval and consent to participate

The CHARLS team obtained ethical approval for the research from the Ethics Committee of Peking University. All participants provided written informed consent. All methods were performed in accordance with the relevant guidelines and regulations.

Consent for publication

Not applicable.

Availability of data and materials

The datasets analysed for the current study are available in the CHARLS website (http://charls.pku.edu.cn/pages/data/harmonized_charls/en.html).

Competing interests

Jane Murray Cramm is an associate editor of BMC Geriatrics. The authors declare that they have no other competing interests related to this manuscript.

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Authors' contributions

ZF drafted the manuscript and was a major contributor in writing the manuscript. TvB, JC and AN contributed to its refinement. TvB and ZF performed the statistical analysis. ZF and TvB interpreted the analytical data. AN and JC supervised the whole process. All authors read and approved the final manuscript.

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Tables

Table 1. Sample characteristics (*n* = 8439)

Characteristic	Wave 1	Wave 2	Wave 4
Covariates			
Age (years), mean (SD)	61.1 (7.3)	63.1 (7.3)	65.2 (7.4)
Gender (female), *n* (%)	4287 (50.8)		
Educational level, *n* (%)			
Less than lower secondary school	7612 (90.2)		
Upper secondary school or more	831 (9.8)		
Residence (rural), *n* (%)	5453 (64.6)		
Marital status (married/partnered), *n* (%)	7368 (87.3)	7221 (85.5)	7028 (83.2)
Number of living children, *n* (%)			
0	187 (2.2)	150 (1.8)	80 (0.9)
1	1157 (13.7)	1008 (11.9)	859 (10.2)
2	2721 (32.2)	2646 (31.4)	2634 (31.2)
3	2129 (25.2)	2192 (26.0)	2213 (26.2)
4+	2245 (26.5)	2443 (29.0)	2653 (31.5)
Co-residence with a child, *n* (%)	4559 (54.0)	3852 (45.6)	4216 (50.0)
Manifest items			
Physical activity, *n* (%)			
Inactive	1506 (42.7)	1521 (49.2)	2117 (51.7)
Active	2025 (57.3)	1571 (50.8)	1980 (48.3)
Missing[a]	4908	5347	4342
Social participation, *n* (%)			
Inactive	4535 (53.7)	4057 (48.1)	4621 (54.8)
Active	3901 (46.2)	4381 (51.9)	3821 (45.2)
Missing	4	1	1
Current smoker, *n* (%)			
Yes	2697 (32.0)	2374 (29.5)	2367 (28.1)
No	5740 (68.0)	5279 (70.5)	6065 (71.9)
Missing	2	386	7

Distal outcome variable			
CES-D 10 score (range 0–30), mean (SD)	8.6 (6.4)	8.0 (5.8)	8.4 (6.5)

No data on age, gender, residence, educational level (all time-invariant), or marital status were missing.
[a]Data collected for a randomly selected subsample (half of the total sample).

SD, standard deviation; CES-D 10, 10-item Centre for Epidemiologic Studies Depression Scale.

Figures

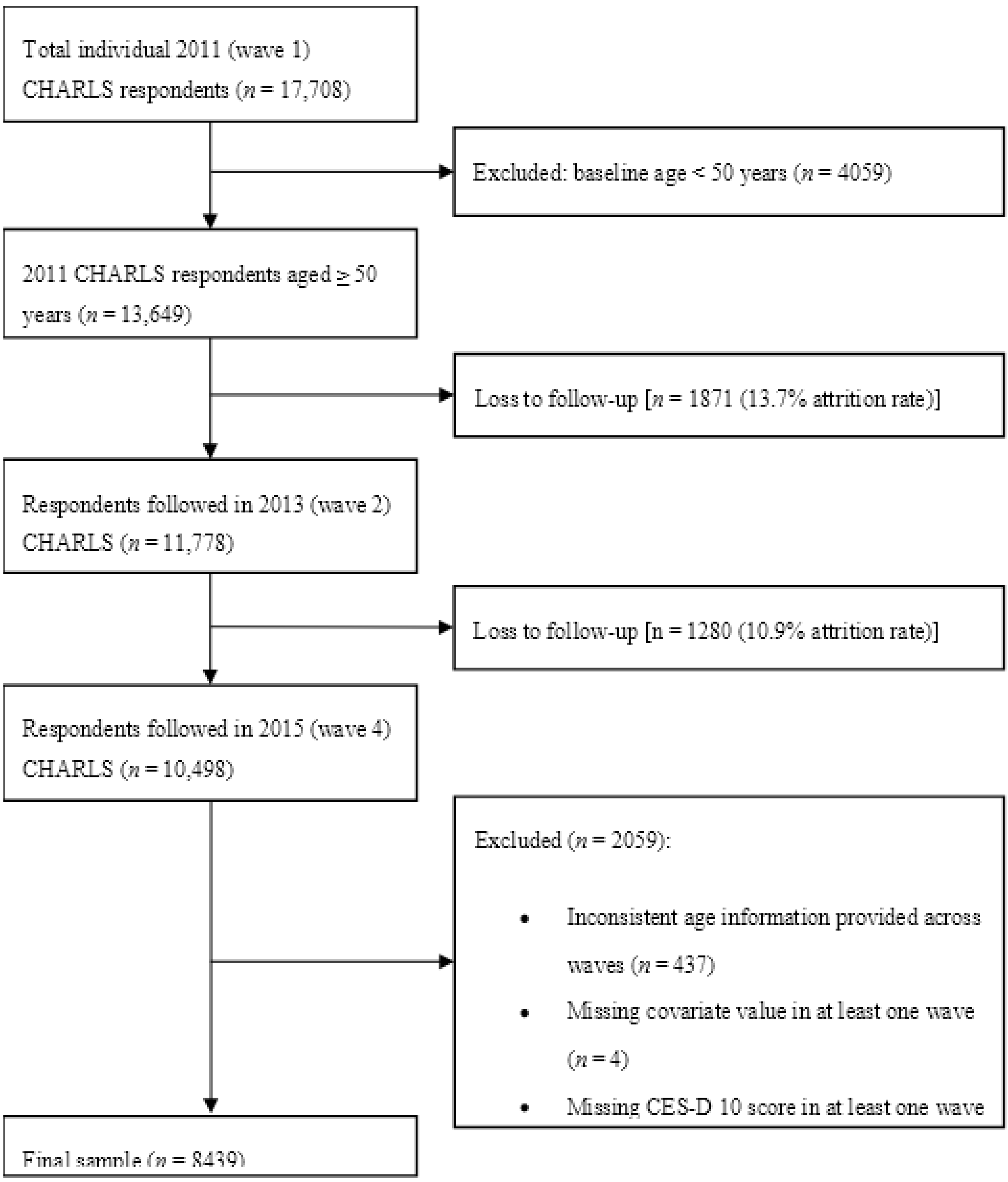
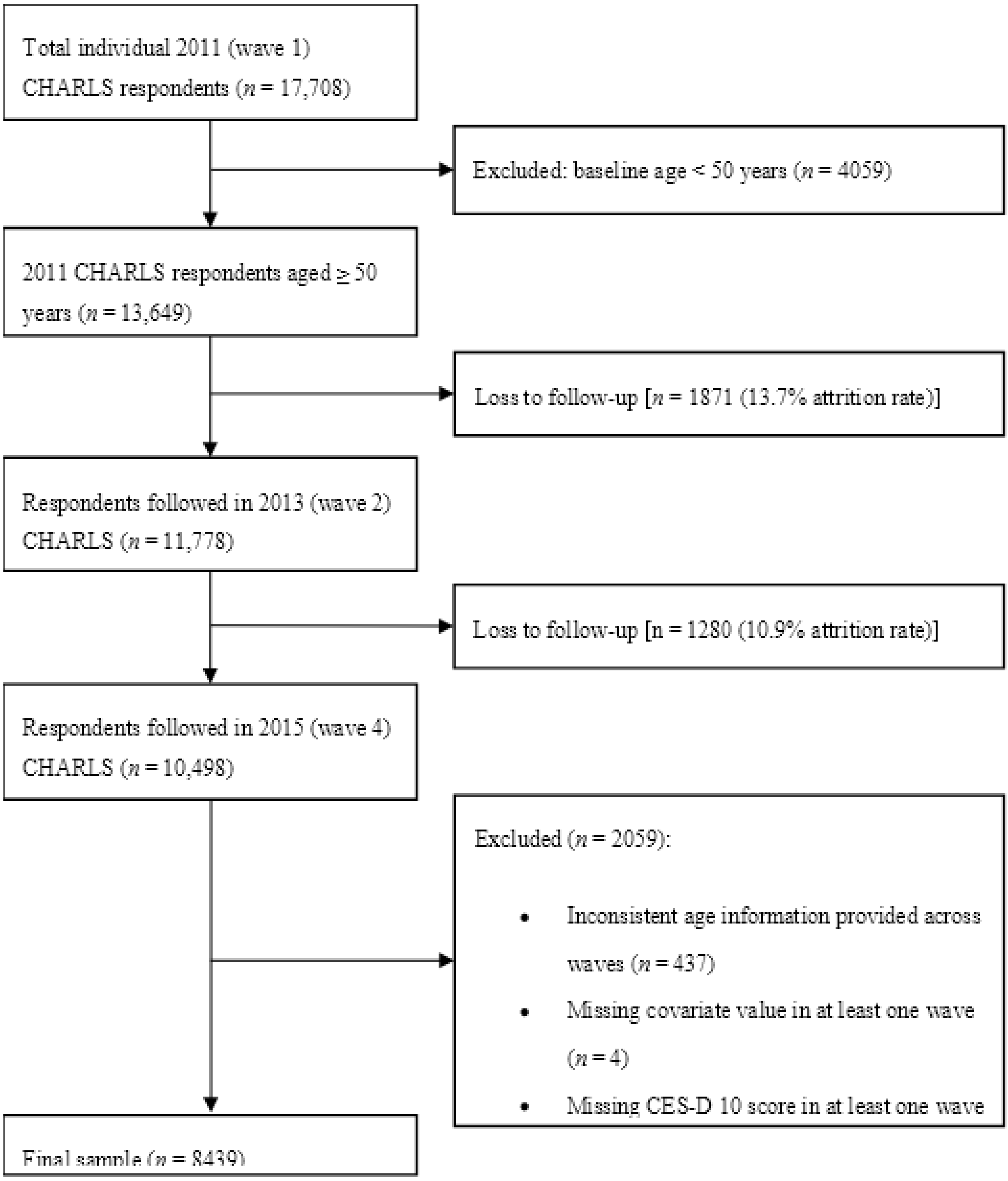


Figure 1

Flow chart of sample selection. CHARLS, China Health and Retirement Longitudinal Study; CES-D 10, 10-item Centre for Epidemiologic Studies Depression Scale.



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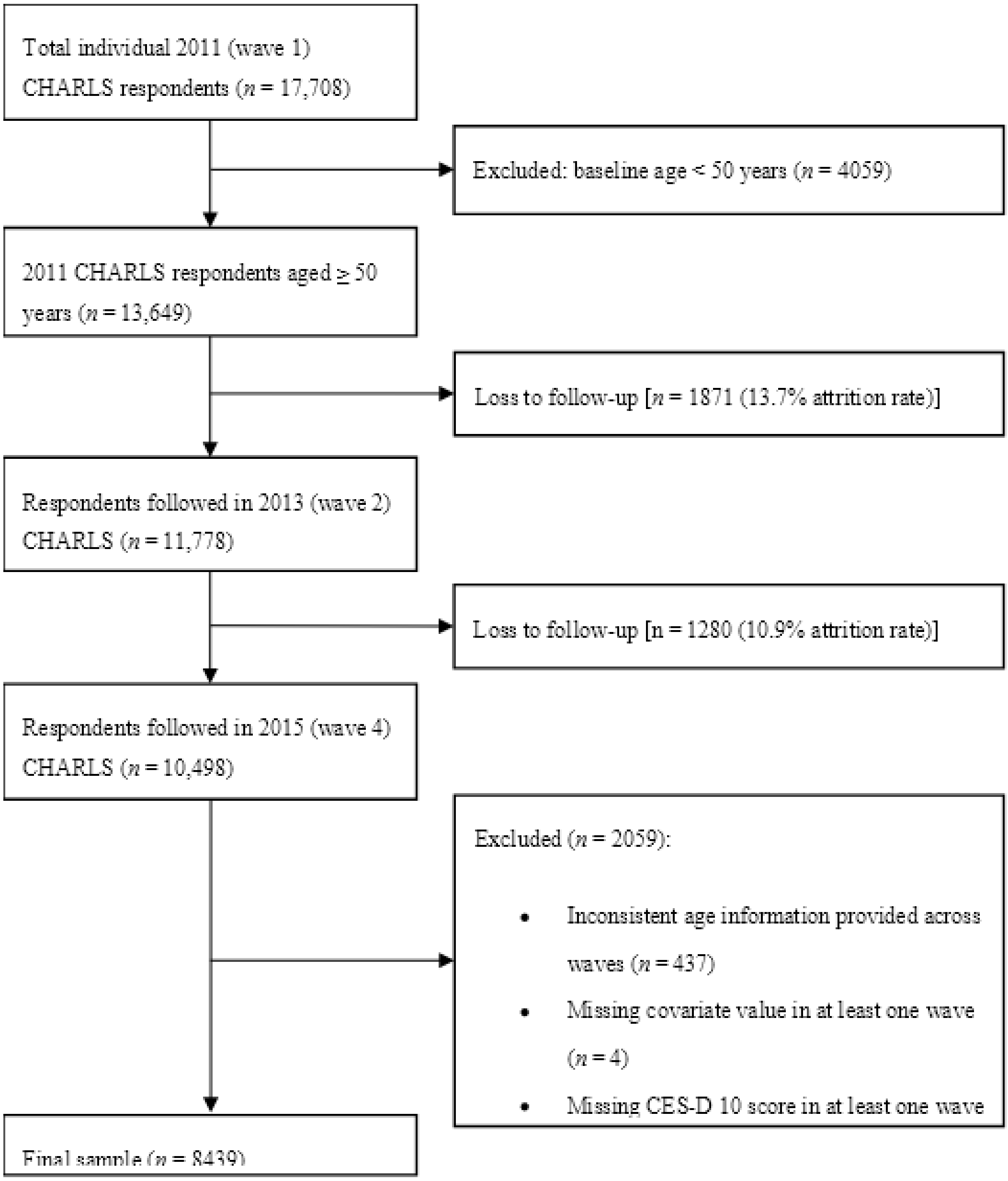

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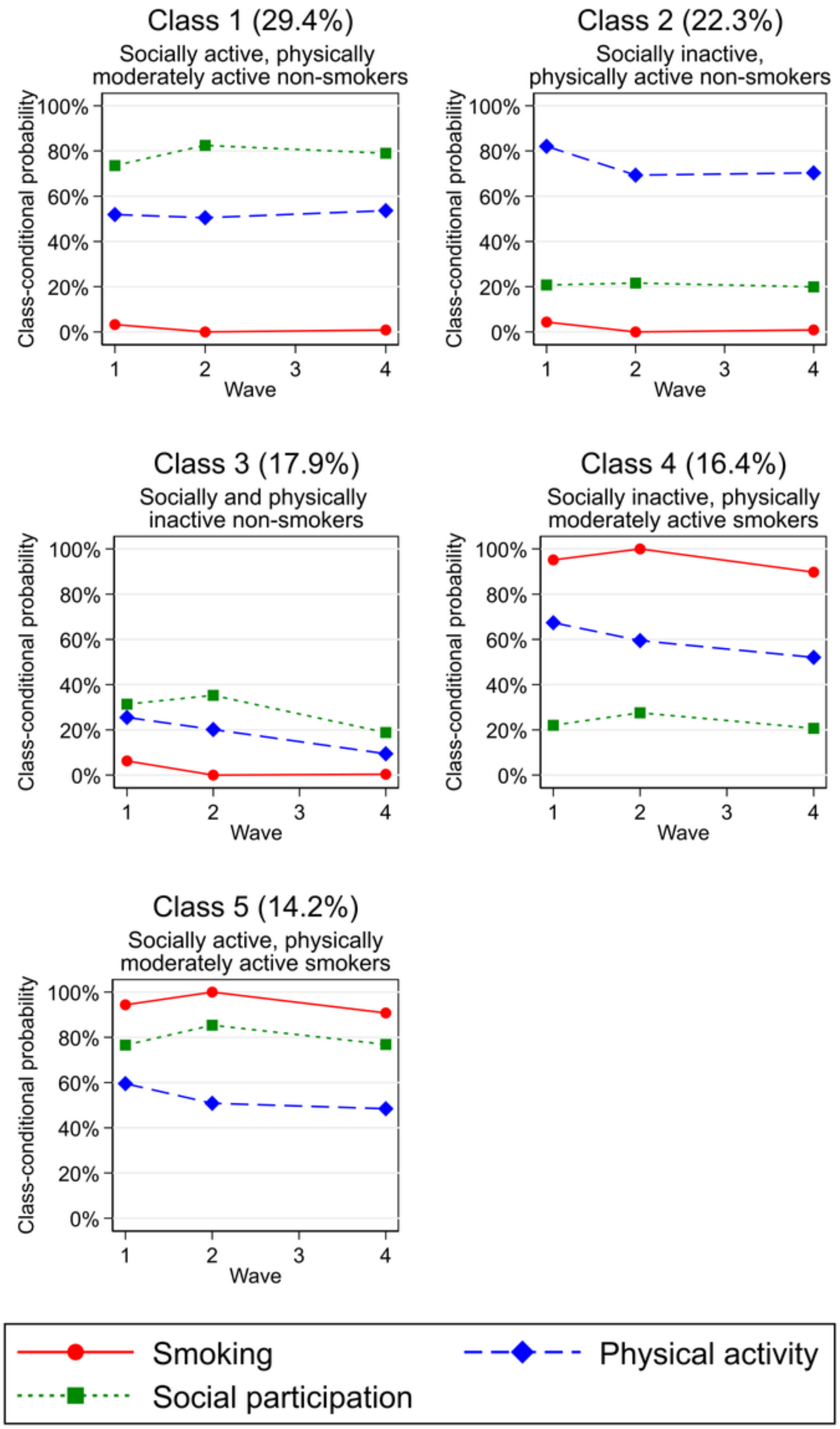
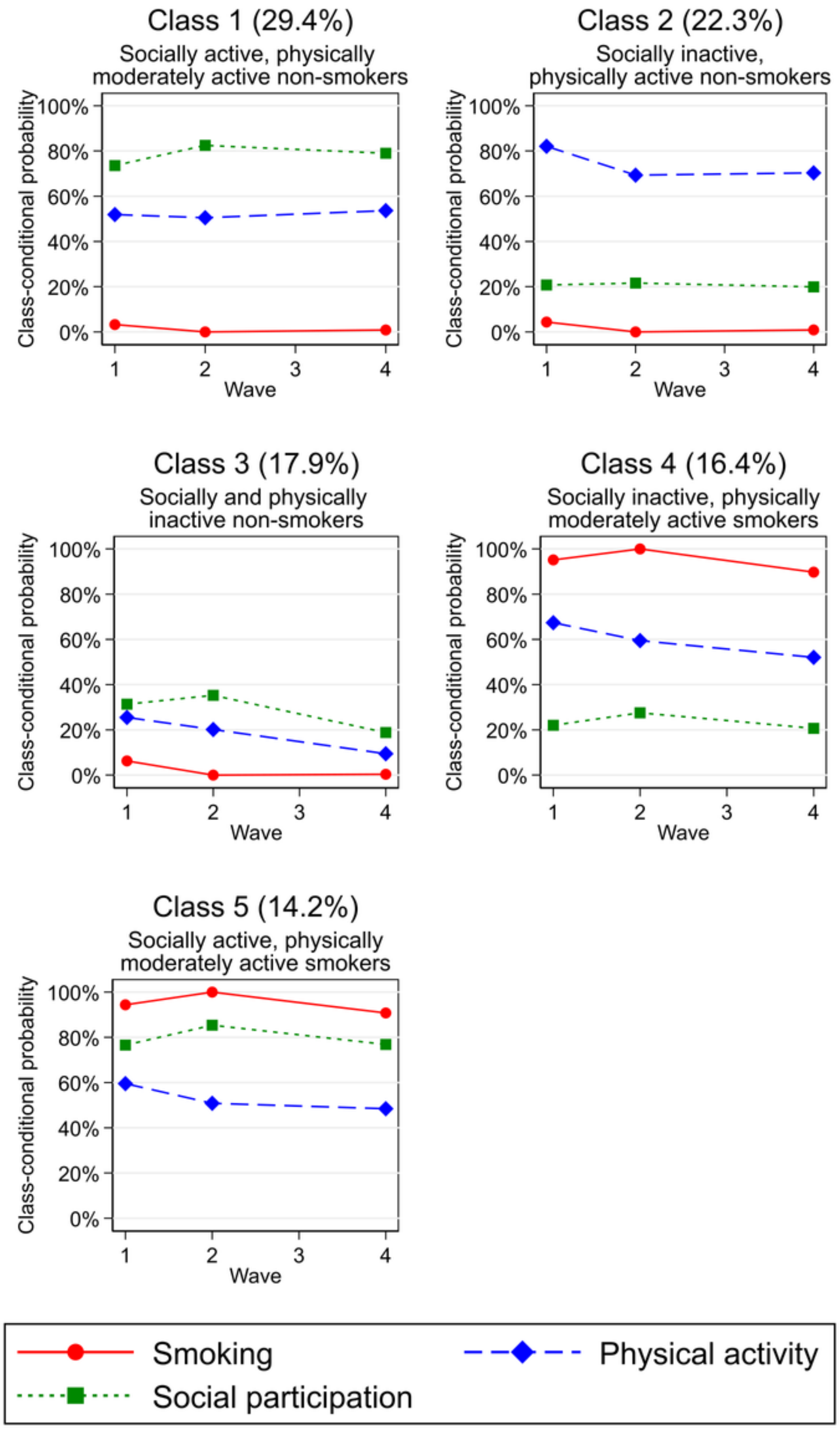


Figure 2

Five multiple health behavior patterns and their trajectories across three CHARLS waves. Class-conditional probability denotes the probability that a class member answered “yes” to a question about behavior (e.g., a member of class 1 has nearly 0% probability of being a smoker and 50% probability of being physically active). CHARLS, China Health and Retirement Longitudinal Study.



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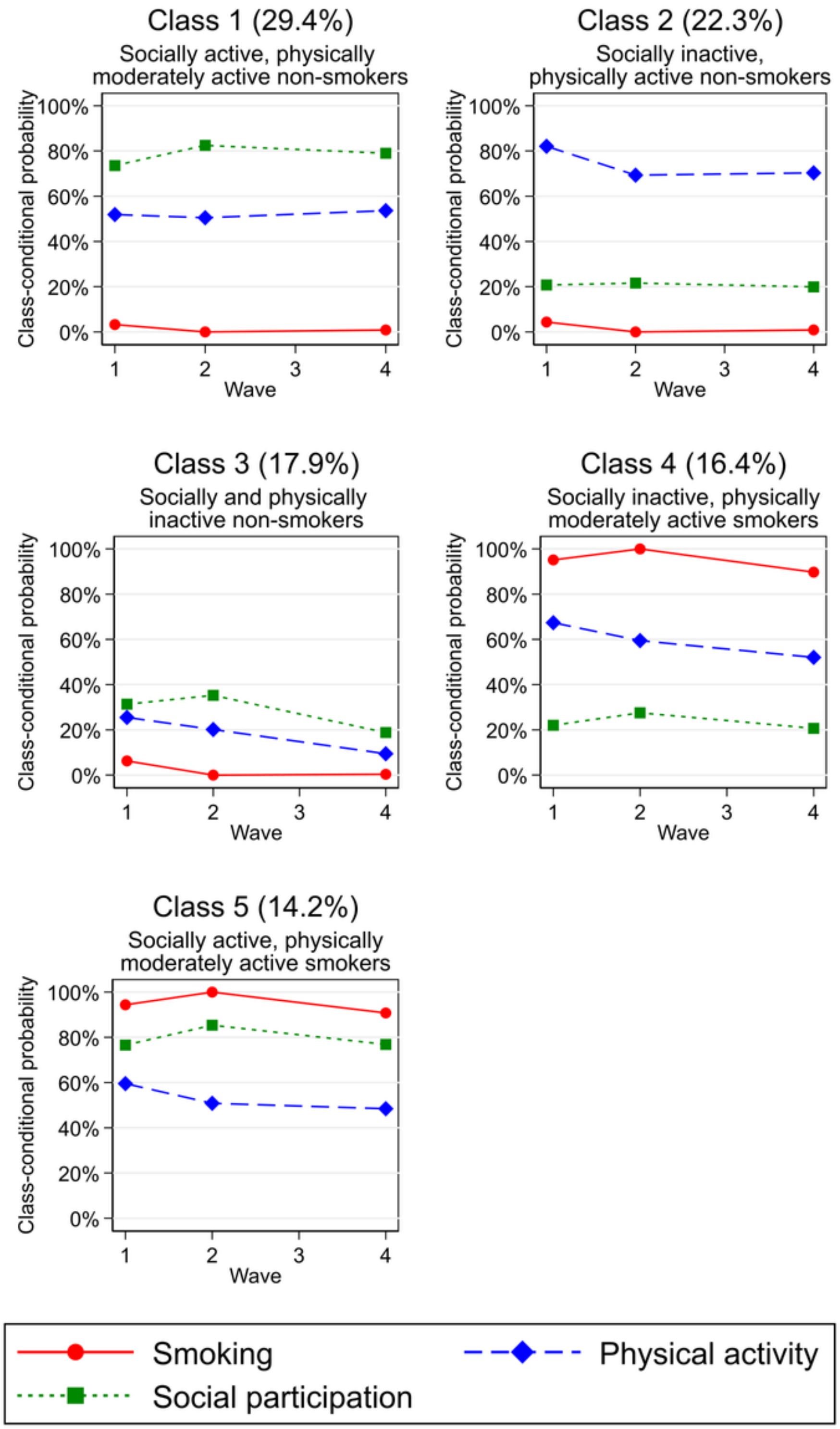

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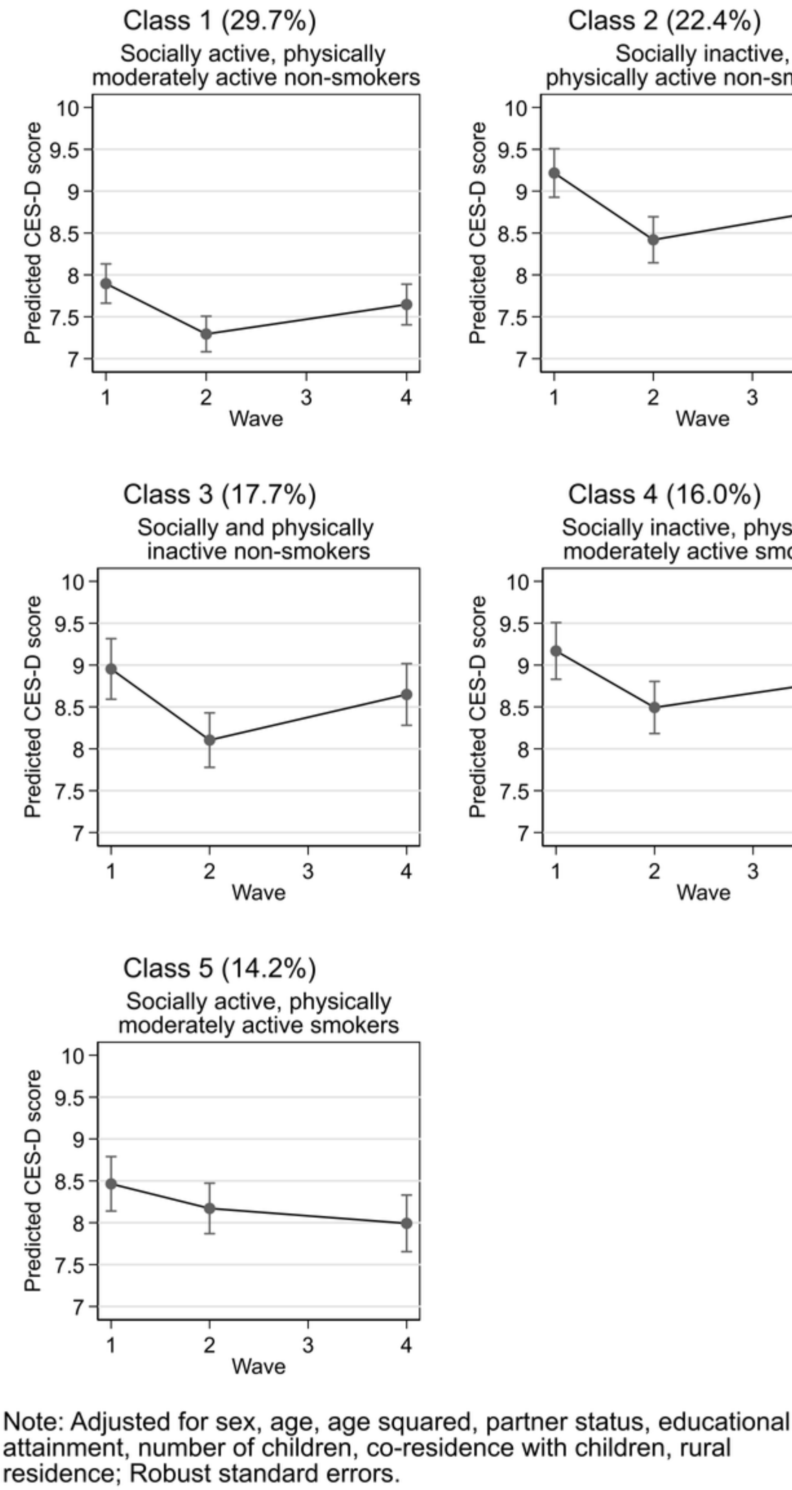
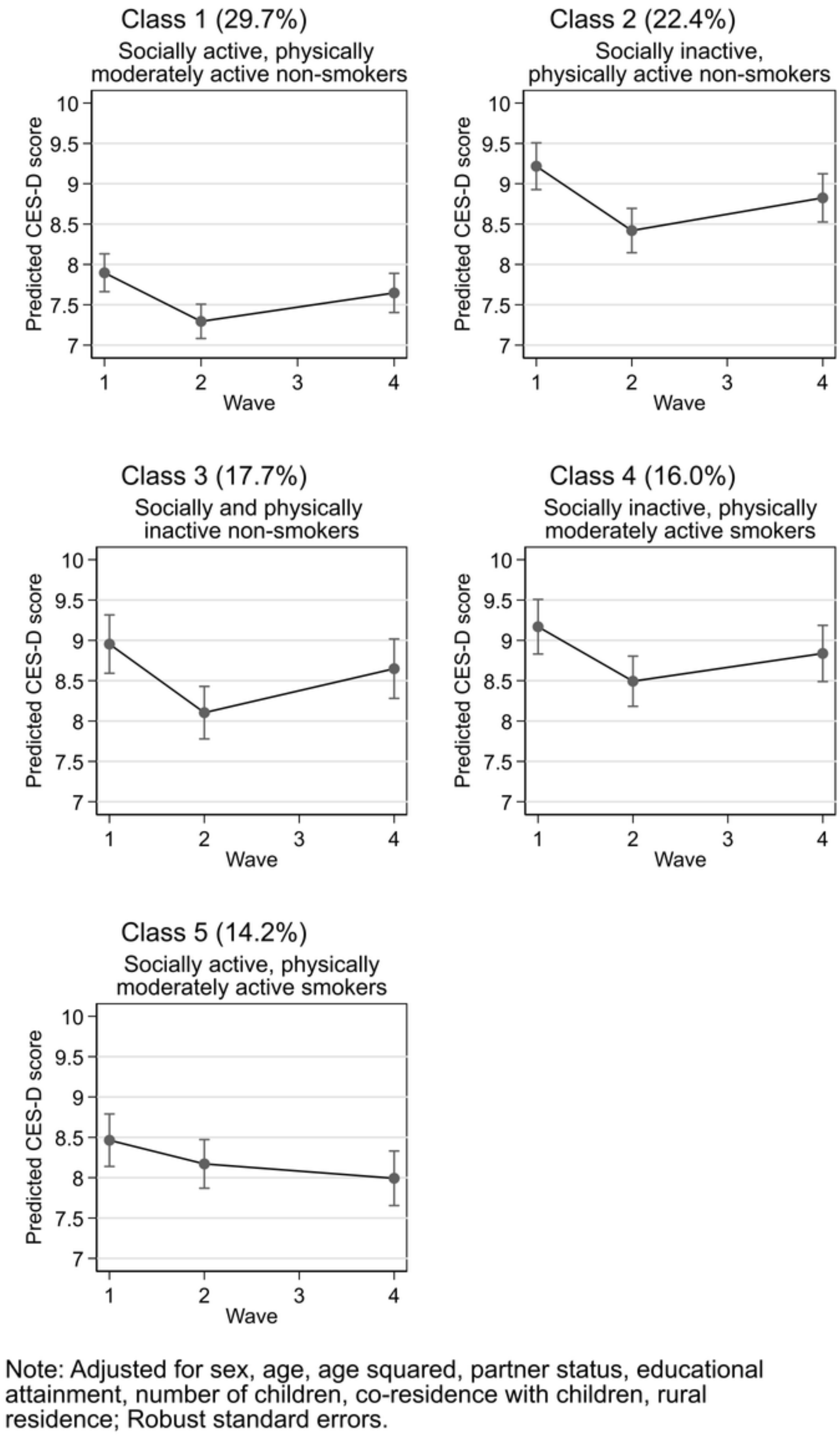


Figure 3

Predicted CES-D 10 score trajectories by health behavior class. Analyses were adjusted for age, age squared, gender, residence, educational level, marital status, and co-residence with children. Bars represent robust standard errors. CES-D 10, 10-item Centre for Epidemiologic Studies Depression Scale.



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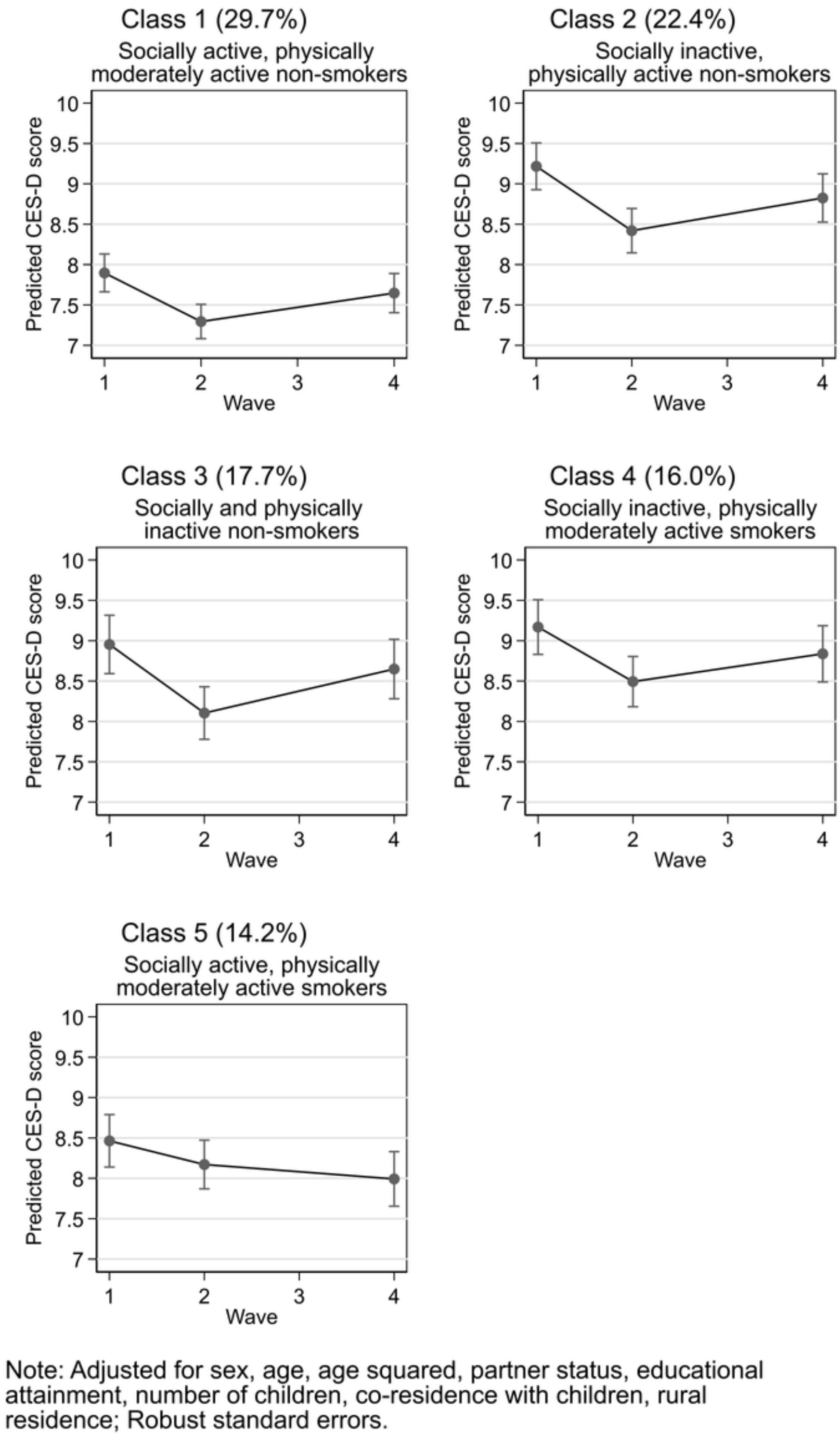

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