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Multimorbidity patterns and cognitive trajectories in older adults: functional, behavioral, and environmental pathways —a longitudinal analysis of CHARLS

Yanhui Jiao[1], Xiaohui Zhai[1], Jiaxin Li[2], Xiaohan Sun[3], Qing Li[1*]

[1]Department of Health Policy and Management, Chinese Academy of Medical Sciences and Peking Union Medical College, Beijing, China
[2]Department of Respiratory and Critical Care Medicine, Cangzhou Central Hospital Yanshan Branch, Cangzhou, China
[3]Department of Clinical Medicine, Jitang College of North China University of Science and Technology, Tangshan, China

*Corresponding Author. Email: Liq8557@163.com

Abstract. Multimorbidity may affect cognitive aging differently according to disease patterns rather than disease counts alone. This study analyzed 2011–2020 data from the China Health and Retirement Longitudinal Study (CHARLS), including 5,979 Chinese adults aged 45 years or older. Fifteen chronic conditions were used to identify multimorbidity patterns through latent class analysis. Latent growth curve models examined associations with baseline cognition and cognitive decline, while mediation and moderation analyses assessed Activities of Daily Living (ADL), social and intellectual engagement, and Living Environment Quality (LEQ). Five patterns were identified: minimal morbidity, Sensory-Psychiatric-Musculoskeletal Multimorbidity (Sensory-PMM), cardiometabolic multimorbidity, extensive multisystem multimorbidity, and Respiratory-Psychiatric-Sensory multimorbidity (Respiratory-PSS). In fully adjusted models, Sensory-PMM (β = −0.757; 95% CI, −0.92 to −0.59) and extensive multisystem multimorbidity (β = −0.469; 95% CI, −0.73 to −0.21) were associated with lower baseline cognition. Both showed slower subsequent decline, suggesting a floor effect. Time-varying models showed faster cognitive decline in the cardiometabolic group (β = −0.028; 95% CI, −0.052 to −0.005; p = 0.019). ADL function mediated associations across all nonreference patterns, whereas social and intellectual engagement mediated only the Sensory-PMM association. Unfavorable LEQ was associated with lower baseline cognition (β = −0.487; 95% CI, −0.749 to −0.225; p = 0.001), and even moderate environmental adversity amplified the cognitive burden of extensive multisystem disease (interaction β = −0.921; 95% CI, −1.770 to −0.071; p = 0.035). These findings support phenotype-aware cognitive risk screening and interventions targeting function, engagement, and living environments.

Keywords: multimorbidity, cognitive trajectories, latent class analysis, latent growth curve model, CHARLS, aging

1. Introduction

By 2050, approximately one in six people worldwide will be over 65 years of age [1]. This demographic shift is already pushing age-related cognitive decline to the forefront of public health, with dementia now affecting more than 55 million individuals and Alzheimer's disease accounting for the bulk of the burden—approximately 10 million new cases every year [2]. Multimorbidity has become the norm in later life, and it is closely associated with poorer cognitive performance, faster decline, and elevated dementia risk [3]. However, simply counting diseases or relying on composite comorbidity indices often masks the clinically important heterogeneity that distinguishes one cluster of chronic conditions from another [4, 5]. Diseases do not accumulate at random; they coalesce into recognizable patterns, each carrying its own biological signature and functional footprint [6]. Capturing these latent structures should, in theory, flag cognitive risk more effectively than crude tallies, allowing for a far more nuanced reading of how specific disease combinations shape cognitive outcomes.

Nevertheless, the temporal relationship between multimorbidity patterns and cognitive aging remains unclear. Most studies have looked at cognition at a single point or over short follow-ups, usually failing to separate baseline cognitive levels from the pace of subsequent change [7]. However, different profiles may have distinct temporal signatures—some might depress initial performance, while others could accelerate the decline [8]. Disentangling these possibilities calls for longitudinal designs that explicitly separate starting cognition from its trajectory. Another gap is equally important: most investigations have treated multimorbidity as a fixed baseline exposure, ignoring the added risks that emerge as disease configurations shift during follow-up. By modeling time-varying comorbidity patterns within linear mixed-effects frameworks, one can capture the evolving interplay between dynamic disease transitions and both the concurrent cognitive level and the rate of change.

Moreover, the mechanisms linking multimorbidity patterns to cognitive aging are still largely unclear. The disablement process framework posits that accumulating chronic diseases erode physical reserves, compromise Activities of Daily Living (ADLs), and ultimately reverberate through cognitive health [9]. Functional limitations, sensory impairment, and emotional distress can also constrict social interaction and curtail participation in cognitively stimulating pursuits, thereby depleting the very stimulation and support that help sustain cognition [10]. Until recently, however, physical function and social participation have usually been studied in silos; few investigations have considered ADL function and engagement in social and intellectual activities as parallel explanatory pathways running from multimorbidity profiles to cognitive trajectories [11]. Beyond the individual, the surrounding living environment adds another layer. Housing quality, clean fuel access, tap water availability, and ambient air pollution shape physical function, mobility, social engagement, and ultimately cognitive well-being [12, 13]. Yet longitudinal evidence on whether such contextual conditions modify the multimorbidity–cognition link remains scarce.

This study aimed to address these research gaps by combining five waves of the China Health and Retirement Longitudinal Study (2011–2020) with city-level air-pollution data. Specifically, Latent Class Analysis (LCA) was used to identify multimorbidity profiles, and Latent Growth Curve Models (LGCMs) were applied to chart changes in cognition from 2011 to 2020. ADL function and social and intellectual engagement were then examined as parallel mediators, and Living Environment Quality (LEQ) was tested as a moderator. Wave-specific multimorbidity patterns were additionally treated as time-varying exposures to evaluate how dynamic disease transitions were related to cognitive level and change. Together, these analyses were intended to provide clinicians and policymakers with more actionable evidence than disease counts alone.

2. Method

2.1. Research design and content

Data were drawn from the 2011, 2013, 2015, 2018, and 2020 waves of the China Health and Retirement Longitudinal Study (CHARLS), a nationally representative prospective cohort of Chinese adults aged 45 years and older spanning 28 provinces [14]. CHARLS relies on a multistage, stratified, probability-proportional-to-size sampling strategy, in which detailed information on health, economic, social, and cognitive domains is gathered. Ethics approval was granted by the Review Committee of Peking University for all waves, and every participant provided written informed consent.

Participants were excluded if they were younger than 45 years at baseline; reported a physician diagnosis of dementia, Parkinson's disease, or another memory-related disorder; had missing baseline cognitive or chronic disease data; had baseline cognitive impairment (total score < 5); or lacked cognitive assessments in two or more follow-up waves. After applying these criteria, 5,979 participants were included in the analyses (Figure 1).

Air pollution data were obtained from the China High Air Pollutants (CHAP) database, which supplies annual ambient PM2.5 concentrations at a 1 km resolution for mainland China starting in 2000 [15]. Because CHARLS withholds residential addresses for privacy protection, city-level annual mean PM2.5 was used as a proxy for individual exposure, aligning each survey year with the corresponding or preceding annual average (for instance, the 2010 mean was matched to the 2011 wave to allow for lag effects). Reporting follows the STROBE guidelines [16].

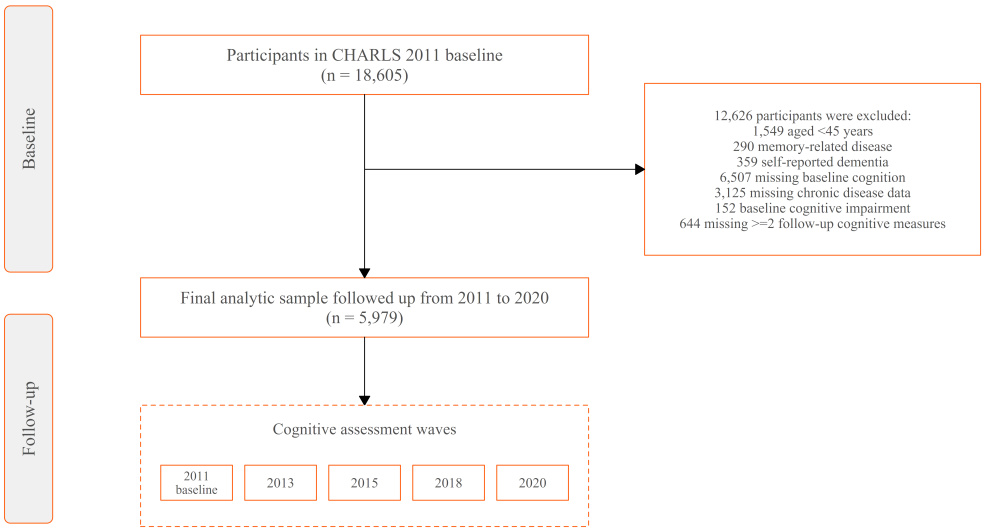

Figure 1. Flow diagram for participants selection in the study

Note: The flowchart details the exclusion criteria applied to the initial China Health and Retirement Longitudinal Study (CHARLS) 2011 baseline cohort to reach the final analytical sample (n = 5,979). The bottom panel displays the five cognitive assessment waves conducted during the 2011–2020 follow-up period.

2.2. Variable description

2.2.1. Exposure: multimorbidity patterns

The exposure comprised fifteen chronic conditions: hypertension, diabetes, dyslipidemia, heart disease, stroke, chronic lung disease, asthma, arthritis, digestive disease, liver disease, kidney disease, cancer, psychiatric and depressive disorders, hearing impairment, and visual impairment. Hearing impairment was defined as self-reported hearing loss, poor hearing, or current hearing aid use; visual impairment was defined as self-reported blindness or poor vision [17]. All other conditions were ascertained through self-reported physician diagnosis or current medication use. Each condition was coded as binary (1 = present, 0 = absent). For descriptive purposes, multimorbidity meant having two or more of the aforementioned conditions simultaneously. In the LCA, all baseline participants were retained—including those free of any chronic condition—so that the resulting low-burden class could serve as a natural reference. The 2011 LCA solution anchored the primary analysis, with each participant assigned to the class carrying the highest posterior probability. Because psychiatric and depressive disorders were already embedded in the LCA indicators, depressive symptoms were deliberately omitted from subsequent models to avoid overadjusting for an exposure component.

2.2.2. Outcome: cognitive function

Cognitive function was assessed at every wave through interviewer-administered tests: mental status and attention via the 10-item Telephone Interview for Cognitive Status (TICS-10), episodic memory via immediate and delayed word recall, and visuospatial ability via a figure-drawing task. Global scores ranged from 0 to 21, with higher values indicating better cognition. Because word-recall procedures in 2018 and 2020 diverged from earlier waves, memory scores were first harmonized across waves using a published CHARLS cognitive calibration protocol before the global score was computed [18].

2.2.3. Mediators

Two parallel mediators were examined. The first mediator was ADL function, computed from six basic (BADL) and five instrumental (IADL) activities of daily living; after harmonized scoring, higher values reflected better function. The second mediator was social and intellectual engagement, built from four social and four intellectual activity items in CHARLS that standardized and summed so that higher scores indicated greater participation. For the primary mediation specification, 2011 data were used. To tighten temporal ordering, a lagged specification repeated the same constructions with 2013 data.

2.2.4. Living environment quality

Living Environment Quality (LEQ) was based on five indicators—housing type, indoor temperature adequacy, drinking water source, cooking and heating fuel type, and outdoor PM2.5 exposure dichotomized at the Chinese Ministry of Ecology and Environment threshold of 35.0 μg/m³. These scores were summed into a 0-to-6 composite, with higher scores indicating greater cumulative environmental adversity. The LEQ was then trichotomized as favorable (0–1), moderate (2–3), or unfavorable (4–6) [19] (Appendix Table A5).

2.2.5. Covariates

Baseline covariates included age, sex, urban–rural residence, marital status, educational attainment (illiterate, primary school, junior middle school, or senior high school or above), per capita household income (tertiles), smoking status (never, former, or current), drinking frequency (never, moderate, or frequent), physical activity level (low, moderate, or high), sleep duration (≤ 6 h, 7–8 h, or ≥ 9 h), and body mass index.

2.3. Statistical analysis

Baseline characteristics were summarized according to 2011 multimorbidity patterns. Continuous variables are presented as means ± standard deviations, and categorical variables as frequencies and percentages. Group

differences were assessed using one-way ANOVA, χ^2 tests, or Fisher's exact tests, as appropriate. Missing baseline covariates, mediators, and LEQ were imputed using an iterative random forest algorithm to generate twenty complete datasets, and estimates were pooled according to Rubin's rules [20]. Missing repeated cognitive outcomes were handled using full information maximum likelihood in Latent Growth Curve Model–Structural Equation Model (LGCM-SEM) and maximum likelihood estimation in Linear Mixed-effects Model (LMMs).

Latent Class Analysis (LCA) models were fitted using the poLCA package (version 1.6) for *R*, with the fifteen binary chronic conditions entered as class indicators. Models with one to six classes were estimated via the Expectation-Maximization (EM) algorithm with maximum likelihood, using 100 random sets of starting values (maximum iterations = 5,000; convergence tolerance = 1×10^{-8}) to reduce the risk of local maxima. Class selection balanced the Bayesian Information Criterion (BIC), adjusted BIC (aBIC), Average Posterior Probability (AvePP), class size, and clinical interpretability (Appendix Table A1) [21]. The final five-class solution showed acceptable classification quality, with an entropy of 0.602 and an overall AvePP of 0.752 (class-specific AvePPs ranged from 0.662 to 0.929) (Appendix Table A2). Participants were assigned to the class with the highest posterior probability (modal assignment rule). The five classes were labeled according to their distinctive conditional probability profiles (Appendix Figure A1) as Minimal morbidity, Cardiometabolic, Extensive multisystem, Sensory-psychiatric-musculoskeletal multimorbidity, and Respiratory-psychiatric-sensory multimorbidity. For brevity, these classes are referred to hereafter as Minimal morbidity, Cardiometabolic, Extensive multisystem, Sensory-PMM, and Respiratory-PSS. For time-varying analyses, separate LCAs were fitted at each follow-up wave (2013, 2015, 2018, 2020) with identical specifications; wave-specific classes were labeled by manual comparison of conditional probability profiles against the baseline class structure (Appendix Table A2).

LGCMs served to relate baseline multimorbidity profiles to cognitive trajectories between 2011 and 2020 [22]. The intercept represented baseline cognitive level, and the slope represented cognitive change over time. Time scores were set as 0, 2, 4, 7, and 9. Three models were fitted: Model 1 adjusted for age and sex; Model 2 further adjusted for urban-rural residence, marital status, education, and household income; and Model 3 additionally included smoking, drinking, physical activity, sleep duration, and Body Mass Index (BMI). Model fit was assessed using Comparative Fit Index (CFI), Tucker–Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), and Standardized Root Mean Square Residual (SRMR).

Parallel pathway analyses within the LGCM-SEM framework examined whether ADL function and social and intellectual engagement explained the associations between multimorbidity patterns and cognitive intercept and slope [23, 24]. These analyses were implemented using the lavaan package (version 0.6) with Maximum Likelihood Robust (MLR) estimation and Full Information Maximum Likelihood (FIML) for missing cognitive outcomes. Indirect effects were computed using the product-of-coefficients method (a-path × b-path) with standard errors approximated by the multivariate delta method. Two specifications were compared: Model 1 without residual covariances between cognitive indicators, and Model 2 with residual covariances between adjacent-wave indicators. Model 2 was retained as the final specification. All mediation estimates were pooled across 20 multiply imputed datasets using Rubin's rules. Lagged mediation analyses used 2013 mediators and cognitive outcomes from 2015 to 2020, adjusted for baseline cognition, applying a two-stage Linear Mixed-effects Model (LMM) approach via the nlme package: multimorbidity patterns predicted 2013 mediators (a-paths), and 2013 mediators in turn predicted subsequent cognitive trajectories in an LMM with random intercepts and slopes (b-paths). Lagged indirect effects used the product-of-coefficients method with delta-method standard errors, pooled across imputations. Moderation analyses tested whether LEQ modified the associations between multimorbidity patterns and cognitive trajectories. LEQ was first

entered as a main effect without interaction terms; LEQ × multimorbidity pattern interaction terms were then added to test effect modification. Additional linear mixed-effects models [25] treated wave-specific multimorbidity patterns as time-varying exposures.

Sensitivity analyses were conducted by repeating the primary LGCM using the four-class LCA solution and by performing a complete-case analysis excluding physical activity and household income because of their high missing rates. All analyses were performed using *R* version 4.4.3. All tests were two-sided, with $p < 0.05$ considered statistically significant.

3. Results

3.1. Multimorbidity pattern identification and sample characteristics

Appendix Table A1 shows the fit indices for the one- to six-class LCA models in 2011. Although the four-class solution had the lowest BIC, its advantage over the five-class solution was minimal. The five-class solution had a lower aBIC and additionally identified an extensive multisystem class that was not separated in the four-class model. This model also showed acceptable classification quality, with an entropy of 0.602 and an average posterior probability of 0.752. Wave-specific LCAs from 2013 to 2020 showed similar classification stability, with average posterior probabilities ranging from 0.724 to 0.751. Therefore, the five-class solution was used in the primary analyses, and the four-class solution was retained for sensitivity analyses.

Table 1. Patient demographics and baseline characteristics

Characteristic	LCA2011					*p*-value
	Minimal-Morbidity-Profile *n* = 3,410	Cardiometabolic-Multimorbidity *n* = 837	Sensory-Psychiatric-Musculoskeletal-Multimorbidity *n* = 1,208	Respiratory-Psychiatric-Sensory-Multimorbidity *n* = 143	Extensive-Multisystem-Multimorbidity *n* = 381	
Age, Mean ± SD	56 ± 8	58 ± 7	57 ± 8	60 ± 8	58 ± 8	< 0.001[1]
Sex, *n* (%)						< 0.001[2]
Male	1,893 (55.5%)	407 (48.6%)	546 (45.2%)	93 (65.0%)	142 (37.3%)	
Female	1,517 (44.5%)	430 (51.4%)	662 (54.8%)	50 (35.0%)	239 (62.7%)	
Residence, *n* (%)						< 0.001[2]
Rural	2,071 (60.7%)	443 (52.9%)	848 (70.2%)	99 (69.2%)	254 (66.7%)	
Urban	1,339 (39.3%)	394 (47.1%)	360 (29.8%)	44 (30.8%)	127 (33.3%)	
Educational level, *n* (%)						< 0.001[2]
Illiterate	999 (29.3%)	269 (32.1%)	482 (39.9%)	55 (38.5%)	169 (44.4%)	
Primary school	817 (24.0%)	210 (25.1%)	321 (26.6%)	43 (30.1%)	101 (26.5%)	
Middle school	1,014 (29.7%)	213 (25.4%)	295 (24.4%)	28 (19.6%)	69 (18.1%)	
High school and above	580 (17.0%)	145 (17.3%)	110 (9.1%)	17 (11.9%)	42 (11.0%)	
Marital status, *n* (%)						
Married	3,206 (94.0%)	770 (92.0%)	1,096 (90.7%)	135 (94.4%)	330 (86.6%)	
Widowed	169 (5.0%)	60 (7.2%)	94 (7.8%)	7 (4.9%)	38 (10.0%)	

Table 1. Continued

Separated or divorced or single	35 (1.0%)	7 (0.8%)	18 (1.5%)	1 (0.7%)	13 (3.4%)	
Total household wealth, *n* (%)						< 0.001[2]
Low income	555 (28.9%)	167 (30.9%)	331 (42.0%)	35 (36.1%)	118 (43.2%)	
Mid income	656 (34.2%)	162 (30.0%)	272 (34.5%)	37 (38.1%)	79 (28.9%)	
High income	708 (36.9%)	211 (39.1%)	186 (23.6%)	25 (25.8%)	76 (27.8%)	
Body mass index, Mean ± SD	23.6 ± 3.5	25.9 ± 3.7	22.9 ± 3.4	22.8 ± 3.9	24.6 ± 4.2	< 0.001[1]
Sleep duration, *n* (%)						< 0.001[2]
Short sleep (≤ 6 h)	684 (20.1%)	199 (23.9%)	471 (39.1%)	52 (36.6%)	164 (43.4%)	
Normal sleep (7–8h)	2,436 (71.6%)	581 (69.7%)	639 (53.0%)	80 (56.3%)	199 (52.6%)	
Long sleep (≥ 9 h)	282 (8.3%)	54 (6.5%)	95 (7.9%)	10 (7.0%)	15 (4.0%)	
Current smoking status, *n* (%)						< 0.001[2]
Current smoking status	1,196 (35.1%)	228 (27.3%)	396 (32.8%)	50 (35.0%)	102 (26.8%)	
Alcohol consumption, *n* (%)						< 0.001[2]
Weekly drinking or more	687 (21.4%)	142 (17.7%)	179 (15.6%)	27 (19.6%)	38 (10.3%)	
Less than weekly drinking	2,530 (78.6%)	661 (82.3%)	969 (84.4%)	111 (80.4%)	332 (89.7%)	
Physical activity level, *n* (%)						< 0.001[2]
Low (< 600 MET-min/week)	357 (24.7%)	139 (38.9%)	107 (20.9%)	18 (32.1%)	37 (23.9%)	
Moderate (600–3,000 MET-min/week)	183 (12.7%)	48 (13.4%)	61 (11.9%)	9 (16.1%)	26 (16.8%)	
High (> 3,000 MET-min/week)	903 (62.6%)	170 (47.6%)	343 (67.1%)	29 (51.8%)	92 (59.4%)	
Limitation, *n* (%)						
BADL limitation	150 (4.4%)	111 (13.3%)	262 (21.7%)	28 (19.6%)	115 (30.2%)	< 0.001[2]
IADL limitation	238 (7.0%)	133 (15.9%)	267 (22.1%)	30 (21.0%)	117 (30.7%)	< 0.001[2]
Functional limitation	340 (10.0%)	189 (22.6%)	394 (32.6%)	45 (31.5%)	162 (42.5%)	< 0.001[2]
Social activity score, *n* (%)						< 0.001[2]
0	1,990 (58.4%)	454 (54.2%)	774 (64.1%)	81 (56.6%)	211 (55.4%)	
1–2	657 (19.3%)	146 (17.4%)	233 (19.3%)	30 (21.0%)	81 (21.3%)	
≥ 3	763 (22.4%)	237 (28.3%)	201 (16.6%)	32 (22.4%)	89 (23.4%)	
Intellectual activity score, n (%)						< 0.001[2]
0	2,513 (73.7%)	596 (71.2%)	996 (82.5%)	102 (71.3%)	304 (79.8%)	
1–2	617 (18.1%)	156 (18.6%)	165 (13.7%)	31 (21.7%)	56 (14.7%)	

Table 1. Continued

≥ 3	280 (8.2%)	85 (10.2%)	47 (3.9%)	10 (7.0%)	21 (5.5%)	
Living environmental quality, *n* (%)						< 0.001[2]
Unfavorable	805 (26.7%)	168 (24.3%)	434 (39.3%)	60 (45.5%)	139 (40.5%)	
Moderate	1,593 (52.8%)	375 (54.3%)	540 (48.9%)	55 (41.7%)	167 (48.7%)	
Favorable	619 (20.5%)	148 (21.4%)	130 (11.8%)	17 (12.9%)	37 (10.8%)	

Note: Data are presented as mean ± SD for continuous variables and *n* (%) for categorical variables. *p* values indicate differences across the five multimorbidity patterns. [1]One-way analysis of variance; [2]Pearson's chi-squared test; [3]Fisher's exact test. Sensory-PMM = Sensory–Psychiatric–Musculoskeletal Multimorbidity; Respiratory-PSS = Respiratory–Psychiatric–Sensory Multimorbidity; BMI = Body Mass Index; ADL = Activity of Daily Living; IADL = Instrumental Activity of Daily Living.

In 2011, participants were classified into Minimal morbidity (57.0%, n = 3,410), Sensory-PMM (20.2%, n = 1,208), Cardiometabolic (14.0%, n = 837), Extensive multisystem (6.4%, n = 381), and Respiratory-PSS (2.4%, n = 143). Minimal-morbidity participants were younger, more educated, and had higher baseline cognitive scores. Sensory-PMM participants were more often women, rural residents, and less educated, with lower social and intellectual engagement. Cardiometabolic participants had the highest BMI but baseline cognition comparable to the Minimal morbidity group. Respiratory-PSS participants were the oldest, predominantly male, and had poorer living environments and greater functional limitations. Extensive multisystem participants had the lowest baseline cognitive scores and greater socioeconomic and functional disadvantages. Baseline characteristics differed significantly across multimorbidity patterns, including age, sex, education, residence, household wealth, BMI, sleep duration, social and intellectual engagement, ADL/IADL function, living environment quality, and baseline cognition. For detailed characteristics, see Table 1 and Appendix Figure A1.

3.2. Association between baseline comorbidity patterns and cognitive trajectories

The unconditional LGCM revealed a linear downward drift in overall cognition from 2011 to 2020, with a mean intercept of 12.87 and an average annual decrease of 0.247 points. Significant intercept and slope variances indicated considerable individual heterogeneity in the starting level and pace of change. The two were moderately positively correlated (r = 0.307), suggesting that participants who began higher tended to decline more slowly. A linear specification was retained because the quadratic term showed limited pattern-related variation. The conditional LGCM fit well (Model 3: CFI = 0.959, TLI = 0.935, RMSEA = 0.039, SRMR = 0.014). Full parameter estimates are presented in Table 2.

The groups differed markedly in baseline cognition. In Model 1, Sensory-PMM, Extensive multisystem, and Respiratory-PSS all fell significantly below Minimal morbidity, whereas Cardiometabolic did not. After full adjustment in Model 3, Sensory-PMM still carried the heaviest cognitive penalty (β = −0.757, 95% CI: −0.922 to −0.593), followed by Extensive multisystem (β = −0.469, 95% CI: −0.726 to −0.212); Cardiometabolic and Respiratory-PSS no longer separated from Minimal morbidity. Scaled to the unconditional intercept SD of 2.30, these differences corresponded to Cohen's d values of −0.33 for Sensory-PMM (small-to-moderate effect) and −0.20 for Extensive multisystem (small effect).

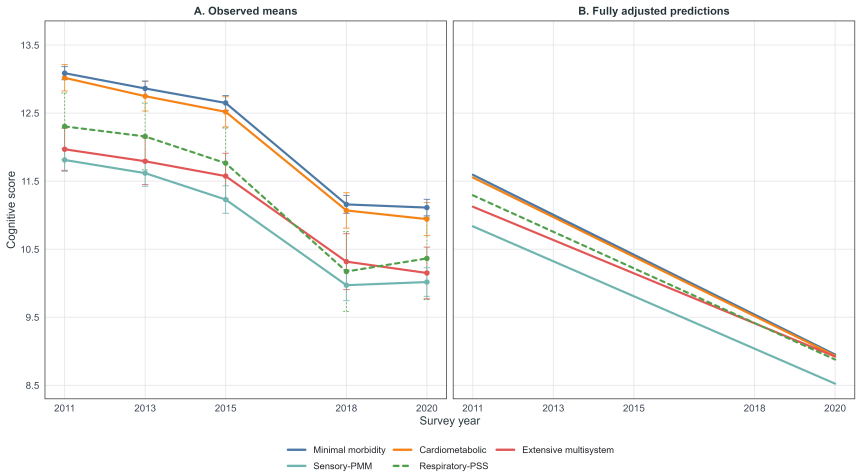

Figure 2. Cognitive trajectories by multimorbidity pattern in CHARLS 2011–2020. (A) Observed means. (B) Fully adjusted predictions

Note: Panel A shows unadjusted observed group means (solid points) across five survey waves. Panel B shows LGCM predicted trajectories from the fully adjusted Model 3, with shaded ribbons representing 95% confidence intervals. The dashed line indicates the Respiratory–Psychiatric–Sensory–Multimorbidity group. Time scores were set to 0 (2011), 2 (2013), 4 (2015),7 (2018), and 9 (2020) to reflect unequal survey intervals.

Slopes told a different story. Extensive multisystem declined most slowly (β = 0.049, p = 0.012), with Sensory-PMM close behind (β = 0.037, p = 0.001); the slopes for the other two groups were not significant. This low-intercept, gentle-slope configuration suggests limited room for further decline among high-burden groups (Figure 2). Model 3 explained 44.3% of the intercept variance and 21.2% of the slope variance (Appendix Table A3). Among the covariates, older age and rural residence predicted both lower baseline cognition and faster decline, whereas higher education predicted better baseline cognition and slower decline.

Table 2. Association between baseline comorbidity patterns and cognitive trajectories: results from latent growth curve models (n = 20 imputations)

Parameter	Model 1 (LCA Only)	Model 2 (LCA + Demographics)	Model 3 (Fully Adjusted)
Intercept			
Cardiometabolic	0.152 (0.101) [−0.06, 0.36], 0.147	0.036 (0.087) [−0.14, 0.21], 0.678	−0.040 (0.090) [−0.22, 0.14], 0.655
Extensive multisystem	−0.754 (0.148) [−1.06, −0.44], < 0.001	−0.438 (0.131) [−0.69, −0.18], < 0.001	−0.469 (0.131) [−0.73, −0.21], < 0.001
Sensory–psychiatric–musculoskeletal	−1.141 (0.091) [−1.33, −0.95], < 0.001	−0.794 (0.084) [−0.96, −0.63], < 0.001	−0.757 (0.084) [−0.92, −0.59], < 0.001
Respiratory–psychiatric–sensory	−0.559 (0.219) [−1.02, −0.10], 0.020	−0.287 (0.203) [−0.69, 0.11], 0.158	−0.301 (0.203) [−0.70, 0.10], 0.138

Table 2. Continued

Slope			
Cardiometabolic	0.005 (0.013) [−0.02, 0.03], 0.682	0.001 (0.012) [−0.02, 0.03], 0.922	0.003 (0.013) [−0.02, 0.03], 0.847
Extensive multisystem	0.039 (0.019) [−0.00, 0.08], 0.060	0.048 (0.019) [0.01, 0.09], 0.012	0.049 (0.019) [0.01, 0.09], 0.012
Sensory–psychiatric–musculoskeletal	0.027 (0.011) [0.00, 0.05], 0.023	0.037 (0.011) [0.02, 0.06], < 0.001	0.037 (0.011) [0.01, 0.06], 0.001
Respiratory–psychiatric–sensory	0.020 (0.031) [−0.04, 0.08], 0.525	0.026 (0.030) [−0.03, 0.09], 0.379	0.025 (0.030) [−0.03, 0.08], 0.404

Note*:* Values are Estimate (SE) [95% CI], *p*-value. Minimal-morbidity profile is the reference class. Model 1: adjusted for comorbidity classes only. Model 2: additionally adjusted for age, sex, residence, marital status, and education. Model 3: additionally adjusted for income, physical activity, drinking, smoking, BMI, and sleep duration. Model fit indices and unconditional parameters are reported in Appendix Table A3; full covariate estimates for Model 3 are shown in Appendix Figure A2.

3.3. Mediating effects of functional and social pathways

Whether ADL function and social and intellectual engagement jointly mediated the effects of multimorbidity patterns on cognitive trajectories was next examined (Figure 3).

3.3.1. Baseline mediation

Table 3. Path coefficients of the parallel mediation analysis

Comorbidity Pattern	Mediator	*β* (SE)	95% CI	*p*
Cardiometabolic	ADL	−0.240*** (0.058)	[−0.362, −0.118]	< 0.001
Extensive−multisystem	ADL	−0.474*** (0.087)	[−0.656, −0.292]	< 0.001
Sensory-PMM	ADL	−0.302*** (0.038)	[−0.381, −0.223]	< 0.001
Respiratory-PSS	ADL	−0.304** (0.098)	[−0.509, −0.100]	0.006
Cardiometabolic	Social/intellectual	0.065 (0.048)	[−0.036, 0.166]	0.193
Extensive-multisystem	Social/intellectual	−0.044 (0.055)	[−0.159, 0.071]	0.429
Sensory-PMM	Social/intellectual	−0.112** (0.035)	[−0.186, −0.039]	0.005
Respiratory-PSS	Social/intellectual	0.085 (0.085)	[−0.092, 0.262]	0.327
Outcome	Mediator	*β* (SE)	95% CI	*p*
Intercept (RI)	ADL	0.163** (0.043)	[0.073, 0.253]	0.001
Intercept (RI)	Social/intellectual	0.256*** (0.032)	[0.189, 0.322]	< 0.001
Slope (RS)	ADL	−0.018*** (0.004)	[−0.027, −0.009]	< 0.001
Slope (RS)	Social/intellectual	−0.006 (0.004)	[−0.015, 0.004]	0.226

Note: Model 2 (adjacent residual covariance) was used as the final model. All estimates are pooled across 20 multiply imputed datasets. *β* = unstandardized regression coefficient; SE = Standard Error; CI = Confidence Interval; ADL = Activities of Daily Living. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

At baseline, all nonreference patterns were associated with poorer ADL function, which in turn predicted higher cognitive intercepts. Path coefficients for the parallel mediation model are presented in Table 3.

Indirect pathways through ADL function were significant across all four patterns. Social and intellectual engagement showed a more selective pattern: only Sensory-PMM was associated with reduced engagement, generating a significant indirect association with baseline cognition. Direct, indirect, and total effects are summarized in Table 4. Total indirect effects on the cognitive intercept were significant for Extensive multisystem (indirect effect = −0.089, 95% CI: −0.146 to −0.031; p = 0.004) and Sensory-PMM (indirect effect = −0.078, 95% CI: −0.114 to −0.042; $p < 0.001$). Their direct effects remained significant, indicating partial rather than full mediation. For the cognitive slope, total indirect effects were significant for Cardiometabolic, Extensive multisystem, and Sensory-PMM, but not for Respiratory-PSS.

Table 4. Direct, indirect, and total effects of comorbidity patterns on cognitive trajectories

Comorbidity Pattern	Effect	Intercept (RI) β (SE)	95% CI	p	Slope (RS) β (SE)	95% CI	p
Cardiometabolic	Direct effect	0.091 (0.095)	[−0.108, 0.289]	0.350	−0.007 (0.014)	[−0.036, 0.022]	0.610
	Indirect via ADL	−0.039** (0.012)	[−0.064, −0.015]	0.003	0.004** (0.001)	[0.001, 0.007]	0.007
	Indirect via social	0.017 (0.012)	[−0.010, 0.043]	0.199	−0.000 (0.000)	[−0.001, 0.000]	0.382
	Total indirect	−0.022 (0.017)	[−0.059, 0.014]	0.213	0.004* (0.001)	[0.001, 0.007]	0.017
	Total effect	0.068 (0.095)	[−0.130, 0.267]	0.481	−0.003 (0.014)	[−0.032, 0.025]	0.817
Extensive-multisystem	Direct effect	−0.481** (0.145)	[−0.785, −0.177]	0.004	0.049* (0.021)	[0.005, 0.092]	0.031
	Indirect via ADL	−0.077** (0.023)	[−0.125, −0.029]	0.003	0.008** (0.003)	[0.003, 0.014]	0.005
	Indirect via social	−0.011 (0.014)	[−0.041, 0.018]	0.430	0.000 (0.000)	[−0.001, 0.001]	0.505
	Total indirect	−0.089** (0.027)	[−0.146, −0.031]	0.004	0.009** (0.003)	[0.003, 0.014]	0.004
	Total effect	−0.570*** (0.146)	[−0.875, −0.264]	< 0.001	0.057* (0.021)	[0.014, 0.101]	0.013
Sensory-PMM	Direct effect	−0.580*** (0.094)	[−0.776, −0.384]	< 0.001	0.026 (0.013)	[−0.000, 0.052]	0.054
	Indirect via ADL	−0.049** (0.014)	[−0.079, −0.020]	0.002	0.005*** (0.001)	[0.003, 0.008]	< 0.001
	Indirect via social	−0.029** (0.010)	[−0.049, −0.008]	0.008	0.001 (0.001)	[−0.000, 0.002]	0.257
	Total indirect	−0.078*** (0.017)	[−0.114, −0.042]	< 0.001	0.006*** (0.001)	[0.003, 0.009]	< 0.001
	Total effect	−0.658*** (0.093)	[−0.853, −0.463]	< 0.001	0.032* (0.013)	[0.006, 0.058]	0.020
Respiratory-PSS	Direct effect	−0.293 (0.232)	[−0.779, 0.193]	0.222	0.010 (0.033)	[−0.060, 0.080]	0.774

Table 4. Continued

Respiratory-PSS	Indirect via ADL	−0.050* (0.022)	[−0.095, −0.004]	0.035	0.005* (0.002)	[0.001, 0.010]	0.031
	Indirect via social	0.022 (0.022)	[−0.024, 0.067]	0.331	−0.000 (0.001)	[−0.002, 0.001]	0.444
	Total indirect	−0.028 (0.034)	[−0.098, 0.043]	0.421	0.005 (0.002)	[−0.000, 0.010]	0.061
	Total effect	−0.321 (0.237)	[−0.817, 0.175]	0.191	0.015 (0.034)	[−0.056, 0.085]	0.670

Note: Model 2 (adjacent residual covariance) was used as the final model. All estimates are pooled across 20 multiply imputed datasets. β = unstandardized regression coefficient; SE = Standard Error; CI = Confidence Interval; RI = Random Intercept; RS = Random Slope; ADL = Activities of Daily Living; Soc = Social/intellectual engagement. ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively.

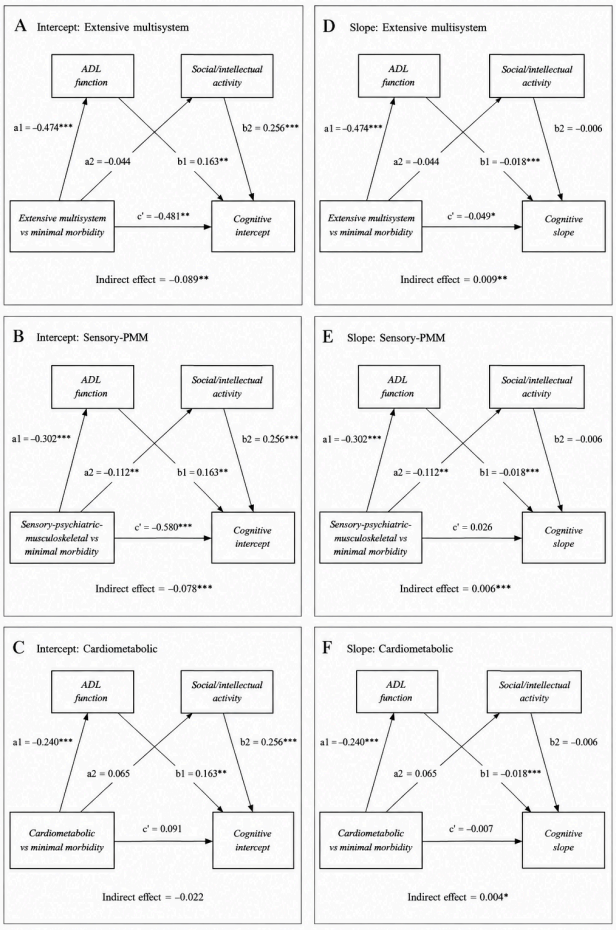

Figure 3. Parallel mediation of baseline multimorbidity patterns on cognitive intercept and slope through ADL function and social/intellectual engagement

Note: Panels A–C depict mediation of the cognitive intercept; panels D–F depict mediation of the cognitive slope. For each panel, the exposure is the multimorbidity pattern versus Minimal morbidity (reference), with ADL function and social/intellectual activity as parallel mediators. Path coefficients are unstandardized regression weights with significance

indicated: ***, ** and * indicate statistical significance at the 1%, 5% and 10% levels respectively. a1 = effect of exposure on ADL function; a2 = effect of exposure on social/intellectual activity; b1 = effect of ADL function on cognition; b2 = effect of social/intellectual activity on cognition; c′ = direct effect of exposure on cognition; total indirect effect = a1×b1 + a2×b2. Sensory-PMM = Sensory–Psychiatric–Musculoskeletal Multimorbidity; Respiratory-PSS = Respiratory–Psychiatric–Sensory Multimorbidity.

3.3.2. Lagged mediation

In the lagged analysis, 2013 ADL function and social and intellectual engagement both predicted higher cognitive levels from 2015 to 2020, but neither predicted the rate of cognitive change. Indirect effects on subsequent cognitive levels remained significant for Extensive multisystem (indirect effect = −0.081, 95% CI: −0.134 to −0.029; p = 0.004) and Sensory-PMM (indirect effect = −0.070, 95% CI: −0.099 to −0.041; p < 0.001), whereas Respiratory-PSS showed only marginal evidence of mediation. Cardiometabolic showed opposite-direction pathways, with poorer ADL function but higher engagement, which canceled each other out and yielded a nonsignificant total indirect effect. Even after accounting for both mediators, Sensory-PMM still showed a lower cognitive intercept and slower decline than Minimal morbidity, suggesting that other unmeasured pathways may also be involved.

3.4. Moderation by living environment quality

The moderating role of LEQ in the associations between multimorbidity patterns and cognitive trajectories was tested. In the main-effect model, unfavorable LEQ was associated with a lower cognitive intercept (β = −0.487, 95% CI: −0.749 to −0.225; p = 0.001), whereas moderate LEQ was not (β = −0.184, 95% CI: −0.386 to 0.018; p = 0.072); neither was associated with the cognitive slope. In the moderation model, only the interaction between moderate LEQ and Extensive multisystem was significantly associated with the cognitive intercept (β = −0.921, 95% CI: −1.770 to −0.071; p = 0.035), suggesting that even moderately deprived environments may amplify the cognitive burden of extensive multisystem disease. Given the number of interactions tested, this isolated finding should be interpreted with caution. Variance inflation factors were all below 8, indicating no severe multicollinearity (Figure 4). Full interaction estimates are available from the corresponding author upon request.

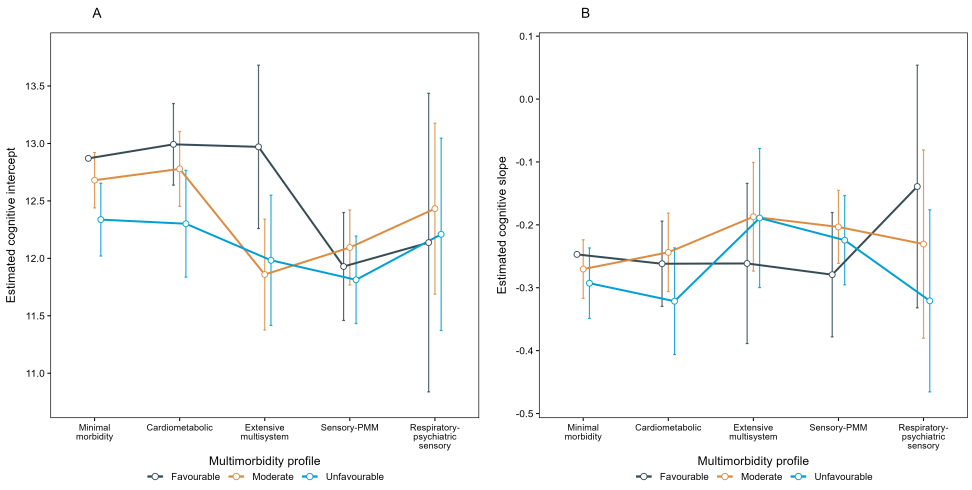

Figure 4. Moderating effect of Living Environment Quality (LEQ) on the association between multimorbidity patterns and cognitive trajectories. (A) Estimated cognitive intercept. (B) Estimated cognitive slope

Note: Panel A shows estimated cognitive intercepts; Panel B shows estimated cognitive slopes. Points represent marginal estimated means from the fully adjusted latent growth curve model–structural equation model, with error bars indicating 95% confidence intervals. LEQ was trichotomized as favorable (0–1), moderate (2–3), or unfavorable (4–6). The significant interaction between moderate LEQ and Extensive multisystem on the cognitive intercept ($\beta = -0.921$, $p = 0.035$) is highlighted. Sensory-PMM = Sensory–Psychiatric–Musculoskeletal Multimorbidity; Respiratory-PSS = Respiratory–Psychiatric–Sensory Multimorbidity.

3.5. Time-varying multimorbidity and cognitive trajectories

Linear mixed-effects models were further used to examine whether wave-specific multimorbidity patterns were associated with cognitive change during follow-up (Appendix Table A4, Appendix Figures A3 and A4). In the concurrent model, Extensive multisystem ($\beta = -0.386$, 95% CI: −0.602 to −0.170; $p < 0.001$) and Sensory-PMM ($\beta = -0.270$, 95% CI: −0.388 to −0.151; $p < 0.001$) were associated with lower cognitive scores at a given wave, whereas Cardiometabolic was associated with slightly higher concurrent cognition ($\beta = 0.142$, 95% CI: 0.003 to 0.282; $p = 0.046$), and Respiratory-PSS showed no significant association. For pattern × time interactions, only Cardiometabolic was associated with faster cognitive decline over time ($\beta = -0.028$, 95% CI: −0.052 to −0.005; $p = 0.019$). All pattern × time × urbanicity interactions were nonsignificant, providing little evidence of urban–rural heterogeneity. In the lagged model adjusted for prior-wave cognition, only Sensory-PMM remained associated with lower cognitive performance in the next wave ($\beta = -0.169$, 95% CI: −0.263 to −0.074; $p < 0.001$).

3.6. Sensitivity analyses

The four-class sensitivity analysis and the complete-case analysis ($n = 4{,}991$, excluding physical activity and household income because of high missingness) both produced results broadly consistent with the primary LGCM. In both analyses, Sensory-PMM retained the largest baseline cognitive disadvantage (four-class: $\beta = -0.540$, 95% CI: −0.698 to −0.381, $p < 0.001$; complete-case: $\beta = -0.845$, 95% CI: −1.021 to −0.669, $p < 0.001$) and a slower subsequent decline (four-class: $\beta = 0.036$, $p < 0.001$; complete-case: $\beta = 0.045$, $p < 0.001$). In the complete-case analysis, Extensive multisystem also retained a lower intercept ($\beta = -0.607$, $p < 0.001$) and a gentler slope ($\beta = 0.060$, $p = 0.004$); its association could not be assessed in the four-class analysis because this class was not separated. Cardiometabolic and Respiratory-PSS remained nonsignificant throughout, suggesting that neither the class-number choice nor the missing-data strategy drove the main conclusions.

4. Discussion

In this nine-year longitudinal study of 5,979 community-dwelling Chinese older adults, five multimorbidity patterns were identified, and their associations with cognitive trajectories were examined, together with the functional, behavioral, and environmental pathways involved. Rather than restating each estimate, the following discussion focuses on what these patterns add beyond disease counts, how their cognitive signatures differ over time, and what the pathway analyses imply for prevention.

These findings support the growing view that multimorbidity research should move beyond simple disease counts toward clinically meaningful phenotypes [4, 26]. Sensory-PMM, encompassing sensory impairment, psychiatric conditions, and musculoskeletal disorders, had the strongest and most consistent association with low baseline cognition. This pattern is biologically and socially plausible: sensory loss narrows incoming information, psychiatric symptoms sap motivation and social participation, and chronic pain weakens physical function [27, 28]. Extensive multisystem disease carried a similarly heavy cognitive burden, most likely

through cumulative physiological dysregulation and depletion of reserves [29]. By contrast, Cardiometabolic conditions showed no consistent baseline disadvantage, suggesting that cognitive risk depends not only on disease burden but also on how diseases cluster and shape functional and psychological well-being.

The low-intercept, gentle-slope signature observed in Sensory-PMM and Extensive multisystem should be interpreted as a floor effect rather than a protective mechanism [30]. When baseline cognition is already low, there is simply less territory left to lose, so slope differences flatten out. This pattern is consistent with cumulative disadvantage theory, whereby health inequalities crystallize early and cast long shadows across the life course [31]. The corresponding Cohen's *d* values were small to moderate, indicating clinical rather than merely statistical significance [32]. Because even modest cognitive deficits can disrupt disease self-management, medication adherence, and doctor–patient communication [33], identifying individuals with low cognitive baselines may be as important as tracking rapid decliners.

Time-varying analyses added a temporal dimension. Cardiometabolic participants showed no baseline disadvantage in the primary LGCM but declined faster during follow-up, consistent with the hypothesis that vascular and metabolic insults leave cognition relatively intact initially, only to erode it progressively [34]. In lagged models, only Sensory-PMM remained associated with lower cognition at the next wave, suggesting that this pattern may be a particularly stable harbinger of cognitive difficulty, possibly because its sensory and psychiatric components create persistent barriers to cognitive stimulation and social engagement [35].

The pathway analyses further clarified these associations. ADL function appeared to be a common pathway across all nonreference patterns, suggesting that functional capacity may be central to the multimorbidity–cognition link. Social and intellectual engagement was more selective, mediating mainly the Sensory-PMM association, which suggests that reduced engagement is especially tied to sensory and psychiatric burden rather than to multimorbidity in general. In the Cardiometabolic group, poorer ADL function and higher engagement neutralized each other; one interpretation is compensatory behavioral self-management, consistent with self-efficacy theory [36] and the patient health engagement model [37]. Such compensatory capacity may be less available in Sensory-PMM, where sensory impairment and psychiatric symptoms simultaneously erode function and limit the mobilization of compensatory behaviors.

Living environment quality also mattered. Unfavorable LEQ was associated with substantially lower baseline cognition, in line with evidence linking substandard housing, air pollution, and infrastructure deficits to cognitive harm through inflammation, restricted mobility, and reduced social participation [38, 39]. LEQ was not associated with the rate of decline, suggesting that environmental conditions may shape the cognitive starting point more than later deterioration. The interaction between moderate LEQ and Extensive multisystem was significant, indicating that even moderately deprived environments may amplify the cognitive burden of extensive multisystem disease. This pattern is compatible with the environmental vulnerability hypothesis [40]; however, given the number of interaction terms tested, this isolated finding should be regarded as hypothesis-generating and requires replication in independent cohorts.

These findings have several clinical and policy implications. First, cognitive risk stratification in multimorbidity should move beyond crude disease counts toward pattern-sensitive screening, with earlier cognitive and functional assessment for the Sensory-PMM and Extensive multisystem groups. Second, interventions should be pattern-calibrated: maintaining ADL function is a universal goal, but Sensory-PMM may benefit most from integrated management of sensory loss, depression, pain, and social isolation, whereas Cardiometabolic participants may benefit from structured programs that build on compensatory engagement. Third, cognitive health strategies should not stop at the clinic door—housing upgrades, clean fuel access, and air-quality improvement may need to be incorporated into chronic disease care, particularly for older adults with extensive multisystem burden.

Sensitivity checks supported the robustness of the findings. The four-class LCA and the complete-case analysis (n = 4,991) produced materially similar results, although the independent signal of Extensive multisystem could not be assessed in the four-class solution because this class was not separated. These findings suggest that neither the class-number choice nor the missing-data strategy drove the main conclusions.

Several limitations should be noted. Chronic conditions were ascertained mainly through self-reported physician diagnosis and medication use, which may introduce recall bias and misclassification. The observational design also limits causal inference. In the primary pathway analysis, exposure, mediators, and baseline cognition were measured in the same wave; although lagged models strengthened temporal ordering, reverse causation and residual confounding cannot be ruled out. Therefore, the results should be interpreted as longitudinal associations rather than causal effects. In addition, LCA is data driven, and class structure may vary according to the selected conditions, sample composition, and class number. Although posterior probabilities were acceptable, some classification uncertainty remains inherent to LCA. The small Respiratory-PSS group particularly requires external validation. Finally, mortality may compete with cognitive decline, as frailer participants may die before further cognitive deterioration is observed, raising the possibility of selection bias.

5. Conclusion

In this nine-year cohort of 5,979 Chinese older adults, five multimorbidity patterns showed distinct cognitive signatures. Sensory-PMM and Extensive multisystem multimorbidity were associated with lower baseline cognition but attenuated subsequent decline, consistent with floor effects, whereas Cardiometabolic multimorbidity predicted faster decline over time. ADL function constituted a shared pathway across patterns, social and intellectual engagement specifically mediated the Sensory-PMM association, and unfavorable living environments were associated with lower baseline cognition, with even moderate environmental adversity amplifying the burden of extensive multisystem disease. These findings support pattern-sensitive cognitive risk screening and interventions that preserve daily functioning, sustain social and intellectual engagement, and improve living environments for older adults with multimorbidity.

Author contributions

Conceptualization was led by Y.J.; Methodology was developed by Y.J. and X.S.; Validation was conducted by J.L.; Formal analysis was performed by Y.J.; Data curation was managed by Y.J. and J.L.; Writing – Original Draft Preparation was exclusively done by Y.J.; Writing – Review & Editing was executed by Q.L., X.Z., J.L., and X.S.; Supervision was provided by Q.L. and X.Z.; Project administration was managed by X.Z.

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Ethics approval and consent to participate

The study has received ethical approval from the Biomedical Ethics Review Committee of Peking University (IRB00001052-11015), with adherence to the Declaration of Helsinki's ethical guidelines. All participants provided signed informed consent.

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Appendix

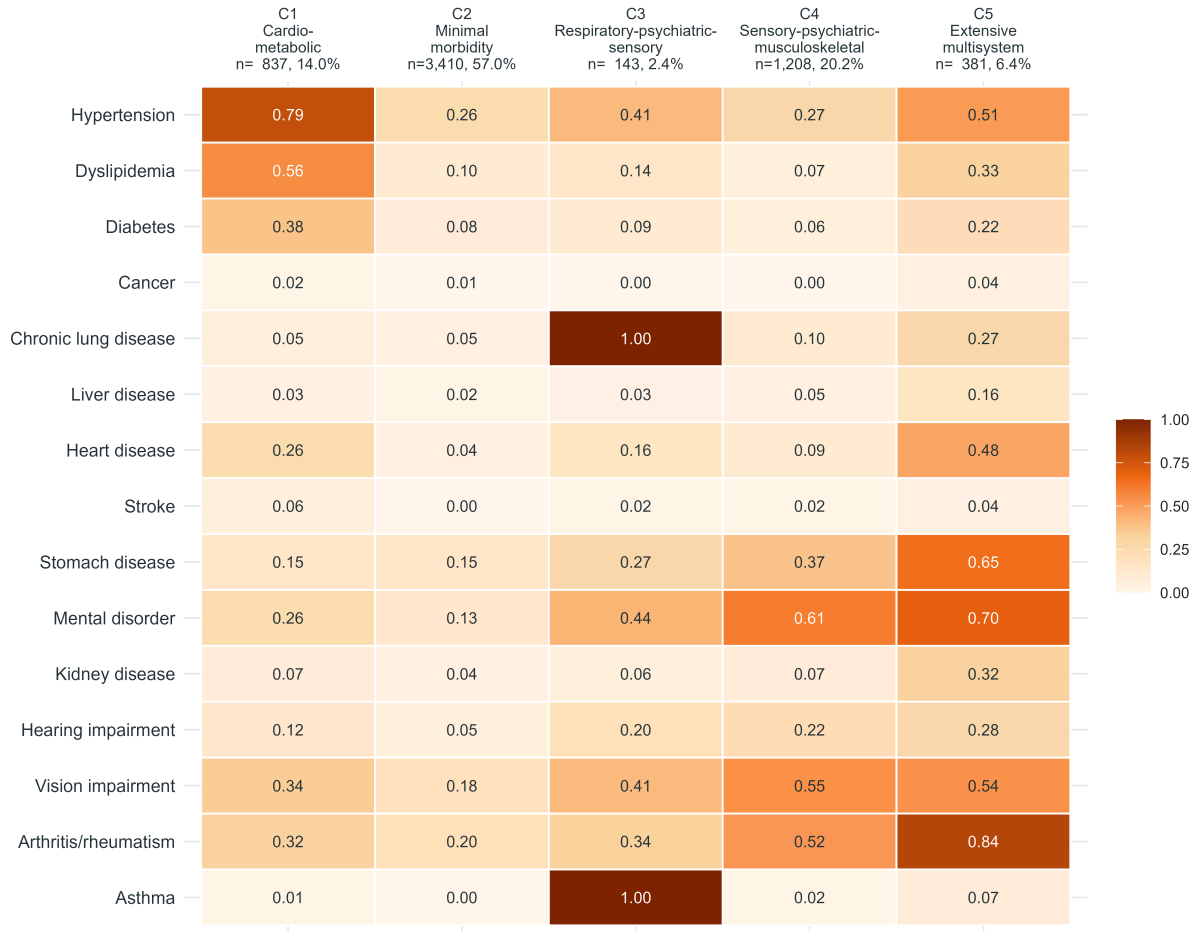

Figure A1. Conditional probability heatmap of the five-class Latent Class Analysis (LCA) model

Note: Rows represent individual chronic conditions, and columns represent the five identified multimorbidity profiles (C1–C5). The colour intensity indicates the conditional probability (range 0–1) of endorsing a given condition within each class. C1, Cardiometabolic; C2, Minimal morbidity; C3, Respiratory–PSS; C4, Sensory–PMM; C5, Extensive multisystem. Class prevalence and sample size are shown in the column headers.

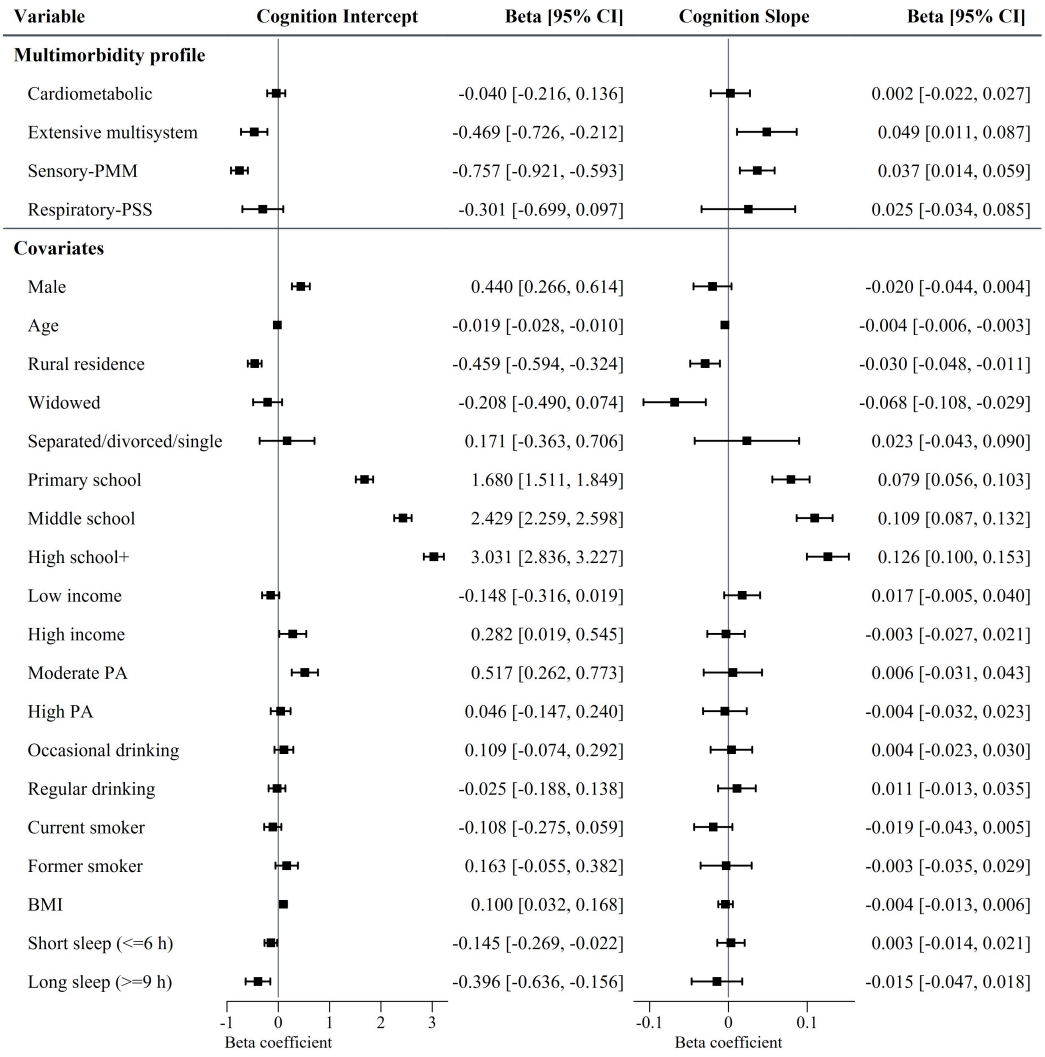

Figure A2. Forest plot of fully adjusted latent growth curve model (Model 3) estimates for cognitive intercept and slope

Note: Squares denote unstandardized beta coefficients and horizontal lines represent 95% confidence intervals. The reference line at zero indicates no effect. Estimates are adjusted for all covariates listed and are pooled across 20 multiply imputed datasets. PA = Physical Activity; BMI = Body Mass Index. Multimorbidity profiles are referenced against Minimal morbidity.

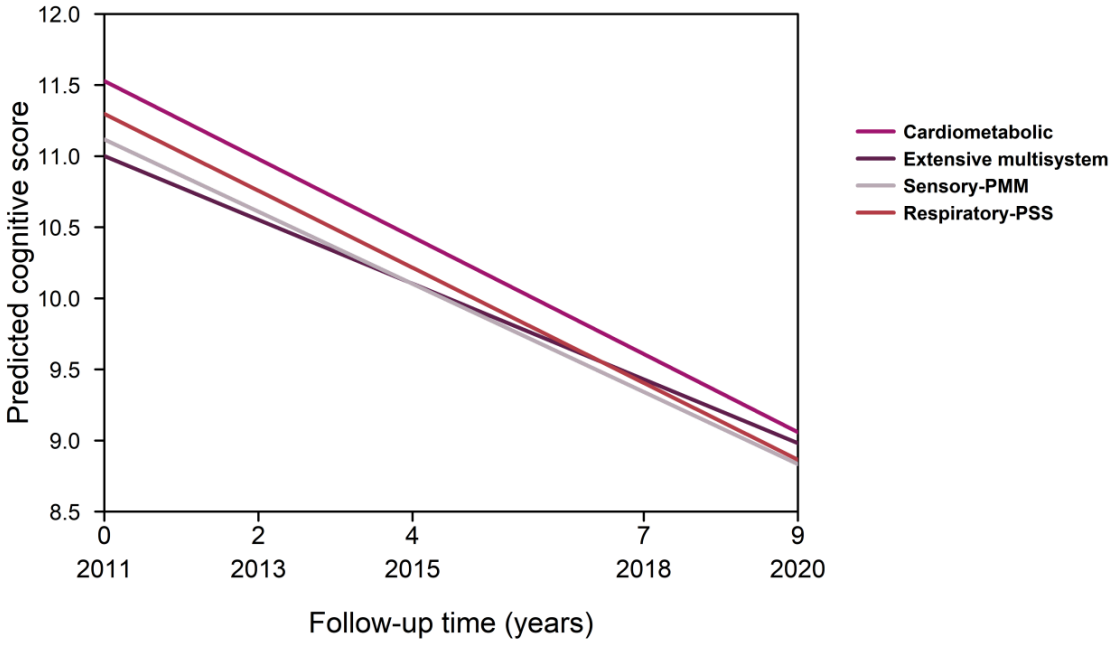

Figure A3. Predicted cognitive trajectories by time-varying multimorbidity profiles from the Linear Mixed-effects Model (LMM)

Note: Lines represent estimated marginal means of cognitive scores over the 9-year follow-up period (2011–2020), with the x-axis indicating years since baseline. The four multimorbidity profiles are contrasted against the Minimal morbidity reference group. Predictions are derived from the fully adjusted LMM (Model 3), with all covariates held at their mean or reference values. Estimates are pooled across 20 multiply imputed datasets.

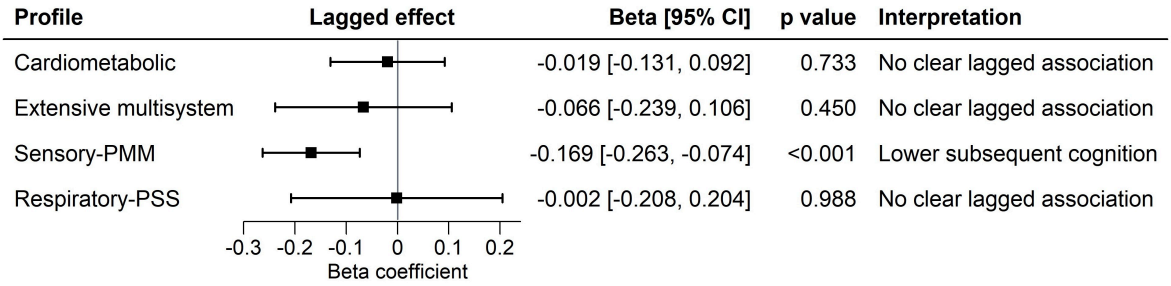

Figure A4. Lagged associations between time-varying multimorbidity profiles and subsequent cognitive score from the linear mixed-effects model

Note: Squares denote unstandardized beta coefficients and horizontal lines represent 95% confidence intervals for the effect of multimorbidity profile at one wave on cognitive score at the next wave (lagged by approximately 2 years). The reference line at zero indicates no effect. Multimorbidity profiles are referenced against Minimal morbidity. Estimates are adjusted for all covariates and are pooled across 20 multiply imputed datasets.

Table A1. Fit statistics for latent class analysis models with one through six classes at baseline (2011, *n* = 5,979)

Class	AIC	BIC	aBIC	cAIC	Entropy	AvePP
1	69,149.95	69,250.39	69,202.72	69,265.39	1.000	1.000
2	67,584.55	67,792.92	67,693.61	67,823.92	0.517	0.856
3	67,073.21	67,387.63	67,238.57	67,434.63	0.583	0.819
4	66,711.09	67,132.94	66,932.74	67,195.94	0.680	0.826
5*	66,605.06	67,134.04	66,883.00	67,213.04	0.602	0.752
6	66,558.03	67,194.15	66,892.27	67,289.15	0.604	0.732

Note: *Final model selected based on cross-wave consistency and clinical interpretability. Bold indicates the minimum BIC. AIC = Akaike's Information Criterion; BIC = Bayesian Information Criterion; aBIC = adjusted Bayesian Information Criterion; cAIC = consistent Akaike's Information Criterion; AvePP = Average Posterior Probability.

Table A2. LCA class profiles and longitudinal distribution (*n* = 5,979)

LCA Class Distribution by Wave				
Year	Class	*n*	Percentage (%)	AvePP
2011	Class 1 (Cardiometabolic)	837	14.00	0.697
	Class 2 (Minimal)	3,410	57.03	0.794
	Class 3(Respiratory-PSS)	143	2.39	0.929
	Class 4 (Sensory-PMM)	1,208	20.21	0.662
	Class 5 (Extensive)	381	6.37	0.701
2013	Class 1 (Minimal)	3,001	50.19	0.757
	Class 2 (Sensory-PMM)	1,374	22.98	0.666
	Class 3 (Extensive)	241	4.03	0.743
	Class 4 (Cardiometabolic)	1,180	19.74	0.725
	Class 5 (Respiratory-PSS)	183	3.06	0.855
2015	Class 1 (Cardiometabolic)	1,117	18.68	0.688
	Class 2 (Sensory-PMM)	1,689	28.25	0.684
	Class 3 (Extensive)	332	5.55	0.705
	Class 4 (Respiratory-PSS)	281	4.70	0.811
	Class 5 (Minimal)	2,560	42.82	0.760
2018	Class 1 (Respiratory-PSS)	412	6.89	0.783
	Class 2 (Minimal)	2,678	44.79	0.776
	Class 3 (Cardiometabolic)	1,137	19.02	0.715
	Class 4 (Sensory-PMM)	1,302	21.78	0.684
	Class 5 (Extensive)	450	7.53	0.731
2020	Class 1 (Respiratory-PSS)	334	5.59	0.858
	Class 2 (Cardiometabolic)	1,325	22.16	0.726
	Class 3 (Minimal)	2,422	40.51	0.784
	Class 4 (Extensive)	511	8.55	0.761

Class 5 (Sensory-PMM)	1,387	23.20	0.665

Note: LCA = Latent Class Analysis. *n* = class size; % = percentage of total sample; AvePP = Average Posterior Probability.

Table A3. Model fit indices, unconditional parameters, and R^2 summary

A. Model Fit Indices

Model	χ^2	df	*p*-value	CFI	TLI	RMSEA	SRMR	AIC	BIC	npar
Unconditional	651.35	10	< 0.001	0.955	0.955	0.104 [0.097–0.110]	0.058	137,121.7	137,188.7	10
Model 1 (LCA only)	685.42	28	< 0.001	0.956	0.937	0.063 [0.059–0.067]	0.030	136,346.3	136,493.6	22
Model 2 (LCA + demographics)	757.19	52	< 0.001	0.959	0.937	0.048 [0.045–0.051]	0.020	134,126.7	134,381.2	38
Model 3 (Fully adjusted)	788.80	79	< 0.001	0.959	0.935	0.039 [0.036–0.041]	0.014	134,086.8	134,461.7	56
Quadratic Model 3	636.72	52	< 0.001	0.966	0.919	0.043 [0.040–0.046]	0.011	133,988.7	134,544.4	83

B. Unconditional model parameters

Parameter	Estimate (SE) [95% CI], *p*-value
Intercept mean	12.87 (0.036) [12.80, 12.95], < 0.001
Slope mean	−0.247 (0.004) [−0.26, −0.24], < 0.001
Intercept variance	5.310 (0.141) [5.02, 5.60], < 0.001
Slope variance	0.032 (0.003) [0.03, 0.04], < 0.001
Intercept–slope covariance	0.126 (0.014) [0.10, 0.16], < 0.001
Intercept–slope correlation	0.307

C. R^2 summary

Model	Intercept R^2	Slope R^2
Model 1 (LCA only)	0.1330	0.0810
Model 2 (LCA + demographics)	0.4333	0.2064
Model 3 (Fully adjusted)	0.4426	0.2118

Note. All models were estimated across 20 multiply imputed datasets and pooled using Rubin's rules. RMSEA = Root Mean Square Error of Approximation; CFI = Comparative Fit Index; TLI = Tucker-Lewis Index; SRMR = Standardized Root Mean Square Residual; AIC = Akaike Information Criterion; BIC = Bayesian Information Criterion.

Table A4. Results from the time-varying linear mixed-effects model predicting global cognitive scores (2011-2020, n = 5,979)

Variable	Estimate (β)	SE	95% CI	z	p
Multimorbidity pattern (ref: Minimal)					
Cardiometabolic	0.142	0.071	0.003 to 0.282	1.996	0.046
Extensive	-0.386	0.110	-0.602 to -0.170	-3.504	< 0.001
Sensory-PMM	-0.270	0.061	-0.388 to -0.151	-4.453	< 0.001
Respiratory-PSS	-0.089	0.155	-0.394 to 0.216	-0.572	0.567
Year (continuous)	-0.246	0.006	-0.259 to -0.234	-38.690	< 0.001
Demographics					
Age, years (centered)	-0.033	0.004	-0.041 to -0.025	-8.065	< 0.001
Male (ref: female)	0.416	0.083	0.254 to 0.579	5.025	< 0.001
Rural residence (ref: urban)	-0.548	0.063	-0.672 to -0.423	-8.630	< 0.001
Widowed (ref: married/partnered)	-0.399	0.119	-0.632 to -0.165	-3.349	< 0.001
Separated/divorced/single (ref: married/partnered)	0.213	0.251	-0.280 to 0.706	0.848	0.397
Education (ref: illiterate)					
Primary school	1.909	0.075	1.763 to 2.056	25.535	< 0.001
Middle school	2.743	0.078	2.591 to 2.895	35.347	< 0.001
High school and above	3.404	0.096	3.216 to 3.593	35.433	< 0.001
Household income (ref: moderate)					
Low	-0.125	0.077	-0.277 to 0.027	-1.620	0.106
High	0.293	0.129	0.024 to 0.561	2.274	0.034
Smoking (ref: never)					
Current smoker	-0.182	0.082	-0.342 to -0.023	-2.237	0.025
Former smoker	0.129	0.113	-0.092 to 0.350	1.148	0.251
Drinking (ref: none)					
Occasional	0.112	0.089	-0.062 to 0.286	1.265	0.206
Regular	0.016	0.082	-0.145 to 0.176	0.192	0.848
Physical activity (ref: low)					
Moderate	0.533	0.127	0.284 to 0.782	4.194	< 0.001
High	0.019	0.092	-0.162 to 0.200	0.203	0.839
Health indicators					
BMI, kg/m² (centered)	0.100	0.030	0.041 to 0.159	3.310	0.001
Sleep duration (ref: 7–8 h)					
Short (≤ 6 h)	-0.167	0.059	-0.282 to -0.052	-2.851	0.004
Long (≥ 9 h)	-0.454	0.109	-0.667 to -0.241	-4.169	< 0.001
Multimorbidity × Year interaction					
Cardiometabolic× Year	-0.028	0.012	-0.052 to -0.005	-2.346	0.019
Extensive × Year	0.022	0.018	-0.013 to 0.056	1.242	0.214
Sensory-PMM × Year	-0.007	0.011	-0.030 to 0.015	-0.648	0.517

Respiratory-PSS × Year	−0.024	0.023	−0.069 to 0.021	−1.054	0.292

Note: Bold indicates statistically significant results ($p < 0.05$). SE = Standard Error; CI = Confidence Interval; ref = reference category; BMI = Body Mass index. Sleep duration was categorized as short (≤ 6 h) or long (≥ 9 h), with 7-8 h as the reference. The model included random intercepts for participants. Estimates were pooled across 20 multiply imputed datasets using Rubin's rules.

Table A5. Definition of living environment factors

Component	score	Measurement	Definition
Building type			
One-story building	1	"Is the building one story or multi-level building, how many stories?"	No
Multi-story building	0		Yes
Household water source			
Non-tap water use	1	"Does your residence have running water?"	No
Tap water use	0		Yes
Household fuel types			
All solid fuel	2	"What is the main heating energy source?""What is the main source of cooking fuel?"	Natural gas, biogas, liquefied petroleum gas, and electricity for cooking; and natural gas, liquefied petroleum gas, solar energy, electricity, and municipal heating for heating
Mixed-fuel use	1		Use of solid fuels for either cooking or heating
All clean fuel	0	"What is the main heating energy source?""What is the main source of cooking fuel?"	Coal, crop residues, wood, and charcoal for cooking; and crop residues, coal, wood, and charcoal for heating
Room temperature			
Unfavorable	1	"How is the temperature in this household?"	Very hot, hot, cold, or very cold
Suitable	0		Bearable
Ambient concentration of PM2.5			
Polluted	1	Measured by NASA Earth Observing System Distributed Information System	≥ 35ug/m^3
Good	0		＜ 35ug/m^3

Table A5. Continued

Component	score	Measurement	Definition
Living environment quality			
unfavorable	4-6		
moderate	2-3	Sum up 5 items above	—
favorable	0-1		