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The impact of living environmental factors on cognitive function and mild cognitive impairment: evidence from the Chinese elderly population

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Abstract

Objectives Mild cognitive impairment represents a pivotal stage in the cognitive decline of older adults, with a considerable risk of advancing to dementia. Recognizing how living environmental factors affect cognition is crucial for crafting effective prevention and intervention strategies. This study seeks to elucidate the relationship between various living environmental factors and cognitive function, with a specific focus on mild cognitive impairment, within a Chinese elderly population.

Methods This is a cross-section and longitudinal study. Utilizing data from CHARLS, our cross-sectional analysis included 4,401 participants, while the cohort study comprised 3,177 individuals. We assessed living environmental factors based on household fuel types, water sources, indoor temperatures, residential building types, and ambient PM2.5 levels. We employed multiple linear regression for cross-sectional analyses and Cox proportional hazards regression models for longitudinal assessments to determine the effects of living environments on cognitive function and MCI risk. Stratified analyses, interaction tests, and sensitivity analyses were conducted to further validate our findings.

Results The findings revealed that, compared to those in high-risk environments, participants in low-risk settings exhibited higher cognitive scores (β = 1.25, 95%CI: 0.85, 1.65), better mental status (β = 0.70, 95%CI: 0.48, 0.92), and improved episodic memory (β = 0.27, 95%CI: 0.13, 0.41). Over a 7-year follow-up, the use of low-risk living environments (HR = 0.67, 95%CI: 0.49, 0.91), including clean fuels (HR = 0.74, 95%CI: 0.57, 0.95) and tap water (HR = 0.84, 95%CI: 0.71, 1.00), demonstrated a protective effect against MCI development. This correlation remained significant regardless of age, gender, residence, education level, smoking, alcohol consumption, and depression.

Conclusion This research provides substantial evidence that living environmental factors significantly affect cognitive function and MCI risk in Chinese older adults. Enhancing living conditions may be a key strategy for promoting cognitive health and preventing MCI in this demographic. Further research is necessary to explore the long-term

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impacts and potential intervention strategies to optimize living environments for better cognitive outcomes in aging populations.

Keywords Living environment, Cognitive function, Mild cognitive impairment, CHARLS

Background

Mild cognitive impairment (MCI) is a state between normal cognitive aging and dementia [1], where a certain degree of cognitive decline exists but does not meet the diagnostic criteria for dementia [2], and is often regarded as a pre-dementia stage [3]. A systematic review indicates that the current global prevalence of MCI among the elderly is approximately 15.56% [4], with age-specific rates of 11.50% for those aged 60–69, 15.76% for those aged 70–79, and 21.27% for those aged 80 or older, suggesting a positive correlation between MCI prevalence and increasing age. In other studies, the prevalence of MCI in the elderly is even as high as 20% ~ 30% [5]. Currently, the overall prevalence of MCI among the elderly in China is 15.5%, which translates to approximately 38.77 million people [6]. This represents a significant portion of the population and highlights the substantial impact of MCI in China. Individuals with MCI are at an elevated risk of transitioning to dementia, with 6%-15% converting annually [7] and nearly 50% progressing within five years [8, 9], imposing significant burdens on patients, families, and society [10]. With China's substantial elderly population and the ongoing demographic shift towards an older society, MCI has emerged as a critical health management concern, both nationally and globally.

Numerous factors contribute to cognitive decline in older adults, including genetic susceptibility [11], education level [12], depression [13], and cardiovascular disease [14]. Environmental factors play a significant role in cognitive health. Research indicates that exposure to high-risk environmental factors, such as elevated levels of heavy metals and occupational hazards, can heighten the risk of dementia [15]. Conversely, long-term exposure to green spaces has been associated with beneficial effects on cognitive function [16]. Moreover, the neighborhood social environment also influences cognitive health in older adults, as highlighted by recent reviews [17]. Moreover, as urbanization progresses, environmental factors such as fuel combustion [18], exposure to particulate matter [19], and environmental pollution [20] have been identified as significant contributors to cognitive decline and impairment. Research from various countries has demonstrated that prolonged exposure to ambient particulate matter (such as PM2.5 and PM10) substantially impairs cognitive function in middle-aged and older adults [19]. Furthermore, the use of solid fuels has been linked to adverse cognitive outcomes; a 7-year cohort study identified solid fuel use as a factor in 3–18% of cognitive decline cases [21]. A study by Luo et al. reported that users of solid fuels scored 0.81 points lower in overall cognition, 0.63 points lower in mental state, and 0.16 points lower in situational memory compared to those using cleaner fuels [22]. Water is essential for human health, especially brain function [23], and studies have shown that non-tap water users have reduced cognitive abilities compared to tap water users [24]. Additionally, the influence of residential type and indoor temperature on cognitive health in this population is not yet well understood.

In contemporary research, while numerous environmental factors have been implicated in the potential degradation of cognitive function among older adults, the majority of studies concentrate on evaluating the impact of individual elements [18, 19, 24], neglecting the interplay and synergistic effects of these factors. The environment is a multifaceted, interconnected system; factors typically do not operate in isolation but interact to influence cognitive health. For instance, exposure to PM2.5 may coincide with the use of solid fuels for domestic heating and cooking, which could exacerbate poor indoor air quality and elevate indoor temperatures [22]. The aggregate effect of such factors may exert a more pronounced negative influence on cognitive function than any single element alone.

This study aims to address this gap by examining environmental factors within the China Health and Retirement Longitudinal Study (CHARLS) dataset, including PM2.5 levels, fuel usage, water sources, residential characteristics, and indoor temperature. We will explore their collective effects on cognitive function and the incidence of MCI among older adults. Utilizing multivariate statistical analysis and controlling for potential confounders, we seek to delineate the specific contributions of various environmental factors to cognitive health and assess their interrelations. This comprehensive approach is expected to yield broader strategies and recommendations for safeguarding cognitive well-being in the elderly.

Methods

Study population

The China Health and Retirement Longitudinal Study (CHARLS) is a comprehensive, ongoing national cohort study initiated in 2011 and conducted biennially. It aims to provide high-quality microdata on households and individuals aged 45 and above in China, with a focus on understanding the aging process and fostering interdisciplinary aging research. The baseline survey employed a multi-stage probability proportionate to size (PPS) sampling method, encompassing 450 villages, 150 counties, and 28 provinces, involving over 17,000 individuals from approximately 10,000 households. The study encompasses a broad spectrum of variables, including household demographics, health status, healthcare utilization, insurance, employment, income, expenditure, assets, and physical measurements, in addition to blood sample collection.

In this study, we analyzed CHARLS data from 2011 to 2018, employing both cross-sectional and longitudinal analyses to investigate the relationship between the living environment and cognitive function in older adults. Stringent inclusion criteria were applied to the study population to ensure data relevance and accuracy. We excluded 10,148 participants under 60 years of age, 1,032 with missing environmental data, and 2,127 without complete cognitive function information. The cross-sectional study included 4,401 participants. For the longitudinal analysis, 440 participants with baseline MCI and 784 without follow-up data were excluded, resulting in a sample of 3,177 participants (Fig. 1).

Definition of living environmental factors

Living environmental factors were evaluated using a structured questionnaire that encompassed five key indicators: outdoor PM2.5 levels, household energy sources, water sources, building types, and indoor temperatures [25, 26]. Annual average PM2.5 values at the city level were obtained from the National Aeronautics and Space Administration's (NASA) Earth Observing System Distributed Information System. Specifically, the Goddard Earth Observing System's chemical transport model and the geographically weighted regression model were utilized to estimate ambient PM2.5 concentrations based on aerosol optical depth data from multiple satellites [27]. The CHARLS database lacks direct information on PM2.5 levels but includes respondents' city data, which allowed us to match NASA's annual city-level PM2.5 averages based on prefecture-level cities. In accordance with the air quality standards set by China's Ministry of Ecology and Environment (https://www.mee.gov.cn/ywgz/fgbz/bz/bzwb/dqhjbh/dqhjzlbz/201203/W020120410330232398521.pdf), PM2.5 levels exceeding 35 μg/m^3 were categorized as polluted, assigned a score of 1, while lower levels were scored as 0.

Household energy sources were dichotomized into clean and solid fuels. Clean fuels comprised natural gas, biogas, liquefied petroleum gas, and electricity for cooking; and natural gas, liquefied petroleum gas, solar energy, electricity, and municipal heating for heating. Solid fuels included coal, crop residues, wood, and charcoal for cooking; and crop residues, coal, wood, and charcoal for heating. Participants using clean fuels for both cooking and heating received 2 points, those using clean fuels for one or the other received 1 point, and those using no clean fuels received 0 points.

Previous research has indicated that residential environment factors, such as residential trajectory and the distance of the residence from major roads, are

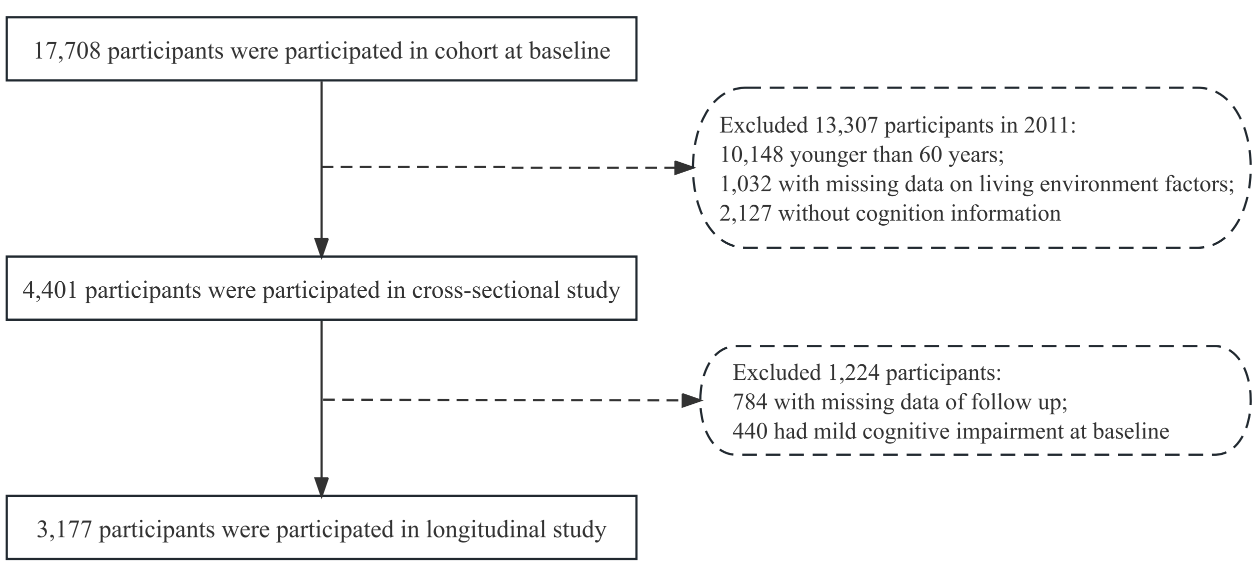

Fig. 1 Visual flowchart for population screening

associated with cognitive function in older adults [28, 29]. These studies suggest that the type of building in which a person resides could potentially influence their cognitive function. Therefore, in our study, we collected data on the type of building to explore its relationship with cognitive function in the elderly. Building type data were collected by asking respondents whether their building was a single-story or multi-story structure and, if so, the number of stories. Multi-story residences were assigned a score of 1, while single-story residences were scored as 0. Access to tap water was indicated by a score of 1, and the absence of tap water by a score of 0. Room temperature assessments were based on the interviewer's subjective evaluation, with very hot, hot, cold, or very cold conditions scored as 0, and all other conditions scored as 1. The overall living environment score was calculated by summing the scores of these five items, with higher scores indicating a better living environment, ranging from 0 to 6. This score was then categorized into three risk levels: high risk (0–2 points), medium risk (3–4 points), and low risk (5–6 points).

Cognitive function assessment

Cognitive functioning was assessed across two dimensions: episodic memory and mental status [30, 31], with a combined score ranging from 0 to 31, where higher scores denote superior cognitive performance [32]. Episodic memory, scored from 0 to 20, was derived from the sum of immediate (0–10 points) and delayed (0–10 points) word recall [33]. Participants were required to recall as many words as possible from a list of ten Chinese words presented by the interviewer for immediate recall and again after completing other assessments for delayed recall, with each correct word earning 1 point.

The mental status dimension, scored from 0 to 11, comprised three components: Orientation (0–5 points), Calculation (0–5 points), and Drawing (0–1 point), with Orientation and Calculation assessed via the Telephone Interview for Cognitive Status (TICS). Orientation tasks included identifying the current year, month, day of the week, and season, with one point awarded for each correct response. The Calculation component involved participants subtracting 7 from 100 consecutively five times, with one point for each correct calculation. The Drawing task required participants to accurately replicate an overlapping pentagon figure, with one point awarded for a precise drawing.

The diagnosis of mild cognitive impairment (MCI) lacks a uniform standard. In this study, we employed the aging-associated cognitive decline (AACD) criteria to define MCI, which is characterized by performance at least one standard deviation below the age-specific norm [34, 35]. Participants over 60 years old were categorized in five-year age brackets, and those meeting the AACD criteria within their respective age group were classified as having MCI.

Definition of covariates

This study incorporated demographic and sociological characteristics as covariates, including age (represented as a continuous variable), sex (designated as male or female), geographic location (urban or rural), marital status (unmarried or married), education level (categorized as primary and below or secondary and above), and household per capita consumption (continuous). Drawing from prior research indicating associations between cognitive function and various factors [18, 36, 37], we also included smoking, alcohol use, hypertension, diabetes mellitus, dyslipidemia, body mass index (BMI), and depression. Smoking and alcohol consumption statuses were categorized into three groups: current, former, and never. Information on hypertension, diabetes mellitus, and dyslipidemia was obtained through participant self-report, in response to the query, "Have a physician diagnosed you with any of the following conditions?" BMI was determined using the standardized formula of weight (in kilograms) divided by height (in meters) squared. The 10-item Centre for Epidemiological Studies Depression Scale (CESD-10)—utilizing a maximum score of 30, with a score of 10 or above suggestive of depression—assessed the presence of depressive symptoms [38]. Lastly, venous blood samples were collected from participants in a fasted state, subsequently transported by a dedicated cold-chain logistics company to the Chinese Center for Disease Control and Prevention in Beijing for further analysis.

Statistical analysis

This study employed a suite of statistical analyses to investigate the influence of environmental factors on cognitive function and MCI in older adults. We began by employing descriptive statistics for continuous variables, depicted as means ± standard deviation (SD), while categorical variables were represented as frequencies and percentages to elucidate baseline characteristics.

Differences between groups were evaluated using chi-square or Kruskal Wallis tests. To ensure the accuracy of our results, we used the variance inflation factor (VIF) method to test for multicollinearity. If VIF values exceed 10, it indicates a serious multicollinearity issue between variables, necessitating the exclusion of the corresponding variables. We further utilized multiple linear regression models to analyze cross-sectional data, thereby exploring the relation between individual environmental risk factors, the living environment risk score, and cognitive function in older adults. To more comprehensively assess the effect of environmental factors on the risk of MCI, a Cox proportional hazards regression model was used for prospective analysis. With follow-up time as the timescale, this model facilitated the computation of hazard ratios (HR) and their corresponding 95% confidence intervals (CI) for each environmental factor, better evaluating the long-term impact of these factors on MCI risk over time.

In creating the models, initial adjustments were made for sociodemographic covariates, such as age, gender, residence, marital status, education level, and household per capita consumption, to account for their potential confounding effects. Model 2 incorporated additional adjustments for health-related variables, including smoking status, alcohol consumption, BMI, diabetes, hypertension, dyslipidemia, depression, and various biomarkers, ensuring the results' precision and reliability.

We conducted interaction analyses to inspect whether individual characteristics (such as age, gender, residence, education level, smoking and drinking habits, and depression status) could potentially modulate the living environment's impact on MCI incidence in older adults. For treatment of missing covariate data, we employed the MissForest technique, applying the missForest package in R. This non-parametric imputation method leverages the robustness of the random forest machine learning algorithm to accurately handle missing values, especially in complex datasets [39]. In addition, sensitivity analyses were performed after excluding covariate data subjected to multiple imputation. All statistical evaluations were conducted using R 4.1.0; a two-tailed P-value of less than 0.05 was considered to indicate statistical significance.

Results

Baseline characteristics of study participants

Table 1 presents the baseline characteristics of the 4,401 participants, with a mean age of 67.17 years (SD: 6.04) and 56.85% males. Consistent with prior research, 17.81% (784 participants) were diagnosed with MCI based on the AACD criteria. Following a mean follow-up of 62.03 months (SD: 23.63), 18.63% (592 participants) of the 3,177 subjects experienced incident MCI. The low-risk group was characterized by higher education levels, urban residency, greater per capita consumption, absence of dyslipidemia (all p-values < 0.05). Furthermore, a superior living environment was correlated with a reduced MCI prevalence and enhanced baseline scores in mental status, episodic memory, and cognitive testing (all p-values < 0.05).

Supplementary Table 1 indicates that participants residing in single-story buildings, using non-tap water, and relying on solid fuels for cooking and heating were more likely to be diagnosed with MCI. Cognitive function, mental status, and episodic memory scores exhibited a decline with increasing age among older adults, as detailed in Supplementary Table 2 and Fig. 2.

Associations between living environmental factors and cognitive function in the cross-sectional study

The multicollinearity screening results indicated that all VIF values were less than 10, suggesting no multicollinearity among the environmental factors. Therefore, all factors could be included in the analysis (Supplementary Table 7). Table 2 delineates the association between aggregated living environment scores and cognitive function. Utilizing multiple linear regression models, we observed that individuals in low-risk living environments exhibited superior cognitive functioning across all three cognitive measures compared to those in medium- and high-risk environments. Specifically, the mean overall cognition score was 0.92 (95% CI: 0.62, 1.23) and 2.65 (95% CI: 2.25, 3.05) higher for older adults in medium- and low-risk environments, respectively, as compared to those in high-risk environments ($p < 0.05$). This pattern persisted after full adjustment [medium risk: $\beta = 0.46$, 95% CI (0.18, 0.74), $p < 0.05$; low risk: $\beta = 1.25$, 95% CI (0.85, 1.65), $p < 0.05$]. In the adjusted model, mental status scores for older adults in medium- and low-risk environments were elevated by 0.37 (95% CI: 0.22, 0.53) and 0.70 (95% CI: 0.48, 0.92) points, respectively, and their episodic memory scores by 0.04 (95% CI: -0.06, 0.14) and 0.27 (95% CI: 0.13, 0.41) points, in comparison to those in high-risk environments.

Supplementary Table 4 reveals that residence in multi-story buildings, access to running water, and use of clean fuels were each associated with higher cognitive test scores [Multi-story building: $\beta = 0.51$, 95% CI (0.24, 0.79), $p < 0.001$; Tap water use: $\beta = 0.78$, 95% CI (0.52, 1.04), $p < 0.001$; Clean fuel use: $\beta = 0.93$, 95% CI (0.58, 1.28), $p < 0.001$], with the type of fuel used for heating and cooking exerting the most significant influence. The impact of individual living environment factors on mental status and memory performance varied, with the use of clean fuels [$\beta = 0.58$, 95% CI (0.38, 0.78), $p < 0.001$] being the most beneficial for mental status, and tap water use [$\beta = 0.23$, 95% CI (0.14, 0.32), $p < 0.001$] being the most effective for enhancing episodic memory.

Associations between living environmental factors and mild cognitive impairment in the longitudinal study

Table 3 presents data indicating that after a mean follow-up of 5.17 years, 592 new cases of MCI were identified, representing an 18.63% prevalence. The MCI prevalence varied across living environments, with 21.67% in high-risk, 18.16% in medium-risk, and 10.14% in low-risk settings. After adjusting for potential confounders,

Table 1 Baseline characteristics for the study population in the baseline

Characteristics	Total population	Living environmental score			*P*-value
		High risk	Middle risk	Low risk	
N	4401	2249	1486	666	
Age, years	67.17 ± 6.04	67.27 ± 5.95	66.96 ± 6.08	67.29 ± 6.27	0.264
Sex, n (%)					0.077
Male	2502 (56.85%)	1314 (58.43%)	813 (54.71%)	375 (56.31%)	
Female	1899 (43.15%)	935 (41.57%)	673 (45.29%)	291 (43.69%)	
Education, n (%)					< 0.001
Primary school and below	3529 (80.19%)	1911 (84.97%)	1200 (80.75%)	418 (62.76%)	
Junior high school and above	872 (19.81%)	338 (15.03%)	286 (19.25%)	248 (37.24%)	
Marital status, n (%)					0.51
married	3611 (82.05%)	1840 (81.81%)	1214 (81.70%)	557 (83.63%)	
unmarried	790 (17.95%)	409 (18.19%)	272 (18.30%)	109 (16.37%)	
Residence, n (%)					< 0.001
Urban	1668 (37.90%)	491 (21.83%)	687 (46.23%)	490 (73.57%)	
Rural	2733 (62.10%)	1758 (78.17%)	799 (53.77%)	176 (26.43%)	
Smoking, n (%)					< 0.001
now	1524(34.63%)	865 (38.46%)	482 (32.44%)	177 (26.58%)	
ever	573 (13.02%)	297 (13.21%)	187 (12.58%)	89 (13.36%)	
never	2304 (52.35%)	1087 (48.33%)	817 (54.98%)	400 (60.06%)	
Drinking, n (%)					0.051
now	1457 (33.11%)	782 (34.77%)	463 (31.16%)	212 (31.83%)	
ever	578 (13.13%)	307 (13.65%)	183 (12.31%)	88 (13.21%)	
never	2366 (53.76%)	1160 (51.58%)	840 (56.53%)	366 (54.95%)	
Hypertension, n (%)					0.055
No	2984 (67.80%)	1555 (69.14%)	1001 (67.36%)	428 (64.26%)	
Yes	1417 (32.20%)	694 (30.86%)	485 (32.64%)	238 (35.74%)	
Diabetes, n (%)					0.21
No	4088 (92.89%)	2101 (93.42%)	1378 (92.73%)	609 (91.44%)	
Yes	313 (7.11%)	148 (6.58%)	108 (7.27%)	57 (8.56%)	
Hyperlipidaemia, n (%)					< 0.001
No	3949 (89.73%)	2052 (91.24%)	1339 (90.11%)	558 (83.78%)	
Yes	452 (10.27%)	197 (8.76%)	147 (9.89%)	108 (16.22%)	
Depression, n (%)					< 0.001
No	3073 (69.83%)	1433 (63.72%)	1104 (74.29%)	536 (80.48%)	
Yes	1328 (30.17%)	816 (36.28%)	382 (25.71%)	130 (19.52%)	
MCI, n (%)					< 0.001
No	3617 (82.19%)	1759 (78.21%)	1253 (84.32%)	605 (90.84%)	
Yes	784 (17.81%)	490 (21.79%)	233 (15.68%)	61 (9.16%)	
Total household per capita consumption, yuan	6561.22 ± 7417.09	5400.53 ± 5254.59	6566.34 ± 7686.87	10,469.29 ± 10,902.30	< 0.001
BMI (kg/m2)	23.28 ± 11.41	22.99 ± 12.00	23.37 ± 12.72	24.04 ± 3.68	0.103
Mental status	7.82 ± 2.65	7.38 ± 2.68	8.01 ± 2.63	8.86 ± 2.22	< 0.001
Episodic memory	6.59 ± 3.11	6.32 ± 2.98	6.61 ± 3.12	7.49 ± 3.38	< 0.001
Baseline cognitive test score	14.41 ± 4.72	13.70 ± 4.61	14.62 ± 4.60	16.35 ± 4.73	< 0.001

a significant inverse relationship was observed between MCI risk and environmental quality, suggesting that older adults residing in superior environments faced a reduced risk of MCI [HR = 0.93, 95% CI: 0.87, 1.00; $p = 0.023$]. When considering the environment score as a categorical variable, both the unadjusted and demographically

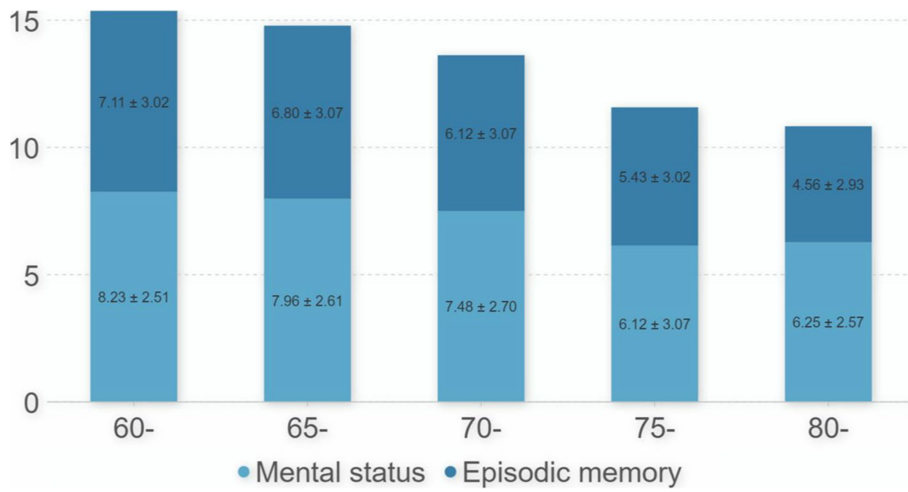

Fig. 2 Cognitive function grouped by age

Table 2 Association between living environmental factors and cognitive function at baseline

	Living environmental score			
	continuous variable	**Low risk**	**Middle risk**	**High risk**
Total cognitive test score				
Crude	0.65 (0.55, 0.74)*	2.65 (2.25, 3.05)*	0.92 (0.62, 1.23)*	Reference
Model 1	0.38 (0.28, 0.47)*	1.41 (1.02, 1.81)*	0.57 (0.29, 0.85)*	Reference
Model 2	0.33 (0.23, 0.42)*	1.25 (0.85, 1.65)*	0.46 (0.18, 0.74)*	Reference
Mental status				
Crude	0.35 (0.30, 0.41)*	1.48 (1.25, 1.70)*	0.63 (0.46, 0.80)*	Reference
Model 1	0.20 (0.15, 0.25)*	0.79 (0.56, 1.01)*	0.43 (0.28, 0.59)*	Reference
Model 2	0.17 (0.12, 0.23)*	0.70 (0.48, 0.92)*	0.37 (0.22, 0.53)*	Reference
Episodic memory				
Crude	0.15 (0.12, 0.18)*	0.59 (0.45, 0.72)*	0.15 (0.05, 0.25)*	Reference
Model 1	0.09 (0.06, 0.12)*	0.31 (0.17, 0.45)*	0.07 (-0.03, 0.17)	Reference
Model 2	0.08 (0.04, 0.11)*	0.27 (0.13, 0.41)*	0.04 (-0.06, 0.14)	Reference

Outcome [β(95%CI)]: Cognition, metal status, episodic memory

Adjusted for: age; gender; education; residential area; marital status; total household per capita consumption; smoking; drinking; hypertension; diabetes; dyslipidemia; BMI; depression

* $P < 0.05$

and sociologically adjusted models demonstrated a significant, monotonic decline in MCI risk with increasing environmental quality ($p < 0.05$ for all trends), indicating that individuals in low- and medium-risk environments were less likely to develop MCI compared to those in high-risk settings.

Supplementary Table 5 details the impact of specific environmental factors on MCI, revealing that access to tap water and use of clean fuels were associated with a lower risk of MCI [Tap water use: HR = 0.84, 95% CI: 0.71, 1.00; $p = 0.038$; Clean fuel use: HR = 0.74, 95% CI: 0.57, 0.95; $p = 0.017$], suggesting a protective effect of these factors against the development of MCI.

Subgroup analyses and sensitivity analyses

Table 4 displays stratified analyses by age, gender, education, residence, smoking status, alcohol consumption, and depression. The findings within each subgroup were largely in agreement with the primary results, with no significant effect modification observed across the strata (all p-values for interaction < 0.05). To ascertain the robustness of our findings, we conducted sensitivity analyses, excluding participants with multiply imputed

Table 3 Longitudinal association between living environment and MCI in different models

Living environmental score	Incidence of MCI, n (%)	Crude	*P*-value	Model 1	*P*-value	Model 2	*P*-value
Continuous	592 (18.63%)	0.85 (0.80, 0.90)	< 0.001	0.91 (0.86, 0.97)	0.006	0.93 (0.87, 0.99)	0.023
Categorized							
High risk	342 (21.67%)	Reference		Reference		Reference	
Middle risk	199 (18.16%)	0.81 (0.68, 0.96)	0.018	0.89 (0.75, 1.07)	0.221	0.93 (0.77, 1.11)	0.425
Low risk	51 (10.14%)	0.44 (0.33, 0.59)	< 0.001	0.63 (0.47, 0.87)	0.004	0.67 (0.49, 0.91)	0.011
P for trend		**< 0.001**		**0.021**		0.069	

Outcome: MCI, HR(95%CI)

Model 1 adjust for: age; gender; education; residential area; marital status; total household per capita consumption

Model 2 adjust for: age; gender; education; residential area; marital status; total household per capita consumption; smoking; drinking; hypertension; diabetes; dyslipidemia; BMI; depression

Table 4 Subgroup analyses of the association between living environmental factors and MCI in longitudinal study

Subgroup	Incidence of MCI, n (%)	*P*-value	Living environmental score			*P* for interaction
			Low risk	Middle risk	High risk	
Age		0.05				0.63
< 75	551 (19.05%)		0.65 (0.47, 0.91)*	0.94 (0.78, 1.13)	Reference	
≥ 75	41 (14.39%)		0.61 (0.07, 5.24)	0.63 (0.07, 5.44)	0.68 (0.07, 6.13)	
Gender		< 0.001				0.72
female	290 (23.39%)		0.69 (0.44, 1.08)	0.88 (0.67, 1.15)	Reference	
male	302 (15.59%)		0.51 (0.18, 1.40)	0.78 (0.29, 2.05)	0.78 (0.29, 2.05)	
Education		< 0.001				0.06
Primary school and below	543 (22.36%)		0.70 (0.51, 0.97)*	0.88 (0.73, 1.06)	Reference	
Junior high school and above	49 (6.56%)		0.10 (0.03, 0.35)*	0.33 (014, 0.77)*	0.21 (0.09, 0.48)*	
Residence		< 0.001				0.12
Urban	161 (13.07%)		0.47 (0.29, 0.74)*	0.75 (0.53, 1.07)	Reference	
Rural	431 (22.16%)		2.36 (0.71, 7.85)	2.73 (0.87, 8.59)	2.74 (0.87, 8.59)	
Smoking		0.33				0.78
never	299 (18.82%)		0.60 (0.38, 0.92)*	0.84 (0.65, 1.09)	Reference	
now	224 (19.33%)		0.61 (0.19, 1.90)	0.89 (0.31, 2.56)	0.83 (0.29, 2.41)	
ever	69 (16.08%)		3.13 (0.29, 34.05)	3.32 (0.37, 30.10)	3.65 (0.39, 33.93)	
Drinking		0.63				0.83
never	314 (19.11%)		0.68 (0.44, 1.05)	0.93 (0.73, 1.19)	Reference	
now	209 (18.51%)		0.50 (0.17, 1.46)	0.66 (0.24, 1.79)	0.82 (0.30, 2.22)	
ever	69 (17.04%)		0.38 (0.04, 3.41)	0.57 (0.08, 4.16)	0.49 (0.06, 3.66)	
Depression		< 0.001				0.18
No	393 (16.95%)		0.57 (0.39, 0.83)*	0.89 (0.71, 1.10)	Reference	
Yes	199(23.22%)		1.06 (0.31, 3.60)	1.07 (0.33, 3.44)	1.00 (0.31, 3.21)	

Outcome: MCI, HR(95%CI)

Adjust for: age; gender; education; residential area; marital status; total household per capita consumption; smoking; drinking; hypertension; diabetes; dyslipidemia; BMI; depression

[*] indicates $p < 0.05$

covariate data. These analyses yielded results that were in concordance with those obtained after imputation, as detailed in Supplementary Table 6.

Discussion

This study scrutinized the relationship between living environment quality and cognitive function, as well as MCI, among elderly individuals in China through both cross-sectional and longitudinal analyses. The findings suggest that when contrasted with those inhabiting high-risk environments, participants residing in low-risk environments demonstrated enhanced cognitive scores. Over a seven-year follow-up period, a low-risk living environment, characterized by the use of clean fuels and tap water, showed a protective association against MCI—an association independent of factors such as age, gender, locality, education, smoking habits, alcohol consumption, and depression status.

Utilization of solid fuels may significantly contribute to cognitive decline and the incidence of MCI, particularly concerning mental state. This may be attributed to the higher release levels of gaseous pollutants (like PM2.5 particles, nitrogen oxides, and ozone) during solid fuel combustion compared to clean fuels. These pollutants, potentially escalating white matter hyperintensity volume and total brain volume, can adversely affect cognitive functionality. They may also induce neurological diseases through mechanisms of oxidative stress [40] and neuroinflammation [41]. Moreover, air pollutants from solid fuel combustion can indirectly engender cerebral damage [42–44], including vascular system damage that leads to cerebral ischemia or the leakage of neurotoxic proteins, and cytokines from lung damage reaching the brain, resulting in secondary neurotoxicity.

Elderly individuals utilizing tap water exhibited superior cognitive test performance, particularly within episodic memory dimensions. Longitudinal findings underscored an inverse correlation between tap water use and MCI—an observation that aligns with Zhai et al.'s findings [24]. Nonetheless, the embedded mechanisms driving this correlation remain ambiguous. The natural characteristics of water predispose it to neurotoxic heavy metals like aluminum, arsenic, copper, and manganese, which can potentially modulate cognition through pathways such as amyloid protein synthesis, proinflammatory signaling, neurodegeneration, and alterations in fundamental genetic expressions within the brain [45, 46]. However, these findings are still a subject of debate. Given that tap water typically undergoes extensive purification—incorporating coagulation, sedimentation, filtration, and disinfection—contaminant levels are significantly reduced. This fact may partially corroborate our conclusions, implying that tap water use mitigates MCI risk [47].

Accommodation types and indoor temperature also emerge as relevant factors for maintaining cognitive health in older adults. Residing in multi-story buildings, typically equipped with superior ventilation and temperature regulation systems, assists in fostering a conducive indoor environment for optimal cognitive function. A comfortable indoor temperature helps minimize physiological stress induced by extreme climates, thereby bolstering cognitive stability [48–50]. Conversely, our study found no substantial impact of PM2.5 on overall cognitive function in older adults, which deviates from Yao et al.'s previous studies that linked environmental particulates to cognitive decline in middle-aged and elderly Chinese subjects [19]. This dissonance could be attributed to PM2.5 not encapsulating all types of environmental particulates and possible heterogeneity within the study population.

This study's main strength lies in its novel application of a comprehensive living environment risk score method, which systematically investigates the cumulative impact of various environmental factors on cognitive function and MCI in older adults. Utilizing the representative CHARLS dataset offers pertinent insights for policymakers and public health officials to ameliorate living environments and promote cognitive health among older adults. Despite its innovative research design and methodology, this study carries several limitations. Firstly, the reliance on self-reported data may introduce recall bias and social desirability bias, affecting the accuracy of information on participants' health behaviors and conditions. Secondly, the environmental measures used in this study have certain limitations. The residential environment encompasses many aspects, but our study only included residential type, indoor temperature, tap water usage, PM2.5 levels, and fuel usage, which provides a limited perspective. Although PM2.5 serves as a crucial air pollution index, it fails to represent all air pollution types. Other contaminants such as ozone, sulfur dioxide, and nitrogen oxides, which could also compromise cognitive health, were not adequately incorporated in this study. Additionally, due to data constraints, the study mainly assessed the impact of baseline living environment scores on cognitive function and MCI risk in older adults, without considering the potential long-term health repercussions of evolving environmental quality. Future research is encouraged to monitor dynamic shifts in environmental quality and analyze the potential impact of these alterations on elderly cognitive health. While this study employed multiple imputation techniques to manage missing data and executed sensitivity analyses to confirm results' robustness, this approach may not entirely extirpate biases originating from missing data. This is because imputation may not fully control for confounding bias, particularly when there are complex interactions between covariates and outcome variables. Moreover, the imputed values may not be fully accurate, especially when there is a high degree of correlation among the covariates.

Conclusion

The results of this study unequivocally confirm a positive association between high-quality living environments and cognitive function, alongside a negative correlation with the susceptibility to mild cognitive impairment (MCI) in elderly Chinese individuals. Significantly, the use of clean fuels and tap water is identified as key protective factors against cognitive decline and MCI onset. These findings amplify the need to integrate environmental factors into research and remedial strategies surrounding cognitive health. Future research should place a higher emphasis on comprehending the intricate relationship between living conditions and cognitive impairment, thereby informing the development of targeted approaches for enhancing cognitive wellbeing and preventing MCI within aging populations.

Abbreviations

MCI	Mild cognitive impairment
CHARLS	China Health and Retirement Longitudinal Study
PPS	Probability Proportionate to Size
NASA	National Aeronautics and Space Administration
TICS	Telephone Interview for Cognitive Status
AACD	Aging-Associated Cognitive Decline
BMI	Body Mass Index
CESD-10	The 10-item Centre for Epidemiological Studies Depression Scale
SD	Standard Deviation
HR	Hazard Ratios
CI	Confidence Intervals

Supplementary Information

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Supplementary Material 1.

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Not Applicable.

Authors' contributions

Huanhuan Luo, Huixiu Hu and Zitian Zheng completed the writing of the first draft, the data analysis, and the revision of the paper, while Kang Yu and Chao Sun were responsible for the research design, the revision of the paper, and the funding of the grant.

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Data availability

CHARLS data is publicly accessible via its official website (charls.ccer.edu.cn/en).

Declarations

Ethics approval and consent to participate

CHARLS data has been approved by the Biomedical Ethics Committee of Peking University (approval number: IRB 00001052–11015), ensuring ethical research conduct with informed consent from all participants.

Consent for publication

Not Applicable.

Competing interests

The authors declare no competing interests.

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