

Health in All Policies: The Impact of the Healthy City Pilot Policy on Cognitive Health and Cognitive Health Inequality Among Older Adults in China—Evidence from Difference-in-Differences and Double Machine Learning

Jialin Xu

Nanjing University of Chinese Medicine

Longyi Huang

Nanjing University of Chinese Medicine

Qianwen Sun

Nanjing University of Chinese Medicine

Yang Luo

Nanjing University of Chinese Medicine

zixuan JiaoYang

Nanjing University of Chinese Medicine

Aijun Xu

Nanjing University of Chinese Medicine

Zhi Liu

China National Health Development Research Center

Xuebin Qiao

qiaoxb@njmu.edu.cn

Nanjing University of Chinese Medicine

Research Article

Keywords: Healthy City pilot policy, cognitive health, cognitive health inequality, older adults, difference-in-differences, double machine learning, CHARLS

Posted Date: July 10th, 2026

DOI: <https://doi.org/10.21203/rs.3.rs-10206685/v1>

License: © ⓘ This work is licensed under a Creative Commons Attribution 4.0 International License.
[Read Full License](#)

Additional Declarations: No competing interests reported.

Title:

Health in All Policies: The Impact of the Healthy City Pilot Policy on
Cognitive Health and Cognitive Health Inequality Among Older Adults in
China—Evidence from Difference-in-Differences and Double Machine
Learning

Author names:

Jialin Xu^{1#}, Longyi Huang^{1#}, Qianwen Sun¹, Yang Luo¹, Yangzixuan Jiao¹,
Aijun Xu^{1,2}, Zhi Liu³, Xuebin Qiao^{1,2*}

1 School of Health Economics and Management, Nanjing University of Chinese
Medicine, Nanjing, China;

2 Jiangsu Research Center for Major Health Risk Management and TCM Control Policy,
Nanjing University of Chinese Medicine, Nanjing, China;

3 China National Health Development Research Center, Beijing, China.

These authors contributed equally to this work and should be considered co-first
authors.

* Corresponding author.

Corresponding author: Xuebin Qiao

Mail address: School of Health Economics and Management, Nanjing University of
Chinese Medicine, Nanjing, China

E-mail address: njucmjialinxu@163.com.

Health in All Policies: The Impact of the Healthy City Pilot Policy on Cognitive Health and Cognitive Health Inequality Among Older Adults in China—Evidence from Difference-in-Differences and Double Machine Learning

Abstract

Background

Cognitive decline among older adults is an important public health concern in the context of population aging. Although cognitive health in later life is shaped by broader social and environmental conditions, limited evidence exists on whether health-oriented urban governance can improve cognitive health and reduce cognitive health inequality. This study evaluated the impact of China's Healthy City pilot policy on cognitive health and cognitive health inequality among older adults.

Methods

Data were drawn from the 2013, 2015, 2018, and 2020 waves of the China Health and Retirement Longitudinal Study, combined with city-level socioeconomic data and Healthy City pilot information. The final sample included 28,193 observations from adults aged 60 years and above. Cognitive health was measured using CHARLS cognitive assessment items, and cognitive health inequality was measured using the cognitive health relative deprivation index. Difference-in-differences models with city and year fixed effects were used to estimate policy effects. Double machine learning with Lasso and five-fold cross-fitting was also used to account for high-dimensional

covariates and nonlinear relationships. Mechanism and heterogeneity analyses were conducted.

Results

The Healthy City pilot policy significantly improved cognitive health and reduced cognitive health inequality. In the fully adjusted difference-in-differences model, the policy increased cognitive health by 0.677 points and reduced the cognitive health relative deprivation index by 0.018. Double machine learning produced similar estimates, with effects of 0.6678 on cognitive health and -0.0182 on the cognitive health relative deprivation index. Robustness checks supported the stability of the findings. Mechanism analyses suggested that the policy reduced inequality through improved clean energy use, increased social participation and physical activity, reduced smoking, and enhanced digital inclusion. The effect was stronger among older individuals, men, older adults without children, and those living in western China, but weaker among older adults with ADL impairment.

Conclusions

The Healthy City pilot policy improved cognitive health and reduced cognitive health inequality among older adults in China. Health-oriented urban governance may promote cognitive health equity through living environments, health behaviors, social participation, and digital inclusion. Future healthy city and healthy aging strategies should emphasize cognitive health promotion and targeted support for vulnerable older adults.

Keywords

Healthy City pilot policy; cognitive health; cognitive health inequality; older adults;
difference-in-differences; double machine learning; CHARLS

Abbreviations:

ADL: Activities of daily living

CHARLS: China Health and Retirement Longitudinal Study

CH: Cognitive health

CH-RDI: Cognitive health relative deprivation index

DID: Difference-in-differences

DML: Double machine learning

PSM-DID: Propensity score matching difference-in-differences

Background

As population aging deepens and life expectancy continues to rise, the focus of health issues among older adults in China is shifting from merely prolonging life to improving quality of life. Among the multiple dimensions of older adults' health, cognitive decline has become a common yet often overlooked public health concern. Existing studies indicate that the prevalence of cognitive impairment among Chinese adults aged 60 years and above is approximately 22.24% [1]. The growing burden of dementia and mild cognitive impairment has also been widely documented both globally and in China, indicating that cognitive decline has become a major challenge for healthy ageing and public health systems [2,3]. In 2021, the number of older adults with disability or dementia reached 45 million, and it is projected that by 2060, the number of

people aged 65 years and above with cognitive impairment and functional disability will increase more than fourfold [4]. Cognitive decline not only impairs memory, attention, and executive function, but may also progress to cognitive impairment or dementia, thereby increasing the risks of disability, depression, and mortality [5]. Therefore, delaying cognitive decline among older adults has become an important issue in promoting healthy aging.

Increasing evidence suggests that cognitive health in later life is shaped not only by individual biological factors and medical care, but also by broader social and environmental conditions, including living environments, public services, social participation, health behaviors, and access to health resources [6-8]. Previous studies on cognitive ageing and urban health further suggest that built environments, neighbourhood conditions, city planning, and health-supportive urban governance may influence older adults' health through environmental, behavioural, and social pathways [9-11]. These factors are closely related to the framework of Health in All Policies, which emphasizes that health outcomes can be improved through coordinated actions across multiple sectors beyond the health system [12-14]. Healthy city construction represents an important policy practice of this framework. By improving urban environments, strengthening health-supportive infrastructure, optimizing public service provision, and encouraging healthy lifestyles, healthy city policies may create conditions that are conducive to cognitive health among older adults.

In China, the Healthy City pilot policy was promoted as part of the broader healthy city construction strategy, and pilot cities were gradually selected for implementation [13]. As Healthy Cities initiatives are complex, multi-sectoral interventions rather than single-component health programmes, empirical evaluation of their health effects requires population-level evidence and

careful policy evaluation designs [15]. This policy provides a valuable quasi-natural experiment for evaluating whether city-level health-oriented governance can improve cognitive health and reduce cognitive health inequality among older adults. However, existing studies have paid limited attention to the cognitive health effects of healthy city policies, and even less is known about whether such policies can reduce inequalities in cognitive health or through which mechanisms these effects may occur.

Accordingly, this study uses data from the China Health and Retirement Longitudinal Study (CHARLS) from 2013 to 2020 and applies difference-in-differences and double machine learning methods to evaluate the effects of the Healthy City pilot policy on cognitive health and cognitive health relative deprivation among older adults in China. This study further explores potential mechanisms, including clean energy use, social participation, physical activity, smoking behavior, and digital inclusion. The findings provide empirical evidence on the role of health-oriented urban governance in promoting cognitive health and health equity in aging populations.

Conceptual framework and hypotheses

The theory of social determinants of health posits that residents' health is shaped not only by biological factors and medical services, but also by external social environments, including living conditions, social participation, health behaviors, and public policies. The theory of health equity further argues that health disparities do not arise solely from individual endowments, but are also rooted in differences across groups in access to health resources, health opportunities, and supportive health environments. As an important practice of Health in All Policies, healthy city construction may not only improve cognitive health among older adults by enhancing health-

supportive environments, optimizing the allocation of public resources, and promoting healthy behaviors, but also alleviate cognitive health inequalities across different socioeconomic groups by improving vulnerable populations' access to health resources [6-8,12-15]. Accordingly, this study constructs the theoretical analytical framework shown in Figure 1 and proposes the following research hypotheses.

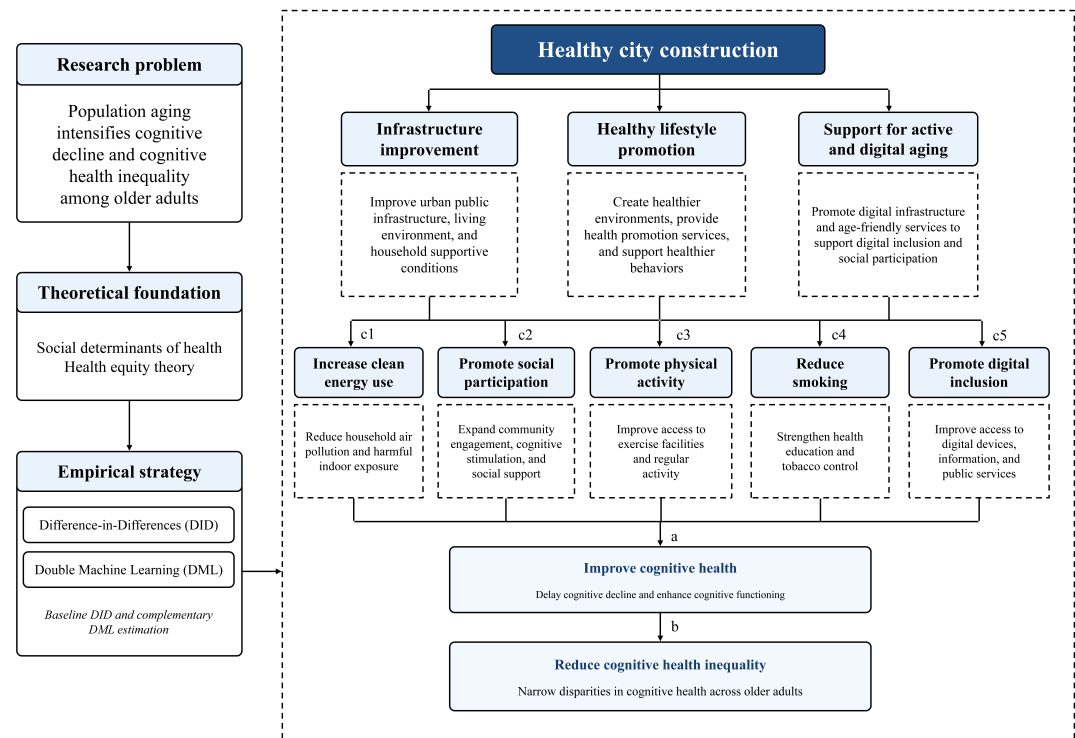


Figure 1 Research Framework and Theoretical Hypotheses

Hypothesis H1: Healthy city construction can improve cognitive health among older adults.

Hypothesis H2: Healthy city construction can mitigate inequalities in cognitive health among older adults.

The theory of social determinants of health further suggests that health policies can influence health outcomes by improving residents' lifestyles and health-supportive environments.

Accordingly, the following mechanism hypotheses are proposed.

The use of clean energy can reduce household exposure to indoor air pollution and mitigate the damage caused by harmful substances, such as particulate matter and carbon monoxide, to the respiratory system, cerebrovascular function, and the nervous system. Since low-income and rural older adult households are more likely to rely on traditional fuels, improved access to clean energy may help narrow cognitive health disparities [16]. Therefore, Hypothesis H3a is proposed: Healthy city construction mitigates cognitive health inequalities by increasing the use of clean energy in older adult households.

Social participation can increase cognitive stimulation and emotional support among older adults, thereby reducing loneliness and social isolation. Social interaction involves various cognitive activities, such as memory, language, attention, and emotional regulation, and helps maintain cognitive reserve [17,18]. By improving community activities and creating age-friendly environments, healthy city construction may promote social participation among older adults. Therefore, Hypothesis H3b is proposed: Healthy city construction mitigates cognitive health inequalities by promoting social participation among older adults.

Physical activity can improve cardiopulmonary function and cerebral blood and oxygen supply, reduce the risks of chronic diseases and inflammation, and may exert protective effects on cognitive function by promoting neuroplasticity [19,20]. By improving fitness facilities, parks and green spaces, and pedestrian environments, healthy city construction can lower the barriers to physical activity among older adults. Therefore, Hypothesis H3c is proposed: Healthy city construction mitigates cognitive health inequalities by promoting physical activity among older adults.

Smoking impairs vascular function and increases the risks of chronic inflammation, oxidative stress, and cerebral hypoxia, thereby adversely affecting cognitive health among older adults [21,22]. Tobacco control campaigns, smoking restrictions in public places, and health education, as important components of healthy city construction, can help improve health behaviors among older adults and reduce the cognitive health risks associated with smoking. Therefore, Hypothesis H3d is proposed: Healthy city construction mitigates cognitive health inequalities by reducing smoking among older adults.

Digital inclusion helps older adults access health information, use public services, and maintain social connections [23]. At the same time, the use of digital devices involves cognitive activities such as information retrieval, learning and memory, and problem-solving. By promoting smart health services and age-friendly digital adaptation, healthy city construction can help reduce barriers to digital use among older adults and enhance their access to health resources [6-8]. Therefore, Hypothesis H3e is proposed: Healthy city construction mitigates cognitive health inequalities by promoting digital inclusion among older adults.

Methods

Study design and population

This study uses data from the 2013, 2015, 2018, and 2020 waves of the China Health and Retirement Longitudinal Study (CHARLS) [24]. CHARLS is a nationwide longitudinal survey of middle-aged and older adults aged 45 years and above in China. The survey covers a wide range of information, including individual characteristics, family structure, income status, and health conditions, and is well suited to the research needs of this study on cognitive health and related

inequalities among older adults. Regarding macro-level data, information on the Healthy City pilot policy was obtained from publicly released lists of pilot cities issued by relevant national authorities, while city-level socioeconomic variables were mainly derived from publicly available statistical sources, such as the China Urban Statistical Yearbook. In line with the research objectives, the sample was processed as follows: observations with missing values for core variables, such as cognitive health indicators, and key control variables were excluded; observations from respondents younger than 60 years were excluded; and observations for which city-level information could not be matched were excluded. After these procedures, 28,193 observations were included in the final unbalanced panel dataset. The CHARLS study was approved by the Biomedical Ethics Review Committee of Peking University (approval number: IRB00001052-11015), and all participants provided written informed consent before participating in the survey. The present study used publicly available de-identified CHARLS data and did not involve additional contact with participants.

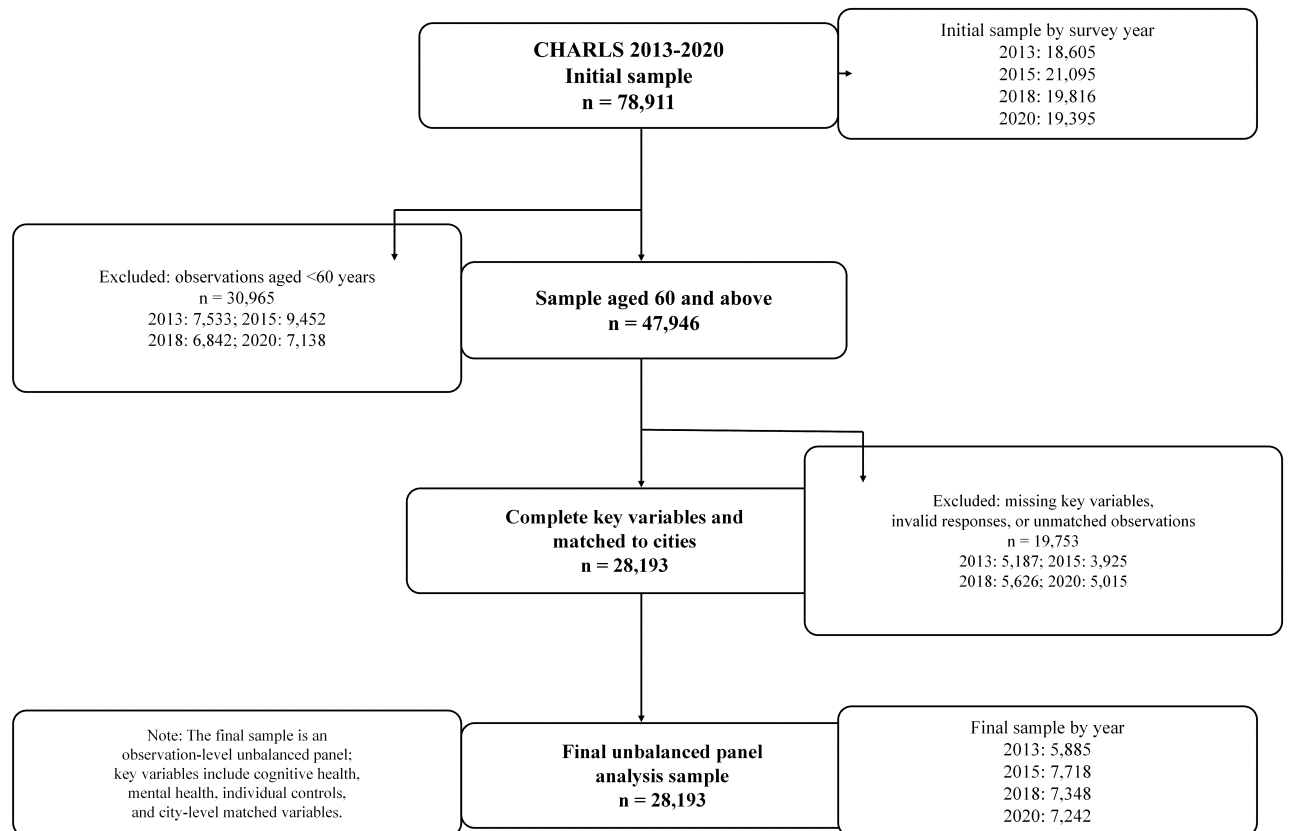


Figure 2 Flowchart of sample selection from the CHARLS 2013–2020 waves

Figure 3 shows the spatial distribution of the CHARLS sample cities and the first-batch Healthy City pilot cities included in the CHARLS sample. The highlighted pilot cities represent only the pilot cities observed in this study sample, rather than all first-batch pilot cities nationwide, and provide spatial variation for identifying the policy effect of the Healthy City pilot policy.

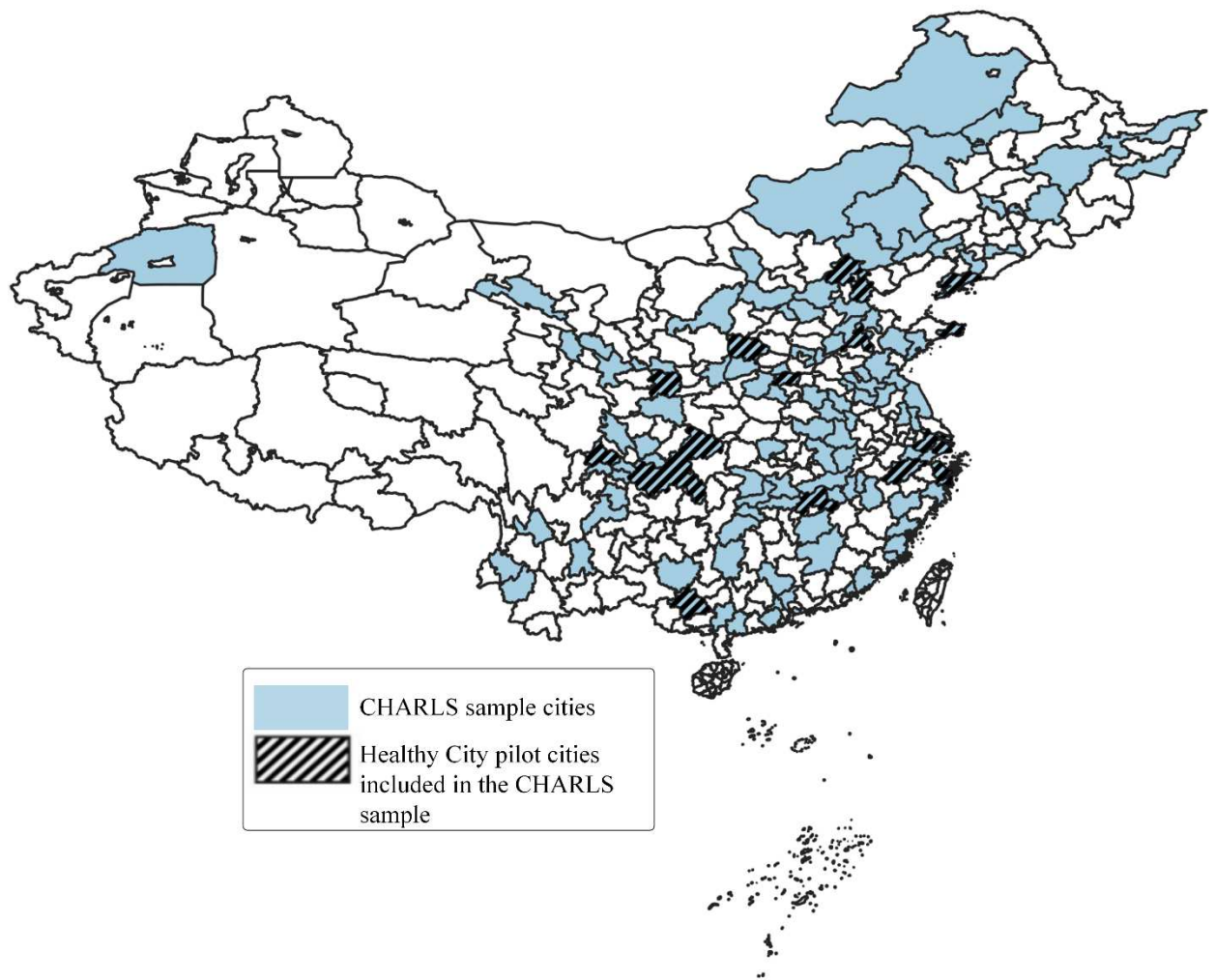


Figure 3 Distribution of CHARLS Sample Cities and the First Batch of Healthy City Pilot Cities

Measurements

Cognitive health and CH-RDI

The dependent variables in this study include cognitive health among older adults and cognitive health inequality. It should be noted that "cognitive health" in this study primarily refers to cognitive function as measured by the cognitive assessment items in CHARLS. In other words, cognitive function is regarded as an important dimension of older adults' health and is measured using the CHARLS cognitive assessment indicators, including episodic memory, time orientation,

calculation ability, and figure drawing [25,26]. The total score ranges from 0 to 31, with higher scores indicating better cognitive health among older adults.

Cognitive health inequality was measured using the cognitive health relative deprivation index (CH-RDI) [27,28]. The CH-RDI reflects the relative disadvantage of an individual's cognitive health level compared with a reference group. A higher CH-RDI indicates a greater degree of cognitive health relative deprivation and, therefore, more severe cognitive health inequality. Specifically, assuming that the cognitive health scores of the sample are arranged in ascending order as $(Y = (y_1, y_2, \dots, y_n))$, with $(y_1 \leq y_2 \leq \dots \leq y_n)$, the CH-RDI for individual i is expressed as follows:

$$RDI_i = \frac{1}{n\mu_y} \sum_{j=1}^n \max(y_j - y_i, 0)$$

Furthermore, the above equation can also be written in the following equivalent form:

$$RDI_i = \frac{\lambda_i^+}{\mu_y} (\mu_i^+ - y_i)$$

where RDI_i denotes the cognitive health relative deprivation index of older adult i ; y_i denotes the cognitive health score of older adult i ; y_j denotes the cognitive health score of older adult j in the sample; n denotes the sample size; μ_y denotes the mean cognitive health score of the sample; λ_i^+ denotes the proportion of individuals whose cognitive health scores are higher than y_i ; and μ_i^+ denotes the mean cognitive health score among individuals whose cognitive health scores are higher than y_i . A higher value of this index indicates a more pronounced cognitive health disadvantage of the individual relative to the reference group and, consequently, a higher level of cognitive health inequality.

Healthy City pilot policy

The independent variable in this study is the Healthy City pilot policy. Based on the 2016 national list of Healthy City pilot cities, pilot cities were classified as the treatment group [13], while non-pilot cities were classified as the control group. The period from 2018 onward was defined as the post-implementation period. The Healthy City pilot policy variable was generated by interacting the treatment group dummy variable with the post-implementation dummy variable. It was coded as 1 if the respondent's city had entered the pilot implementation phase, and 0 otherwise. (Table 1)

Mechanism variables

This study included clean energy use, social participation, physical activity, smoking behavior, and digital inclusion as mechanism variables [16-23] to examine the specific pathways through which the Healthy City pilot policy affects cognitive health inequality among older adults. The measurement methods and coding criteria for these mechanism variables are shown in Table 1.

Covariates

Drawing on existing studies, this study controlled for relevant variables at both the individual and city levels. Individual-level covariates included age, gender, the logarithm of per capita household income, marital status, educational attainment, place of residence, and number of children. City-level covariates included the logarithm of city-level GDP per capita and the logarithm of population size. In addition, year fixed effects and city fixed effects were incorporated into the model to control for common time shocks and time-invariant unobservable factors at the city level.

Statistical analysis

Difference-in-differences model

Given that the Healthy City pilot policy was launched nationwide in 2016, this study treats it as a quasi-natural experiment and employs a difference-in-differences model to assess the effects of healthy city construction on cognitive health and cognitive health inequality among older adults [29,30]. The model is specified as follows:

$$Y_{\{ict\}} = \alpha + \beta DID_{\{ct\}} + \theta X_{\{ict\}} + \gamma Z_{\{ct\}} + \mu_c + \lambda_t + \varepsilon_{\{ict\}} \quad (1)$$

In Eq. (1), Y_{ict} denotes the cognitive health status or cognitive health relative deprivation of individual i in city c in year t ; DID_{ct} denotes the Healthy City pilot policy variable; X_{ict} and Z_{ct} represent individual-level and city-level covariates, respectively; μ_c and λ_t denote city fixed effects and year fixed effects, respectively; ε_{ict} is the random error term; and α , β , θ , and γ are parameters to be estimated. To mitigate the underestimation of standard errors caused by within-group autocorrelation, standard errors in the main regression results are clustered at the city level [31]. To further examine the reliability of the estimation results, this study conducts a series of robustness checks. On this basis, mechanism analysis is used to examine the pathways through which healthy city construction affects cognitive health inequality, and interaction terms between the policy variable and group characteristics are constructed to identify heterogeneity in policy effects across different groups of older adults.

Double machine learning

In evaluating the policy effects of the Healthy City pilot policy, traditional difference-in-differences models mainly rely on linear functional form assumptions. If complex nonlinear

relationships exist between the covariates and the outcome variable, model specification bias may arise. At the same time, the covariates in this study include individual-level and city-level variables, as well as city and year fixed effects, resulting in a relatively high-dimensional set of controls. To further enhance the reliability of the estimation results, this study introduces double machine learning as a complementary estimation approach based on the difference-in-differences framework.

Double machine learning, proposed by Chernozhukov et al. [32], is based on the use of machine learning algorithms to handle high-dimensional covariates and nonlinear relationships. More generally, machine learning methods have been increasingly used in causal inference settings to address complex functional forms and high-dimensional covariates [33]. By employing orthogonalization and cross-fitting to reduce overfitting bias, this method can yield more robust estimates of causal effects. In this study, the Healthy City pilot policy variable is treated as the treatment variable, while the cognitive health index and cognitive health relative deprivation index among older adults are used as outcome variables. Accordingly, the following partially linear double machine learning model is constructed:

$$Y_{ict} = \theta_0 DID_{ct} + g_0(X_{ict}, Z_{ct}, \mu_c, \lambda_t) + U_{ict} \quad (2)$$

$$DID_{ct} = m_0(X_{ict}, Z_{ct}, \mu_c, \lambda_t) + V_{ict} \quad (3)$$

where Y_{ict} denotes the cognitive health status of individual i in city c in year t , including the cognitive health index and the cognitive health relative deprivation index; DID_{ct} denotes the Healthy City pilot policy variable; X_{ict} represents individual-level covariates, including age, gender, household income, marital status, educational attainment, place of residence, and chronic disease status; Z_{ct} represents city-level covariates, including city-level GDP per capita and

population size; μ_c and λ_t denote city fixed effects and year fixed effects, respectively; $g_0(\cdot)$ and $m_0(\cdot)$ are unknown functions that characterize the effects of covariates on the outcome variable and the policy variable, respectively; U_{ict} and V_{ict} are error terms; and θ_0 represents the Healthy City pilot policy effect of interest in this study. By estimating Equations (2) and (3) using machine learning methods, the predicted values of the outcome variable and the policy variable can be obtained as follows:

$$\hat{g}(X_{ict}, Z_{ct}, \mu_c, \lambda_t) = E(Y_{ict} | X_{ict}, Z_{ct}, \mu_c, \lambda_t) \quad (4)$$

$$\hat{m}(X_{ict}, Z_{ct}, \mu_c, \lambda_t) = E(DID_{ct} | X_{ict}, Z_{ct}, \mu_c, \lambda_t) \quad (5)$$

Next, we obtain the residual terms for the outcome variable and the policy variable:

$$\tilde{Y}_{ict} = Y_{ict} - \hat{g}(X_{ict}, Z_{ct}, \mu_c, \lambda_t) \quad (6)$$

$$\widetilde{DID}_{ct} = DID_{ct} - \hat{m}(X_{ict}, Z_{ct}, \mu_c, \lambda_t) \quad (7)$$

Based on this, we perform a regression on the residualized outcome and policy variables to obtain estimates of the policy effects of the Healthy City pilot policy:

$$\hat{\theta}_0 = \left(\sum_{i,c,t} \widetilde{DID}_{ct}^2 \right)^{-1} \sum_{i,c,t} \widetilde{DID}_{ct} \tilde{Y}_{ict} \quad (8)$$

where $\hat{\theta}_0$ denotes the average treatment effect of the Healthy City pilot policy on cognitive health or the cognitive health relative deprivation index among older adults. When the cognitive health index is used as the outcome variable, $\hat{\theta}_0 > 0$ indicates that healthy city construction improves cognitive health among older adults. When the cognitive health relative deprivation index is used as the outcome variable, $\hat{\theta}_0 < 0$ indicates that healthy city construction alleviates cognitive health inequality among older adults.

In the estimation process, this study uses the Lasso algorithm to estimate the nuisance functions in Eqs. (4) and (5), and employs five-fold cross-fitting to reduce overfitting in machine learning estimation. In addition, considering that the Healthy City pilot policy was implemented at the city level, standard errors are clustered at the city level [31]. The double machine learning results provide complementary evidence to the baseline difference-in-differences estimates, further supporting the estimated effects of the Healthy City pilot policy on cognitive health and cognitive health inequality among older adults.

Table 1 Variable definitions and descriptive statistics

Variable category	Variable name	Variable coding	Mean	Standard deviation
Dependent variable	CH	0–31 points; higher scores indicate better cognitive health	14.79	6.03
	CH-RDI	0–1; higher values indicate greater cognitive health relative deprivation and more severe cognitive health inequality	0.23	0.24
Independent variable	Healthy City pilot policy	Not in the pilot implementation phase = 0; in the pilot implementation phase = 1	0.07	0.25
	Clean energy use	Not using clean energy = 0; using clean energy = 1	0.22	0.42
Mechanism variable	Social participation	No participation in social activities = 0; participation in social activities = 1	0.55	
	Physical activity	No physical activity = 0; engaging in physical activity = 1	0.45	0.50
	Smoking	Non-smoking = 0; smoking = 1	0.31	0.46
	Digital inclusion	Not using the Internet = 0; using the Internet = 1	0.14	0.34
Covariate	Gender	Male = 1; female = 0	0.46	0.50
	Age	Years	67.75	6.10
	Marital status	Married = 1; unmarried or not currently married = 0	0.82	0.39
	Educational attainment	Illiterate = 0; primary school or below = 1; junior high school = 2; senior high school or above = 3	2.13	0.90
	Residence	Rural = 0; urban = 1	0.41	0.49
	Chronic disease status	No chronic disease = 0; one chronic disease = 1; two or more chronic diseases = 2	0.58	0.82

Number of children	2.96	1.43
Per capita household income(log)	8.48	1.74
City-level GDP per capita(log)	10.69	0.66
City population size(log)	6.20	0.63

Continuous variable

Abbreviations: CH, cognitive health; CH-RDI, cognitive health relative deprivation index.

Results

Baseline difference-in-differences estimates

Before examining the effect of healthy city construction on cognitive health inequality, this study first tested whether it improved cognitive health among older adults. This is because the reduction of cognitive health inequality should be based on actual improvements in cognitive health. If healthy city construction does not substantially improve cognitive health, then changes in the relative deprivation index alone would make it difficult to determine whether the policy has truly generated health gains.

The baseline regression results are shown in Table 2. Columns (1)–(3) use cognitive health as the outcome variable, while Columns (4)–(6) use CH-RDI as the outcome variable. These columns report the results from models that include only city and year fixed effects, further adjust for individual-level covariates, and additionally include city-level covariates, respectively. The estimated coefficients of the Healthy City pilot policy on cognitive health were consistently positive and statistically significant across different model specifications. After adjusting for both individual- and city-level covariates, the coefficient of the policy

variable was 0.677 and significant at the 1% level, indicating that healthy city construction significantly improved cognitive health among older adults.

Meanwhile, the estimated coefficients of the Healthy City pilot policy on CH-RDI were consistently negative. In the fully adjusted model, the coefficient was statistically significant at the 5% level, suggesting that healthy city construction significantly reduced cognitive health relative deprivation among older adults and alleviated cognitive health inequality.

Overall, the baseline regression results support Hypotheses H1 and H2.

Table 2 Baseline difference-in-differences estimates of the effects of the Healthy City pilot policy

Variable	CH(1)	CH(2)	CH(3)	CH-RDI(4)	CH-RDI(5)	CH-RDI(6)
Healthy City pilot policy	0.632** (0.244)	0.598** (0.249)	0.677*** (0.251)	-0.016** (0.007)	-0.015* (0.008)	-0.018** (0.008)
Observations	28,193					
<i>Adj R</i> ²	0.090	0.265	0.266	0.105	0.359	0.359

Note: Robust standard errors clustered at the city level are reported in parentheses. Models (1) and (4) include city and year fixed effects only; Models (2) and (5) additionally adjust for individual-level covariates; Models (3) and (6) additionally adjust for city-level covariates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Double machine learning estimates

Table 3 reports the double machine learning estimates. The coefficient of the Healthy City pilot policy was 0.6678 for cognitive health and -0.0182 for CH-RDI, both statistically significant at the 1% level. These results indicate that, after controlling for covariates and fixed effects and applying five-fold cross-fitting with the Lasso algorithm, the Healthy City pilot policy still significantly improved cognitive health and reduced cognitive health inequality among older adults. The findings are consistent with the baseline DID estimates, further supporting the use of double machine learning as a complementary estimation approach in high-dimensional causal inference settings [33].

Table 3 Estimates based on double machine learning

Variable	CH	CH-RDI
Healthy City pilot policy	0.6678*** (0.1743)	-0.0182*** (0.0064)
Control variables	Yes	Yes
Year fixed effects	Yes	Yes
City fixed effects	Yes	Yes
Observations	28,193	28,193

Note: Robust standard errors clustered at the city level are reported in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Robustness checks

Several robustness checks were conducted to assess the reliability of the baseline results. First, a placebo test was performed by randomly assigning the treatment group 500 times. The randomly estimated coefficients were mainly concentrated around zero, and the average p-value was 0.467, suggesting that the baseline findings were unlikely to be driven by random factors (Supplementary Fig. S1). Second, given that only two pre-policy waves were available before the implementation of the Healthy City pilot policy, a pre-trend test was conducted using the 2013 and 2015 samples [34]. The interaction term between the treatment group and the 2015 dummy variable was not statistically significant, indicating that there was no significant differential pre-policy trend between pilot and non-pilot cities. Third, a PSM-DID analysis was performed to reduce potential selection bias between pilot and non-pilot cities [35-37] (Supplementary Fig. S2). The estimated coefficient remained negative and statistically significant after matching. Fourth, after excluding municipalities directly under the central government, the estimated coefficient remained negative and significant. Fifth, after restricting the sample to individuals observed at least once before and after policy implementation [38], the estimated coefficient was still negative and significant. Finally, after additionally controlling for the National Demonstration Areas for Comprehensive

Prevention and Control of Chronic Diseases, the estimated effect of the Healthy City pilot policy remained negative and statistically significant. Overall, these robustness checks consistently support the conclusion that healthy city construction reduced CH-RDI among older adults. Detailed results are presented in Table 4.

Table 4 Robustness checks

	Pre-trend test	PSM-DID	Excluding municipalities	Restricted sample	Other-policy control
Key coefficient	-0.014 (0.009)	-0.018** (0.007)	-0.020** (0.009)	-0.025*** (0.008)	-0.018** (0.008)
Observations	13,603	21,644	27,628	20,321	28,193
<i>Adj R</i> ²	0.346	0.356	0.359	0.340	0.359

Note: Robust standard errors clustered at the city level are reported in parentheses. The outcome variable is CH-RDI. In the pre-trend test, the key coefficient refers to the interaction between the treatment group and the 2015 dummy variable; in the remaining columns, it refers to the Healthy City pilot policy. All models adjust for individual- and city-level covariates, as well as city and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Mechanism analysis

Table 5 presents the results of the mechanism analysis. The findings suggest that healthy city construction reduced CH-RDI among older adults through multiple pathways. First, regarding infrastructure improvement, the Healthy City pilot policy significantly increased the use of clean energy in older adult households, and clean energy use was further associated with a lower CH-RDI, supporting Hypothesis H3a. Second, regarding health-related behaviors and social engagement, the policy significantly promoted social participation and physical activity and reduced smoking among older adults. Social participation and physical activity were associated with lower CH-RDI, whereas smoking was associated with higher CH-RDI, supporting Hypotheses H3b, H3c, and H3d. Third, regarding digital inclusion, the policy significantly improved Internet use among older adults, and digital inclusion was further associated with lower CH-RDI, supporting Hypothesis H3e. Overall, these findings indicate that healthy city

construction reduced cognitive health inequality not through a single pathway, but through multiple channels related to living environments, health behaviors, social participation, and digital inclusion.

Table 5 Mechanism analysis

Pathway	Policy effect on mediator	Policy effect on CH-RDI	Mediator effect on CH-RDI
Clean energy use	0.086** (0.036)	-0.017** (0.008)	-0.019*** (0.004)
Social participation	0.032** (0.013)	-0.018** (0.008)	-0.015*** (0.002)
Physical activity	0.046** (0.022)	-0.018** (0.008)	-0.016*** (0.003)
Smoking behavior	-0.096*** (0.024)	-0.017** (0.008)	0.014*** (0.003)
Digital inclusion	0.082*** (0.013)	-0.017** (0.008)	-0.010*** (0.003)
Observations	28,193	28,193	28,193

Note: Robust standard errors clustered at the city level are reported in parentheses. All models adjust for individual- and city-level covariates, as well as city and year fixed effects. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Heterogeneity analysis

Further heterogeneity analyses were conducted to examine whether the effect of the Healthy City pilot policy differed across subgroups of older adults. The results showed that the inequality-reducing effect of the policy was stronger among older individuals and older men. In terms of family support, the positive interaction coefficient for having children suggests that older adults with children benefited relatively less from the policy, indicating a stronger compensatory effect among those with weaker family support. No significant heterogeneity was observed by place of residence or chronic disease status. However, the policy effect was relatively weaker among older adults with ADL impairment. Regionally, the effect did not differ significantly between the central

and eastern regions, whereas the policy had a stronger effect in reducing CH-RDI among older adults in the western region. Overall, these findings suggest that the Healthy City pilot policy had heterogeneous effects across demographic, functional, and regional groups. Detailed estimates are provided in Supplementary Table S1.

Discussion

Main findings and interpretation

This study found that the Healthy City pilot policy significantly improved cognitive health among older adults and reduced CH-RDI, suggesting that healthy city construction may contribute not only to health promotion but also to the reduction of cognitive health inequality. Given the growing emphasis on dementia prevention and modifiable risk factors across the life course [39], these findings are of public health relevance. Cognitive health in later life is shaped not only by aging and individual physiological decline, but also by broader social and environmental conditions, including living environments, health behaviors, social participation, and access to public services [40,41]. From this perspective, healthy city construction provides a policy pathway for cognitive health promotion that goes beyond medical treatment and individual-level interventions. These findings highlight the importance of integrating cognitive health into broader urban governance and public health strategies.

Potential mechanisms

The mechanism analysis showed that healthy city construction reduced CH-RDI through multiple pathways, including clean energy use, social participation, physical activity, smoking reduction,

and digital inclusion. Improvements in household energy use may reduce exposure to indoor air pollution and related environmental risks [42,43]. Greater social participation and physical activity may increase cognitive stimulation, social support, and opportunities for active aging [18,20,44]. Smoking reduction may help mitigate the long-term adverse effects of unhealthy behaviors on cerebrovascular and neural function [21,22,45]. Digital inclusion may further improve access to health information, public services, and social connections among older adults [23,46,47]. These results suggest that healthy city construction may reduce cognitive health inequality by narrowing disparities in environmental exposure, health behaviors, social support, and information accessibility.

Heterogeneity of policy effects

The heterogeneity analysis indicated that the effects of the Healthy City pilot policy differed across subgroups. The inequality-reducing effect was stronger among older individuals, older men, those without children, and older adults in western China, but relatively weaker among those with ADL impairment. The stronger effect among older individuals and older men is consistent with evidence that cognitive function and cognitive health inequalities vary across age and gender groups [48]. The finding that older adults without children benefited more may reflect the compensatory role of healthy city construction for those with weaker family support, as intergenerational support and perceived social support have been shown to be associated with cognitive function in later life [49,50]. The relatively weaker effect among older adults with ADL impairment may be related to functional limitations that restrict their ability to access and use health-supportive resources, which is consistent with evidence linking cognitive impairment and

dependency in activities of daily living [51]. Regionally, the stronger effect in western China suggests that healthy city construction may have greater marginal benefits in areas with relatively less developed infrastructure and public services. Overall, these findings indicate that general improvements in urban health environments may generate compensatory effects among some vulnerable groups, but additional targeted support is still needed for older adults with functional limitations.

Policy implications

These findings have several policy implications. First, cognitive health among older adults could be further incorporated into healthy aging and healthy city strategies, with greater attention to prevention, early screening, and community-based health management. Second, health-oriented urban governance may help promote cognitive health by improving age-friendly and accessible environments, community activity spaces, clean household energy, tobacco control, and digital assistance for older adults. Third, targeted support may be needed for oldest-old adults, older adults without family support, those with ADL impairment, and those living in less developed regions. In particular, home-based services, accessible environments, digital support, and community care programs may help ensure that vulnerable older adults can benefit from healthy city construction. Overall, promoting cognitive health requires moving beyond disease treatment toward a more integrated policy framework that combines public health, urban governance, and health equity. This is also consistent with evidence from multidomain intervention studies, which suggests that integrated strategies combining lifestyle modification, cognitive training, and vascular risk management may help prevent cognitive decline in older adults [52].

499

500 **Conclusions**

501 This study provides evidence that the Healthy City pilot policy significantly improved cognitive
502 health among older adults in China and reduced cognitive health inequality. The findings suggest
503 that health-oriented urban governance may promote cognitive health equity through multiple
504 pathways, including improvements in living environments, health behaviors, social participation,
505 and digital inclusion. Future healthy city and healthy aging strategies should place greater
506 emphasis on cognitive health promotion and targeted support for vulnerable older adults.

507

508

509 **Supplementary Information**

510 **Additional file 1:** Supplementary material

511

512 **Declarations**

513 **Ethics approval and consent to participate**

514 The CHARLS study was approved by the Biomedical Ethics Review Committee of Peking
515 University (approval number: IRB00001052-11015), and all participants provided written
516 informed consent before participating in the survey. The present study used publicly available de-
517 identified CHARLS data and did not involve additional contact with participants.

518 **Consent for publication**

519 Not applicable.

520 **Availability of data and materials**

The CHARLS datasets analysed during the current study are publicly available from the CHARLS official website: <http://charls.pku.edu.cn/>.

Competing interests

The authors declare that they have no competing interests.

Funding

Major Project of Philosophy and Social Science Research in Colleges and Universities of Jiangsu Province; Graduate Research and Innovation Projects of Jiangsu Province

Authors' contributions

Jialin Xu conceived and designed the study, conducted the data analysis, interpreted the results, and drafted the manuscript. Longyi Huang contributed to the study design, data analysis, interpretation of results, and manuscript drafting and revision. Qianwen Sun contributed to data processing, literature review, and revision of the manuscript. Yang Luo contributed to data organization, figure and table preparation, and manuscript revision. Yangzixuan Jiao contributed to data checking, supplementary material preparation, and manuscript revision. Aijun Xu provided academic supervision and critically reviewed the manuscript. Zhi Liu contributed to manuscript review and revision. Xuebin Qiao supervised the study, provided critical intellectual input, and revised the manuscript. All authors read and approved the final manuscript.

Acknowledgements

The authors thank the CHARLS research team and all participants for providing the data used in this study.

543

544

545

546 **References**

547 1. Qin F, Luo M, Xiong Y, et al. Prevalence and associated factors of cognitive impairment among the
548 elderly population: A nationwide cross-sectional study in China. Front Public Health.

549 2022;10:1032666. <https://doi.org/10.3389/fpubh.2022.1032666>

550 2. Jia L, Du Y, Chu L, et al. Prevalence, risk factors, and management of dementia and mild cognitive
551 impairment in adults aged 60 years or older in China: a cross-sectional study. Lancet Public

552 Health. 2020;5(12):e661-e671. [https://doi.org/10.1016/s2468-2667\(20\)30185-7](https://doi.org/10.1016/s2468-2667(20)30185-7)

553 3. Nichols E, Steinmetz JD, Vollset SE, et al. Estimation of the global prevalence of dementia in 2019
554 and forecasted prevalence in 2050: an analysis for the Global Burden of Disease Study 2019.

555 Lancet Public Health. 2022;7(2):e105-e125. [https://doi.org/10.1016/s2468-2667\(21\)00249-8](https://doi.org/10.1016/s2468-2667(21)00249-8)

556 4. Ansah JP, Chiu CT, Wei-Yan AC, et al. Trends in functional disability and cognitive impairment
557 among the older adult in China up to 2060: estimates from a dynamic multi-state population

558 model. BMC Geriatr. 2021;21(1):380. <https://doi.org/10.1186/s12877-021-02309-4>

559 5. Livingston G, Huntley J, Sommerlad A, et al. Dementia prevention, intervention, and care: 2020
560 report of the Lancet Commission. Lancet. 2020;396(10248):413-446.

561 [https://doi.org/10.1016/s0140-6736\(20\)30367-6](https://doi.org/10.1016/s0140-6736(20)30367-6)

562 6. Marmot M. Social determinants of health inequalities. Lancet. 2005;365(9464):1099-1104.

563 [https://doi.org/10.1016/s0140-6736\(05\)71146-6](https://doi.org/10.1016/s0140-6736(05)71146-6)

- 564 7. Whitehead M. The concepts and principles of equity and health. *Health Promot Int.* 1991;6(3):217-
565 228. <https://doi.org/10.1093/heapro/6.3.217>
- 566 8. Braveman P, Gruskin S. Defining equity in health. *J Epidemiol Community Health.* 2003;57(4):254-
567 258. <https://doi.org/10.1136/jech.57.4.254>
- 568 9. Cassarino M, Setti A. Environment as ‘Brain Training’: A review of geographical and physical
569 environmental influences on cognitive ageing. *Ageing Research Reviews.* 2015;23:167-182.
570 <https://doi.org/10.1016/j.arr.2015.06.003>
- 571 10. Rydin Y, Bleahu A, Davies M, et al. Shaping cities for health: complexity and the planning of urban
572 environments in the 21st century. *Lancet.* 2012;379(9831):2079-2108.
573 [https://doi.org/10.1016/s0140-6736\(12\)60435-8](https://doi.org/10.1016/s0140-6736(12)60435-8)
- 574 11. Giles-Corti B, Vernez-Moudon A, Reis R, et al. City planning and population health: a global
575 challenge. *Lancet.* 2016;388(10062):2912-2924. [https://doi.org/10.1016/s0140-](https://doi.org/10.1016/s0140-6736(16)30066-6)
576 [6736\(16\)30066-6](https://doi.org/10.1016/s0140-6736(16)30066-6)
- 577 12. Amri M. Healthy Governance for Cities: Synergizing Health in All Policies (HiAP) and Healthy
578 Cities Approaches. *J Urban Health.* 2022;99(2):231-234. [https://doi.org/10.1007/s11524-022-](https://doi.org/10.1007/s11524-022-00618-6)
579 [00618-6](https://doi.org/10.1007/s11524-022-00618-6)
- 580 13. Wang Q, Zhou Z, Huang L. Improvement of China’s healthy city construction policies from the
581 perspective of policy instruments. *BMC Public Health.* 2025;25(1):1958.
582 <https://doi.org/10.1186/s12889-025-23111-6>
- 583 14. Gondi S, Chokshi DA. Cities as Platforms for Population Health: Past, Present, and Future.
584 *Milbank Quarterly.* 2023;101(S1):242-282. <https://doi.org/10.1111/1468-0009.12612>

- 585 15. de Leeuw E. Do Healthy Cities Work? A Logic of Method for Assessing Impact and Outcome of
586 Healthy Cities. *J Urban Health*. 2012;89(2):217-231. [https://doi.org/10.1007/s11524-011-](https://doi.org/10.1007/s11524-011-9617-y)
587 [9617-y](https://doi.org/10.1007/s11524-011-9617-y)
- 588 16. Luo Y, Zhong Y, Pang L, et al. The effects of indoor air pollution from solid fuel use on cognitive
589 function among middle-aged and older population in China. *Sci Total Environ*. 2021;754:142460.
590 <https://doi.org/10.1016/j.scitotenv.2020.142460>
- 591 17. Mose A, Chen Y, Tan X, et al. Association of social integration with cognitive function trajectories
592 among Chinese older adults: evidence from the China health and retirement longitudinal study
593 (CHARLS). *Front Aging Neurosci*. 2024;15:1322974.
594 <https://doi.org/10.3389/fnagi.2023.1322974>
- 595 18. Fratiglioni L, Paillard-Borg S, Winblad B. An active and socially integrated lifestyle in late life
596 might protect against dementia. *Lancet Neurol*. 2004;3(6):343-353.
597 [https://doi.org/10.1016/s1474-4422\(04\)00767-7](https://doi.org/10.1016/s1474-4422(04)00767-7)
- 598 19. Iso-Markku P, Aaltonen S, Kujala UM, et al. Physical Activity and Cognitive Decline Among Older
599 Adults. *JAMA Netw Open*. 2024;7(2):e2354285.
600 <https://doi.org/10.1001/jamanetworkopen.2023.54285>
- 601 20. Northey JM, Cherbuin N, Pumpa KL, et al. Exercise interventions for cognitive function in adults
602 older than 50: a systematic review with meta-analysis. *Br J Sports Med*. 2018;52(3):154-160.
603 <https://doi.org/10.1136/bjsports-2016-096587>
- 604 21. Bloomberg M, Brown J, Di Gessa G, et al. Cognitive decline before and after mid-to-late-life
605 smoking cessation: a longitudinal analysis of prospective cohort studies from 12 countries. *Lancet*
606 *Healthy Longev*. 2025;6(9):100753. <https://doi.org/10.1016/j.lanhl.2025.100753>

- 607 22. Anstey KJ, von Sanden C, Salim A, et al. Smoking as a Risk Factor for Dementia and Cognitive
608 Decline: A Meta-Analysis of Prospective Studies. American Journal of Epidemiology.
609 2007;166(4):367-378. <https://doi.org/10.1093/aje/kwm116>
- 610 23. Yu X, Mu A, Wu X, et al. Impact of Internet Use on Cognitive Decline in Middle-Aged and Older
611 Adults in China: Longitudinal Observational Study. J Med Internet Res. 2022;24(1):e25760.
612 <https://doi.org/10.2196/25760>
- 613 24. Zhao Y, Hu Y, Smith JP, et al. Cohort Profile: The China Health and Retirement Longitudinal Study
614 (CHARLS). Int J Epidemiol. 2014;43(1):61-68. <https://doi.org/10.1093/ije/dys203>
- 615 25. Hu Y, Lei X, Smith JP, et al. Effects of social activities on cognitive functions: evidence from
616 CHARLS. In: Smith JP, Majmundar M, editors. Aging in Asia: Findings from New and Emerging
617 Data Initiatives. Washington, DC: National Academies Press; 2012. p. 279-306.
618 <https://www.ncbi.nlm.nih.gov/books/NBK109224/>
- 619 26. Guo S, Zheng XY. New evidence of trends in cognitive function among middle-aged and older
620 adults in China, 2011-2018: an age-period-cohort analysis. BMC Geriatr. 2023;23(1):498.
621 <https://doi.org/10.1186/s12877-023-04166-9>
- 622 27. Yitzhaki S. Relative Deprivation and the Gini Coefficient. Q J Econ. 1979;93(2):321.
623 <https://doi.org/10.2307/1883197>
- 624 28. Adjaye-Gbewonyo K, Kawachi I. Use of the Yitzhaki Index as a test of relative deprivation for
625 health outcomes: A review of recent literature. Soc Sci Med. 2012;75(1):129-137.
626 <https://doi.org/10.1016/j.socscimed.2012.03.004>

- 627 29. Roth J, Sant'Anna PHC, Bilinski A, et al. What's trending in difference-in-differences? A synthesis
628 of the recent econometrics literature. *J Econometrics*. 2023;235(2):2218-2244.
629 <https://doi.org/10.1016/j.jeconom.2023.03.008>
- 630 30. Imbens GW, Wooldridge JM. Recent Developments in the Econometrics of Program Evaluation. *J*
631 *Econ Lit*. 2009;47(1):5-86. <https://doi.org/10.1257/jel.47.1.5>
- 632 31. Colin Cameron A, Miller DL. A Practitioner's Guide to Cluster-Robust Inference. *J Hum Resour*.
633 2015;50(2):317-372. <https://doi.org/10.3368/jhr.50.2.317>
- 634 32. Chernozhukov V, Chetverikov D, Demirer M, et al. Double/debiased machine learning for
635 treatment and structural parameters. *Econometrics J*. 2018;21(1):C1-C68.
636 <https://doi.org/10.1111/ectj.12097>
- 637 33. Athey S, Imbens GW. Machine Learning Methods That Economists Should Know About. *Annu*
638 *Rev Econ*. 2019;11(1):685-725. <https://doi.org/10.1146/annurev-economics-080217-053433>
- 639 34. Rambachan A, Roth J. A more credible approach to parallel trends. *Rev Econ Stud*.
640 2023;90(5):2555-2591. <https://doi.org/10.1093/restud/rdad018>
- 641 35. Heckman JJ, Ichimura H, Todd PE. Matching as an econometric evaluation estimator: evidence
642 from evaluating a job training programme. *Rev Econ Stud*. 1997;64(4):605-654.
643 <https://doi.org/10.2307/2971733>
- 644 36. Rosenbaum PR, Rubin DB. The central role of the propensity score in observational studies for
645 causal effects. *Biometrika*. 1983;70(1):41-55. <https://doi.org/10.1093/biomet/70.1.41>

- 646 37. Austin PC. An introduction to propensity score methods for reducing the effects of confounding in
647 observational studies. *Multivariate Behav Res.* 2011;46(3):399-424.
648 <https://doi.org/10.1080/00273171.2011.568786>
- 649 38. Fitzgerald J, Gottschalk P, Moffitt R. An analysis of sample attrition in panel data: the Michigan
650 Panel Study of Income Dynamics. *J Hum Resour.* 1998;33(2):251-299.
651 <https://doi.org/10.2307/146433>
- 652 39. Livingston G, Huntley J, Liu KY, et al. Dementia prevention, intervention, and care: 2024 report of
653 the Lancet standing Commission. *Lancet.* 2024;404(10452):572-628.
654 [https://doi.org/10.1016/s0140-6736\(24\)01296-0](https://doi.org/10.1016/s0140-6736(24)01296-0)
- 655 40. Barnes LL, Zuelsdorff M. The social determinants of health: disparities in cognitive aging and
656 dementia. *Annu Rev Dev Psychol.* 2025;7(1):485-508. [https://doi.org/10.1146/annurev-](https://doi.org/10.1146/annurev-devpsych-111323-101842)
657 [devpsych-111323-101842](https://doi.org/10.1146/annurev-devpsych-111323-101842)
- 658 41. Adkins-Jackson PB, George KM, Besser LM, et al. The structural and social determinants of
659 Alzheimer's disease related dementias. *Alzheimers Dement.* 2023;19(7):3171-3185.
660 <https://doi.org/10.1002/alz.13027>
- 661 42. Cao L, Zhao Z, Ji C, et al. Association between solid fuel use and cognitive impairment: a cross-
662 sectional and follow-up study in a middle-aged and older Chinese population. *Environ Int.*
663 2021;146:106251. <https://doi.org/10.1016/j.envint.2020.106251>
- 664 43. Hahad O, Lelieveld J, Birklein F, et al. Ambient air pollution increases the risk of cerebrovascular
665 and neuropsychiatric disorders through induction of inflammation and oxidative stress. *Int J Mol*
666 *Sci.* 2020;21(12):4306. <https://doi.org/10.3390/ijms21124306>

- 667 44. Piolatto M, Bianchi F, Rota M, et al. The effect of social relationships on cognitive decline in older
668 adults: an updated systematic review and meta-analysis of longitudinal cohort studies. BMC
669 Public Health. 2022;22(1):278. <https://doi.org/10.1186/s12889-022-12567-5>
- 670 45. Myrstad C, Larssen M, Engdahl B, et al. Smoking is associated with increased risk for dementia:
671 the HUNT study, Norway. BMC Public Health. 2025;26(1):246.
672 <https://doi.org/10.1186/s12889-025-25813-3>
- 673 46. Bengtson JF, Scullin MK. A meta-analysis of technology use and cognitive aging. Nat Hum Behav.
674 2025;9(7):1405-1419. <https://doi.org/10.1038/s41562-025-02159-9>
- 675 47. Mubarak F, Suomi R. Elderly forgotten? Digital exclusion in the information age and the rising
676 grey digital divide. Inquiry. 2022;59:00469580221096272.
677 <https://doi.org/10.1177/00469580221096272>
- 678 48. Yang C, Mao Z, Wu S, et al. Influencing factors, gender differences and the decomposition of
679 inequalities in cognitive function in Chinese older adults: a population-based cohort study. BMC
680 Geriatr. 2024;24(1):371. <https://doi.org/10.1186/s12877-024-04857-x>
- 681 49. Hou X, Luo Y, Yang F, et al. The mediating role of children's intergenerational support in
682 association between grandparenting and cognitive function among middle-aged and older
683 Chinese: findings from the CHARLS cohort study. BMC Public Health. 2024;24(1):597.
684 <https://doi.org/10.1186/s12889-024-18106-8>
- 685 50. Gui S, Wang J, Li Q, et al. Sources of perceived social support and cognitive function among older
686 adults: a longitudinal study in rural China. Front Aging Neurosci. 2024;16:1443689.
687 <https://doi.org/10.3389/fnagi.2024.1443689>

- 688 51. Fu X, Ji S, Li J, et al. Cognitive impairment and dependency in activities of daily living: a cross-
689 lagged analysis. *Front Aging Neurosci.* 2025;17:1663237.
690 <https://doi.org/10.3389/fnagi.2025.1663237>
- 691 52. Ngandu T, Lehtisalo J, Solomon A, et al. A 2 year multidomain intervention of diet, exercise,
692 cognitive training, and vascular risk monitoring versus control to prevent cognitive decline in at-
693 risk elderly people (FINGER): a randomised controlled trial. *Lancet.* 2015;385(9984):2255-2263.
694 [https://doi.org/10.1016/s0140-6736\(15\)60461-5](https://doi.org/10.1016/s0140-6736(15)60461-5)

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- [Supplementarymaterial.docx](#)