Title

The long arm of childhood: The heterogeneous associations between early-life indoor air pollution exposure and cognitive health in old age

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Abstract

A large number of poor people all over the world rely on solid fuels for cooking, directly bringing exposure to indoor air pollution. This exposure has been linked to decreased cognitive health in later life. However, relatively little is known about the long-term effects of early-life indoor air pollution exposure and how this association varies in different population groups. This study used nationally representative data of 7,033 adults aged 45 or older in China. Causal forest approach was applied to capture the complex nonlinear relationships and estimate the average treatment effect (ATE) of early-life indoor air pollution exposure on late-life cognitive health. Additionally, we estimated conditional average treatment effects (CATE) to examine heterogeneous associations across various subgroups (age, gender, education levels, marriage status, living regions, rural-urban areas, later-life self-reported health status). The results demonstrated that, after allowing for 24 covariates, early-life indoor air pollution exposure was associated with poorer late-life cognitive health, with an ATE of -0.67 and a 95% confidence interval of [-0.69, -0.65]. For specific domains of cognitive health, we found this exposure significantly associated with worsen performance of episodic memory but has no significant effects on mental intactness. The CATE analysis further revealed that subgroups aged 45-59, males, individuals with higher education levels, those living in Eastern China and urban areas, married and partnered individuals, and those with poorer later-life self-reported health were more vulnerable to the detrimental long-term cognitive health effects of early-life indoor air pollution exposure. Our findings suggest a need to improve access to clean energy, which may prevent cognitive impairments from the upstream. Overall, our results suggest that early-life indoor air pollution exposure generated long-lasting, negative, but heterogeneous population effects on late-life cognitive health.

Keywords: Indoor air pollution; solid fuel; cognitive health; childhood adversity; causal forest; CHARLS

Introduction

In the context of population aging, cognitive health has become an important public health concern globally. The decline of cognitive health causes a series of social and economic issues, such as more need of long-term care (Comas-Herrera et al., 2007), greater burdens of healthcare (Prince et al., 2015), and higher risk of mortality (Sachs et al., 2011). Currently, there is no effective cure for severe cognition decline like dementia, making it crucial to identify and mitigate cognitive health risks for early prevention. Strong evidence has emphasized the various determinants of cognitive health, inlcuding socioeconomic status (Ruiz et al., 2023; Yang et al., 2016), health behaviors (Lee et al., 2010), mental health issues (Crocco et al., 2010; Weisenbach et al., 2012), living alone (Evans et al., 2019), social activities (Hwang et al., 2018), and childhood living conditions (Ding and He, 2021).

A growing body of research has established the associations between household air pollution exposure from solid fuel use and cognitive health in old age (Dakua et al., 2022; Jana et al., 2022; Luo et al., 2021; Qiu et al., 2019; Rani et al., 2023; Saenz et al., 2018; Wang et al., 2023). For example, linear regression models showed that exposure to household air pollution was significantly linked with worse cognitive health in countries such as China, India, and Mexico (Jana et al., 2022; Qiu et al., 2019; Saenz et al., 2018). Furthermore, studies evaluating the heterogenous effect of exposure to household air pollution on cognitive health have identified vulnerable groups, such as women and adults aged 65+ and older (Dakua et al., 2022; Luo et al., 2021; Wang et al., 2023). These studies have primarily emphasized the short-term effects of household air pollution on cognitive health. However, the long-term influence of household air pollution during childhood on cognitive health in late life remains unclear. In developing countries, solid fuels (e.g., coal, wood, and corn) remain a major energy source for cooking, heating, and other uses, leading to toxic air pollutants and posing significant health risks (Ali et al., 2021). Despite this, the influence of household solid fuel use during childhood on cognitive health in old age has not been examined.

This study aims to use nationally representative data to investigate the effects of household air pollution exposure on cognitive health of middle-aged and aged individuals in China. It will also seek to discern the heterogeneity of these effects across gender, ages, education levels, rural-urban areas and geographic regions.

Method

2.1 Subjects and Design

This study used data from the Life History Survey and wave 3 of the China Health and Retirement Longitudinal Study (CHARLS), conducted in 2014 and 2015 respectively. CHARLS is a nationally representative survey initiated in 2011, focusing on the microdata concerning the health, socioeconomic status and social and family networks of Chinese aged 45 or older spanning 150 counties and 450 villages or resident committees. The Ethics Committee of Peking University approved the ethical review. More details of the survey design are described in detail elsewhere (Zhao et al., 2014). Participants aged below 45 years old and those with missing values were excluded, resulting in a final sample of 7,033 participants in this study.

2.2 Assessments

Childhood household air pollution was assessed using a question from the Life History Survey of CHARLS: ‘From your birth, what are the main sources of cooking fuel (coal, electrify, gas, and others)?’. Strong evidences have supported that solid fuel use for cooking is a valid indicator of household air pollution (Du et al., 2022; Hystad et al., 2019; Liu et al., 2018). We created a binary variable called early-life indoor air pollution exposure, categorizing the use of solid fuel (coal and other solid fuels) from birth time to 17 years old as 1, and the use of clean energy (electricity and fuel gas such as coal gas, liquefied gas, natural gas, biogas) or transitioning from solid fuels to clean energy at or before 17 years as 0.

Following prior studies (Luo et al., 2021; Yang et al., 2020), we measured the cognitive health by summing the scores of episodic memory (EM) and mental intactness (MI). In wave 3 of CHALRS, participants assessed their self-rated cognitive health by two scales: EM and MI. The EM score is the mean score of immediate and delayed recall tests, while the MI score was the sum score of four tests: serially subtracting 7 from 100, redrawing a picture, naming the day of the week, and naming the current date (day of month, month, year, and day of week).

Considering various life-course factors may affect cognitive health in old age, we included 24 confounders from six domains: demographics (gender, age, marital status, education levels, living in rural areas, living geographical regions), as well as physical health (self-reported health, difficulty with activities of daily living), health behaviors (drinking alcohol, smoking), economic situations (pension income, nonfood consumption, public health insurance, private health insurance), and social network (co-residing with children, living near children, weekly contacting with children, social activities in the past month), childhood living conditions (father education, mother education, mother occupation, father occupation, self-reported health during childhood, family financial situation during childhood). Detailed explanations of these confounders can be found in Appendix 1.

2.3 Statistical Analyses

The causal forest approach is a causal machine learning method used to estimate individual treatment effects by combing the strengths of machine learning and causal inference techniques to enhance precision in heterogeneous treatment analysis. This approach has several advantages. For instance, causal forest can capture non-linear relationships and interactions among variables that linear models may miss (Wager and Athey, 2018). Additionally, causal forest excels in handling high-dimensional data, allowing for the inclusion of a wider range of variables potentially influenced treatment effects, without the risk of multicollinearity common in linear models. These advantages make causal forest a powerful tool for accurately evaluating the heterogenous treatment effects. Due to the advantages, causal forest has recently been applied in the environmental and health fields to examine the heterogeneous effects (Elek and Bíró, 2021; Hattab et al., 2024; Lei et al., 2023; Miller, 2020).

In this study, we used casual forest to uncover the average treatment effect (ATE) of early-life indoor air pollution exposure on late-life cognitive health. The ATE stands for the average differences in cognitive health between those with early-life indoor air pollution exposure and those without. We divided the dataset into training (70%) and test (30%) sets to ensure the generalizability of the trained models. After training, we estimated the treatment effects on the test set and calculated a 95% confidence interval. The analysis was conducted in R version 4.3.1, using the 'grf' package.

Results

3.1 Descriptive analysis of the Study Participants

Table 1 demonstrates the demographic characteristics of the 7,033 participants in this study. Among these participants, 96.37% experienced indoor air pollution exposure from solid fuel for cooking during the whole childhood. These participants are middle-aged and aged individuals, over half are female (51.22%). Those exposed to early-life indoor air pollution exposure were generally older, less educated, consumed less alcohol, and morel likely to live in rural areas and Western China compared to those without the exposure. These differences were statistically significant with a p-value of <0.001.

Table 1. Demographic Characteristics of Participants in this study

	No early-life indoor air pollution exposure	Early indoor air pollution exposure	P-value
Cognitive health	17.50 ± 0.27	14.49 ± 0.05	< 0.001
Gender			0.176
Male	135(3.93%)	3,482(96.07%)	
Female	120(3.33%)	3,482(96.67%)	
Age			< 0.001
45-59	208(5.59%)	3,513(94.41%)	
60-74	41(1.52%)	2,658(98.48%)	

75+	6(0.98%)	607(99.02%)	
Marriage status			< 0.05
Married, partnership	236(3.83%)	5,919(96.17%)	
Separated, divorced, widowed, and never married	19(2.16%)	859(97.84%)	
Education			< 0.001
No formal education, illiterate	15(0.86%)	1,727(99.14%)	
Did not finish primary school but capable of reading and/or writing; Sishu	16(1.56%)	1,008(98.44%)	
Elementary school	103(5.23%)	1,867(94.77%)	
Middle school	44(3.09%)	1,382(96.91%)	
High school and above	77(8.84%)	794(91.16%)	
Living geographical regions			< 0.001
Eastern China	151(6.04%)	2,350(93.96%)	
Central China	64(2.83%)	2,196(97.17%)	
Western China	40(1.76%)	2,232(98.24%)	
Living in rural areas			< 0.001
No	187(6.58%)	2,656(93.42%)	
Yes	68(1.62%)	4,122(98.38%)	
Smoke			0.635
No	142(3.53%)	3,876(96.47%)	

Yes	113(3.75%)	2,902(96.25%)	
Alcohol			< 0.001
No	131(2.76%)	4,610(97.24%)	
Yes	124(5.41%)	2,168(94.59%)	

Note: Data are shown as means ± standard deviations or number (percentage %)

3.2 Estimation of Population Average Treatment Effects

Figure 1 illustrates the estimated conditional average treatment effects (CATE) of early-life indoor air pollution exposure on cognition health in late life. The results indicate that childhood exposure to indoor air pollution is, on average, associated with worse cognitive health (estimated coefficient = -0.67; 95% confidence interval, [-0.69, -0.65]). The distribution of treatment effects, as shown in Figure 2, demonstrates that the effects are predominantly negative, suggesting that individuals exposured to early-life indoor air pollution generally report poorer cognitive health in old age. The peak of the density curve around -0.67 demonstrates that most of the effect estimates are not only negative but also significantly deviate from zero.

From Figure 1, it is evident that the influence of early-life indoor air pollution exposure on later-life cognitive health exhibits significant heterogeneity. While the majority of the treatment effect estimates show that early-life indoor air pollution exposure is linked with worse cognitive health, some estimates indicate beneficial effects. These estimates suggest that in some subgroups, childhood indoor air pollution is associated with better cognitive health outcomes. This variation may be influenced by socioeconomic factors such as education and marital status.

We further examined the influence of early-life indoor air pollution exposure on two key components of cognitive health: episodic memory and mental intactness. The result show that early-life indoor air pollution exposure significantly worsens the performance of episodic memory (-0.66, 95%, CI: -0.67, -0.64). However, childhood indoor air pollution did not appear to have a significant effect on mental intactness (0.01, 95%, CI: -0.01, 0.0216).

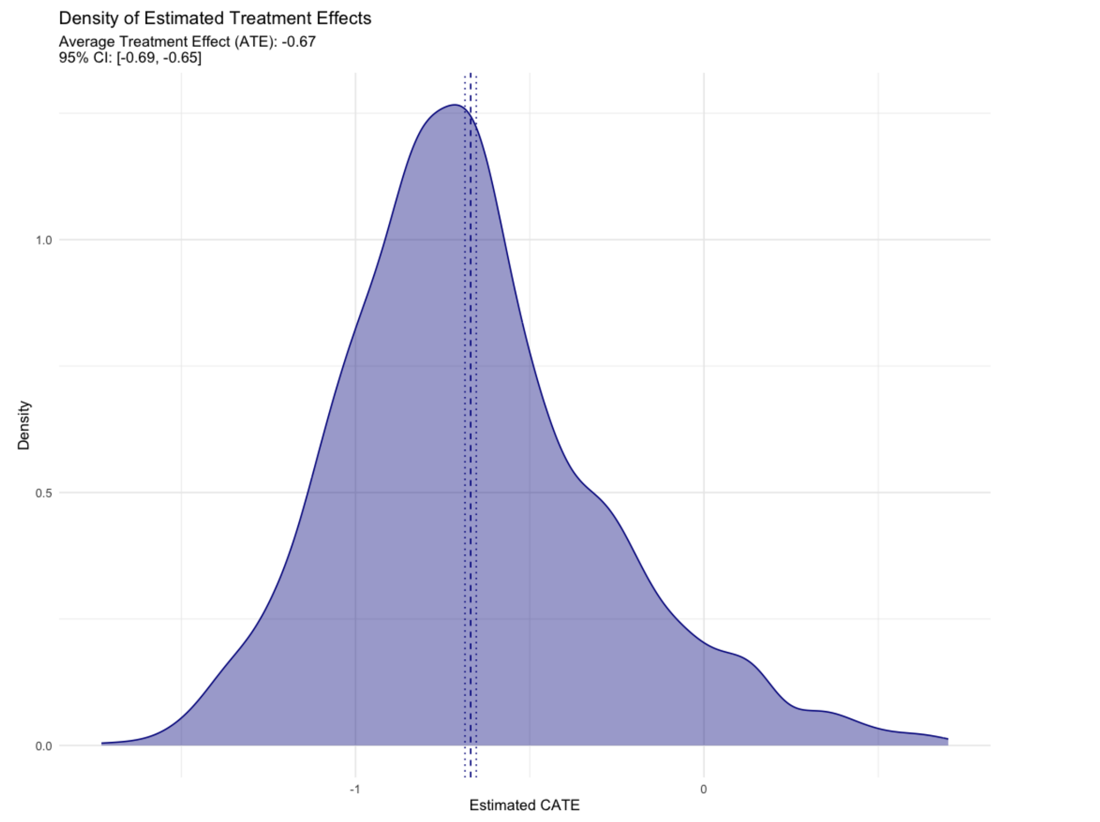

Figure 1. Density of estimated treatment effects of early-life indoor air pollution on late-life cognitive health

3.3Heterogeneous effect across subgroups

To further capture the heterogeneous effects across subgroups, we estimated the conditional average treatment effect (CATE) of early-life indoor air pollution on late-life cognitive health in seven aspects: age, education, gender, marital status, living geographical areas, current self-reported health, and living in rural areas. In Figure 2, individuals with early-life indoor air pollution exposure who are with aged 45-59, males, higher education level, living in Eastern China, living in urban areas, being married and partnered, and having poorer later-life self-reported health, were more likely to have poorer cognitive health in late life.

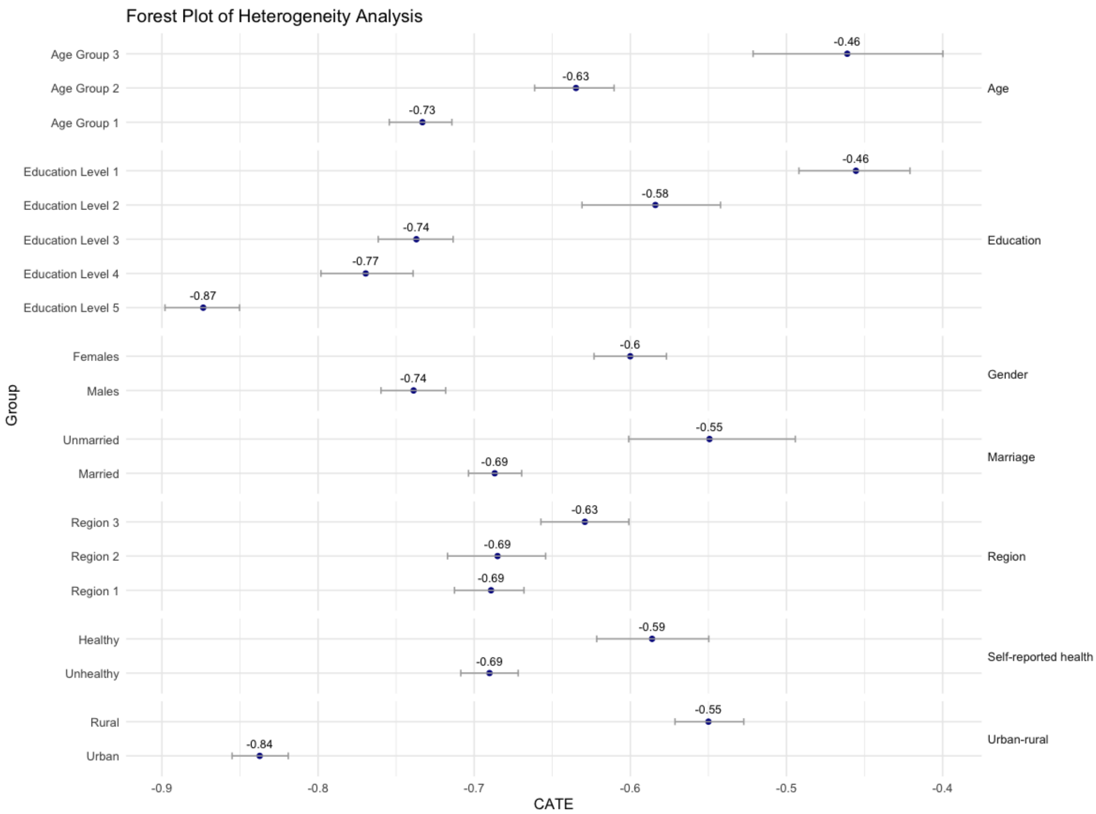

Figure 2. Conditional average estimated heterogeneous effect (CATE) of early-life indoor air pollution on cognitive health across subgroups

Discussion

To the best of our knowledge, this study is the first to examine the relationship between early-life indoor air pollution exposure and cognitive health in old age using nationally representative data. It provides a deeper understanding of long-term effects of indoor air pollution exposure on cognitive health from the life course perspective. First, we uncovered the significant effects of indoor air pollution from solid fuel for cooking throughout early life on cognitive health in old age, employing causal forest approach and controlling for 24 confounders. Second, we captured the heterogenous effects across various subgroups. Males, middle-aged (45-59 years) adults, individuals with higher educational levels, those who were married or partnered, and those with poorer later-life self-reported health were more vulnerable, experiencing large effects. Additionally, Individuals who lived in Eastern China and urban areas also show greater vulnerability. Lastly, our findings support the evidence of long-term health effect of early-life air pollution (Baranyi et al., 2024, 2023), highlighting the urgency of mitigating indoor air pollution exposure from childhood.

We revealed the adverse influence of early-life indoor air pollution exposure on cognitive health among the middle-aged and older adults. Existing studies have primarily focused on the effects of ongoing indoor air pollution exposure rather than early-life exposure, making it difficult to compare our findings directly with theirs. Nonetheless, our study provides further evidence that early-life indoor air pollution exposure poses a significant hazard to cognitive health in late life. Similar studies have showed that ongoing indoor air pollution from solid fuel for cooking is associated with cognitive health decline among the elderly in China, India and Mexico (Dakua et al., 2022; Qiu et al., 2019; Saenz et al., 2018). In addition, our main findings are consist with prior studies on the associations of early-life outdoor air pollution exposure with worse health outcomes among children, adolescents and older adults, such as reduction of cognitive abilities and during childhood (Rivas et al., 2019), higher risk of depression onset during adolescence (Latham et al., 2021; Newbury et al., 2019), and higher odds of limiting long-term illness and all-cause mortality during late adulthood (Baranyi et al., 2024, 2023). This suggests that not only current indoor air pollution exposure, but also early-life air pollution exposure adversely influenced cognitive health from a life course prospective.

Heterogenous analysis found that associations between early-life indoor air pollution exposure and cognitive health in old age were significant across all subgroups. Specifically, we found that males, individuals aged 45 to 59, those married or partnered, those who higher education levels, those with poorer self-reported health, and individuals residing in urban areas and Eastern China, were more vulnerable to early-life indoor air pollution exposure. This aligns with a prior study suggesting that air pollution had larger effects on cognitive health in old age among males (Zhang et al., 2018). However, our results were different from previous studies that focused on ongoing exposure to indoor air pollution, which pointed out that the adverse effects of the exposure on cognitive health in old age are higher in females, individuals with lower education levels, and individuals aged 60 years and older (Luo et al., 2021; Wang et al., 2023). Our results also indicated that individuals with poorer self-reported health are more likely to be aware of the adverse health effects of early-life air pollution exposure, similar to the effects of ongoing exposure among individuals with cardiovascular diseases (Luo et al., 2021). For the subgroup analysis of rural-urban areas, our findings align with a prior study proving significantly strong effects of ongoing indoor air pollution from individuals residing in urban areas(Wang et al., 2023). A possible reason for this is that the average indoor time of rural residents is shorter than urban residents in China.

The potential mechanisms for the effects of early-life indoor air pollution exposure on cognitive health in old age are not yet clearly understood. One potential biological explanation is that early-life air pollution exposure may directly lead to the changes in brain morphology, including smaller corpus callosum, hippocampus and nucleus accumbent (Lubczyńska et al., 2021), which may have long-lasting effects until late adulthood. Another possible mechanism is that early-life air pollution exposure may affect cognitive health in old age by decreasing the cognitive ability, IQ level and academic performance during childhood (Brabhukumr et al., 2020; Grineski et al., 2020; Morales et al., 2009), factors having been proved to be strong predictors of cognitive impairments in late life (Bourne et al., 2007; Dekhtyar et al., 2015; Pudas et al., 2019). However, these mechanisms cannot be verified in our study since these variables are not available from CHARLS.

This study has several strengths. First, by focusing on the effects of early-life indoor air pollution exposure from a life course perspective, we provide new sights into existing studies that predominately consider current exposure. This supports the long-term effects of indoor air pollution exposure in cognitive health across life course. Second, we employed a matching learning approach, causal forest, which can capture nonlinear relationships and interactions among variables, thereby improving the robustness of evaluating the heterogenous treatments effects across different subgroups. Lastly, we used a large-sample national survey data to examine the influence of early-life indoor air pollution exposure on cognitive health in old age, ensuring sufficient statistical power to capture these effects, which may be difficult with smaller sample sizes.

However, there are also several limitations. First, the use of fuel for cooking and the starting time of its use were based on retrospective recall, which may introduce recall bias. Additionally, the adverse effect of early-life indoor air pollution may impair elderly subject memory, potentially increasing recall bias. Second, our results may be specific to these cohorts in which solid fuel for cooking was more prevalent than in current cohorts. Despite this, solid fuel use still exists as an important source of fuel in many households, especially in poorer areas of China and other developing countries in 21st century (Bonjour et al., 2013; Lin et al., 2021; Maes and Verbist, 2012). Lastly, it may be challenging to generalize our findings to young adults since the data used in this study pertains to middle-aged and older adults.

Conclusion

We first revealed the significant associations between early-life indoor air pollution exposure from solid fuel for cooking and cognitive health among Chinese middle-aged and older adults. Our study demonstrates that there are long-term adverse effects of indoor air pollution exposure throughout childhood on cognitive health in late life. Moreover, the effects are heterogenous across age, education, gender, marital status, living geographical areas, current self-reported health, living in rural areas. This underscores an urgent need to take promotion the use of clean fuel in households that reply on solid fuel. Transition from solid fuel to cleaner alternatives can safeguard the cognitive health of children, as well as support their long-term cognitive health as they become old.

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Appendix A

Detailed description of control variables

Domains	Control variables	Meaning of predictors
Demographic variables	gender	Respondent’s gender 1. Man 0. Woman
	age	Respondent’s age at interview 1.45-60 years old 2.60-75 years old 3.75+ years old
	marital status	Respondent’s marital status 1. Separated, divorced, widowed, never married 0. Married or partnership
	education level	Respondent’s education level 1.No formal education illiterate 2.Did not finish primary school but capable of reading and/or writing; Sishu 3.Elementary school

		4.Middle school 5.High school; Vocational school;Two/Three Year College/Associate degree; Four Year College/Bachelor's degree; Post-graduated(Master/PhD)
	living in rural areas	Whether respondent lives in rural or urban area 0. Urban community 1. Rural village
	living geographical regions	Which geographical regions respondent lives in 1 Eastern China, including Beijing, Fujian, Guangdong, Hebei, Jiangsu, Liaoning, Shandong, Shanghai, Zhejiang 2 Central China, including Anhui, Henan, Hunan, Hubei, Jiangxi, Jilin, Shanxi, 3 Western China, including Chongqing, Gansu, Guangxi, Guizhou, Qinghai, Shaanxi, Sichuan, Xinjiang, Yunan
Physical health	self-reported health	Respondent’s self-reported health status: 1.Fair and above (Very good, good, or fair) 2.Less than fair (Poor or very poor)
	ADL	6-item summary of any difficulty with activities of daily

		living (ADL) summaries, including bathing, dressing, eating, getting in/out of bed, using the toilet, and controlling urination.
Health behaviors	drinking alcohol	Whether respondent ever drank any alcohol last year 0.No 1.Yes
	smoking	Whether respondent ever smoked 0.No 1.Yes
Economic status	pension income	Respondent's total pension income
	nonfood consumption	Respondent's non-food consumption last month
	public health insurance	Whether respondent has public health insurance 0.No 1.Yes
	private health insurance	Whether respondent has private health insurance 0.No

		1.Yes
Social network	co-residing with children	Whether respondent co-reside with any child 0.No 1.Yes
	living near children	Whether respondent live near children 0.No 1.Yes
	weekly contacting with children	Whether respondent has weekly contact with children in person/phone/email 0.No 1.Yes
	social activities in the past month	Whether the respondent has any social activities in the past month (The social activities include : Interacted with friends; Played Ma-jong, played chess, played cards, or went to community club; Went to a sport, social, or other kind of club; Took part in a community-related organization; Done voluntary or charity work; Attended an educational or training course)

		0. No 1. Yes
Childhood living conditions	father education	The education level of respondent’s biological father 1. No formal education (illiterate) 2. Did not finish primary school but capable of reading and/or writing; Sishu 3. Elementary school; 4. Middle school 5. High school; Vocational school; Two/Three Year College/Associate degree; Four Year College/Bachelor's degree; Post-graduate(Master); Post-graduate(PhD)
	mother education	The education level of respondent’s biological mother 1. No formal education (illiterate) 2. Did not finish primary school but capable of reading and/or writing; Sishu 3. Elementary school 4. Middle school 5. High school; Vocational school; Two/Three Year College/Associate degree; Four Year College/Bachelor's

		degree; Post-graduate(PhD)
	mother occupation	The occupation of respondent's female dependents in childhood before respondent was age 17 1. Farming 0. Non-Agricultural
	father occupation	The occupation of respondent's male dependents in childhood before respondent was age 17 1. Farming 0. Non-Agricultural
	self-reported health during childhood	Childhood Health Status compared to other children of the same age before the respondent was 15 years old (including 15 years old) 1. Much Healthier; Somewhat Healthier; About Average 0. Somewhat Less Healthy; Much Less Healthy
	family financial situation during childhood	Family's financial situation in childhood compared to the average family in the same community or village, when the respondent was a child before age 17 1. A Lot Better off than Them; Somewhat Better off than

		Them; Same as Them 0. Somewhat Worse off than Them; A Lot Worse off than Them