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Household use of polluting cooking fuels and late-life cognitive function: A harmonized analysis of India, Mexico, and China

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A R T I C L E I N F O

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A B S T R A C T

Introduction: Exposure to high levels of air pollution is associated with poor health, including worse cognitive function. Whereas many studies of cognition have assessed outdoor air pollution, we evaluate how exposure to air pollution from combustion of polluting household fuels relates with cognitive function using harmonized data from India, Mexico, and China.
Materials & methods: We analyze adults age 50+ in three nationally representative studies of aging with common data collection methods: the 2017–2019 Longitudinal Aging Study in India (n = 50,532), 2015 Mexican Health and Aging Study (n = 12,883), and 2013 China Health and Retirement Longitudinal Study (n = 12,913). Use of polluting fuels was assessed by self-report of wood, coal, kerosene, crop residue, or dung for cooking. Cognitive function was measured by performance across several cognitive domains and summarized into a total cognition score. We used linear regression, by country, to test how polluting cooking fuel use relates with cognition adjusting for key demographic and socioeconomic factors.
Results: Approximately 47%, 12%, and 48% of respondents in India, Mexico, and China, respectively, relied primarily on polluting cooking fuel, which was more common in rural areas. Using polluting cooking fuels was consistently associated with poorer cognitive function in all countries, independent of demographic and socioeconomic characteristics. Adjusted differences in cognitive function between individuals using polluting and clean cooking fuel were equivalent to differences observed between individuals who were 3 years of age apart in Mexico and China and 6 years of age apart in India. Across countries, associations between polluting cooking fuel use and poorer cognition were larger for women.
Conclusions: Results suggest that household air pollution from the use of polluting cooking fuel may play an important role in shaping cognitive outcomes of older adults in countries where reliance on polluting fuels for domestic energy needs still prevails. As these countries continue to age, public health efforts should seek to reduce reliance on these fuels.

1. Introduction

Exposure to ambient air pollution has been associated with poorer health across the globe with an estimated impact of 4 million premature deaths and 103 million disability-adjusted life years lost in 2015 worldwide (Cohen et al., 2017). Whereas findings regarding the effects of ambient air pollution on human health have been established for respiratory illnesses, cardiovascular diseases, and mortality, more recent research has suggested that the negative effects of high air pollution exposure may also extend to poorer cognitive outcomes (Ailshire and Crimmins, 2014; Gatto et al., 2014; Kulick et al., 2020a, 2020b; Oudin et al., 2016; Power et al., 2018, 2011; Ranft et al., 2009; Salinas-

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Rodríguez et al., 2018; Tonne et al., 2014; Weuve et al., 2012; Yu et al., 2020).

Most research on the implications of air pollution for cognitive function has focused on air pollution in the outdoor environment, despite known risks of exposure to pollution from the combustion of polluting household fuels. Fewer studies have considered how exposure to air pollution from sources inside the home may relate to cognitive function. Globally, combustion of polluting fuels for cooking and other domestic energy remains a common practice. Approximately 3 billion people rely on solid polluting fuels for cooking needs, the majority of whom live in low- and middle-income countries (World Health Organization [WHO], 2018). Combustion of polluting fuels, especially with poor ventilation, causes household members to be exposed to high levels of pollutants and particulate matter (Smith and Pillarisetti, 2017). In addition to poorer cognitive health, household air pollution (HAP) exposure from polluting fuels is also associated with premature mortality (WHO, 2018), elevated blood pressure (Baumgartner et al., 2011), and poorer respiratory health (Perez-Padilla et al., 2010).

Recent studies have investigated links between polluting cooking fuel use and cognitive health among older adults in low- and middle-income countries and reported poorer cognitive outcomes among those exposed to HAP from using polluting cooking fuels in nationally representative samples of adults age 50 and over in Mexico (Saenz et al., 2018b; Saenz, 2021). Research in China has similarly reported polluting cooking fuel use to relate with poorer cognitive outcomes (Cao et al., 2021; Chen et al., 2021; Cong et al., 2021; Du et al., 2021; Ji et al., 2021; Luo et al., 2021; Qiu et al., 2019). In India, a study of adults age 30–59 in rural Puducherry in South India (Krishnamoorthy et al., 2018) and a study of older adults in six states in India (Rani et al., 2021) similarly found polluting cooking fuel use to relate with worse cognitive outcomes. However, comparisons of published studies on polluting fuel use and cognition are challenging given the differing age ranges of samples, covariates used in analyses, and cognitive outcomes evaluated. We are unaware of any cross-nationally comparative studies of polluting cooking fuel use and cognitive function. This is a limitation as cross-national studies may strengthen the conclusions drawn from population-based research on single populations (National Research Council, 2001).

The current study makes use of harmonized data from nationally representative studies of aging in Mexico, India, and China with common survey protocols and methods of measuring both use of polluting cooking fuels and cognitive functioning to facilitate comparisons across countries. By evaluating this association in each of these unique contexts with consistent measures, we can determine whether findings obtained from one context are in harmony with those observed across our diverse globe. This is an essential step towards understanding whether associations may be general. Cross-nationally comparative research is also vital as polluting cooking fuel use occurs in countries across the globe with differences in the prevalence of polluting fuel use (WHO, 2016), types of polluting fuels used for combustion (IEA, 2006), policies aimed at improving access to clean fuels (The World Bank, 2000), and rural/urban patterning of polluting fuel use across countries (WHO, 2016).

We focus our analyses on data from Mexico, China, and India as three countries where reliance on polluting cooking fuels remains common. The percentages of households primarily using *clean* cooking fuels and technologies are 86%, 57%, and 34% in Mexico, China, and India, respectively (WHO, 2016). These countries were of further interest because the majority of polluting fuel used in both Mexico (Maldonado et al., 2011) and India comes from wood but the use of dung remains prevalent in parts of India (Office of the Registrar General & Census Commissioner, India, 2011) and coal use is common in rural China (Li et al., 2011; Zhang and Smith, 2007). Building on past studies of individual countries (Cao et al., 2021; Chen et al., 2021; Cong et al., 2021; Du et al., 2021; Ji et al., 2021; Krishnamoorthy et al., 2018; Luo et al., 2021, 2021; Qiu et al., 2019; Rani et al., 2021; Saenz et al., 2018b; Saenz, 2021), we describe and compare the associations between polluting cooking fuel use and cognitive function at an international scale, using harmonized data to answer whether the association between polluting household fuel use and cognition is consistent across settings.

2. Materials and methods

2.1. Data

We used data from three harmonized, large, nationally representative studies of aging including the 2015 Mexican Health and Aging Study (MHAS), the 2017–2019 Longitudinal Aging Study in India (LASI), and the 2013 China Health and Retirement Longitudinal Study (CHARLS). The MHAS (Wong et al., 2017), LASI (Arokiasamy et al., 2012), and CHARLS (Zhao et al., 2014) have been described in detail elsewhere and are sister studies of the United States Health and Retirement Study (HRS) with comparable survey protocols. In the LASI, the sample began with 52,393 respondents age 50+. We then excluded any respondents for whom cooking fuel was not obtained (n = 1210), and respondents missing on any other variable used in the analyses (n = 651), resulting in an analytic sample size of 50,532. In the MHAS, the 2015 wave started with 14,203 respondents age 50+. Respondents with missing information on cooking fuel were then removed (n = 126), followed by 1194 respondents who were missing on other variables of interest resulting in an analytic sample size of 12,883. The 2013 CHARLS started with 15,104 respondents age 50+. We then excluded 1586 participants who did not take a cognitive test, 172 participants for whom data on cooking fuel was not obtained, and those missing on any other variables of interest (n = 433). The final analytic sample consisted of 12,913 individuals. Across studies, excluded participants were generally more likely to be living in urban areas, male, not married, and older. Harmonized study data and links to each study's website can be accessed from https://g2aging.org.

2.2. Cognitive function

Each study assessed cognition using several tasks. However, certain tasks were not included in all studies. For this reason, we created two summary measures of cognitive function: one using only the four cognitive tasks that were common across studies (Immediate Word Recall, Delayed Word Recall, Orientation, and Constructional Praxis), and one using all available cognitive information in each study. Focusing first on the tasks common across studies, Immediate Word Recall was assessed as the immediate recall of a word list without delay. The MHAS used an eight-word list (score range: 0–8) and LASI and CHARLS used ten-word lists (score range 0–10). Across studies, respondents recalled the word list and the total number of words recalled correctly was calculated to assess Delayed Word Recall (range 0–8 in MHAS and 0–10 in LASI and CHARLS). Orientation was assessed across studies by asking respondents to identify the day, month, and year. The number of correct responses was calculated, ranging 0–3. Last, the Constructional Praxis task involved the respondent copying a figure. In the MHAS, the drawings were scored with range 0–6 based on correctness, whereas LASI and CHARLS used a binary indicator (ranging 0–1) for whether the respondent copied the figure correctly or failed to draw the figure.

Shifting attention to the tasks that were not common across studies, the MHAS also included a Backwards Counting task (respondent was asked to count backwards from 20, range: 0–2), a one-minute Animal Naming task to assess verbal fluency (range: 0–60), a Visual Memory (respondent recalled a figure after a delay, range: 0–6), and a Visual Scanning task in which the respondent identified a target stimulus in a visual array of stimuli (range: 0–60). The LASI also included additional tasks such as identifying the day of the week to create an additional Orientation to Time score (range: 0–4) based on day, month, year, and day of the week, Orientation to Space (identification of place, street, city, and district, range: 0–4), a Serial 7 Subtraction task (range: 0–5), an

Object Naming task (range: 0–2), an Executive Function task involving folding a piece of paper (range: 0–3), a Verbal Fluency task (range: 0–150), Backwards Counting from 20 (range: 0–1) and 100 (range: 0–1), and a task involving two computations (range: 0–2). CHARLS included no additional tasks.

We created summary measures of cognitive function for each participant in each study, which we used as our primary outcome of interest. This was accomplished by estimating general cognitive function as a latent variable measured by the observed cognitive task scores in separate confirmatory factor analyses (CFA) in each sample. Latent variable approaches to measuring cognitive function are frequently used and valid (Carroll, 2003; Plomin and Spinath, 2002). Latent variables were standardized to a mean of zero and a variance of one and each cognitive task's factor loading was freely estimated and allowed to differ across studies. The standardization of the latent variable to a variance of one allows parameter estimates to be interpreted in terms of standard deviations. CFAs used a Weighted Least Squares (WLSMV) estimator, allowing inclusion of binary/categorical observed variables, because some variables had limited ranges and were best captured as categorical variables (Orientation, Constructional Praxis in LASI and CHARLS, Object Naming, Executive Functioning, Backwards Counting from 20 and 100, and Computation). The CFAs were estimated in the "lavaan" R package (Rosseel, 2012) and factor scores were estimated using the Empirical Bayes Modal method, which were used as our primary outcomes of interest. CFAs used a pairwise approach to missing data, allowing respondents with incomplete information on cognitive tasks to be included. We estimated latent variables and factor scores both using only the cognitive tasks common across studies and using all available cognitive information in each study. Our primary results are based on scores calculated using the former but sensitivity analyses were conducted using the latter.

2.3. Polluting cooking fuel

HAP exposure was proxied using reports of the primary cooking fuel in households. In the MHAS, respondents were asked whether their primary cooking fuel was gas, wood or coal, or other. Respondents in households that primarily used wood or coal were classified as using polluting cooking fuels whereas those who primarily used gas were considered to use clean cooking fuel. LASI respondents were also asked to report their main source of cooking fuel. Respondents in households using kerosene, charcoal/lignite/coal, crop residue, wood/shrub, or dung cake were classified as using polluting cooking fuel whereas those who relied on liquefied petroleum gas, biogas, or electricity were considered to use clean cooking fuel. In CHARLS, respondents in households reporting coal or crop residue/wood burning were classified as using polluting cooking fuels whereas those who relied on natural gas, marsh gas, liquefied petroleum gas, or electricity were classified as using clean cooking fuels.

As a sensitivity analysis, we constructed a second measure combining polluting cooking fuel with other polluting fuels used in the home. Unfortunately, secondary household fuels were only assessed in LASI and CHARLS surveys. LASI assessed if households used any other fuel than the main cooking fuel for other purposes (such as boiling water for bathing, lighting, etc.) and were presented with the same fuel options. A variable for any polluting fuel use was constructed as 1) household relied on a polluting cooking fuel or used a polluting fuel for any other purpose; 0) no polluting fuel use. CHARLS assessed the main heating fuel used in households. Those using coal, crop residue, or wood were considered to use a polluting heating fuel, whereas those using solar, natural gas, liquefied petroleum gas, or electricity were considered to use a clean heating fuel. Similar to LASI, a variable for any polluting fuel use was constructed as 1) household used a polluting cooking or heating fuel and 0) no polluting fuel use.

2.4. Confounding variables

Low socioeconomic status (SES) is associated with reliance on polluting fuels and worse cognitive function, making SES an important potential confounder. For this reason, we adjusted models for a variety of SES indicators at both individual and household levels. Education was classified as no education, low education (1–5 years of education), mid education (6 years in MHAS/CHARLS and 6–9 years in LASI), and high education (7+ years in MHAS/CHARLS, and 10+ in LASI). These categories corresponded roughly with the distribution of education in each country and landmarks of the distinct educational systems, such as completion of elementary or middle school. We included household wealth and per-capita consumption categorized into quartiles. To assess housing quality as an additional SES marker, we created five indicators of poor housing quality based on: 1) the materials of the respondent's dwelling (ceiling, wall material, and floor materials); 2) sanitary facility; 3) electricity; 4) source of water; and 5) crowding, based on prior studies on poverty in Mexico (CONEVAL, 2010). We calculated the total number of indicators in which a respondent's house was classified as poor and categorized this as zero indicators of poor housing, one indicator of poor housing, and two or more indicators of poor housing. Details of the indicators are provided in the Appendix.

Rural dwelling is also associated with polluting fuel use (Bruce et al., 2000) and worse cognitive function (Jia et al., 2014; Saenz et al., 2018a; Xu et al., 2018) making rural dwelling an additional confounder. Thus, we included an indicator of rural dwelling for each study. In Mexico, respondents who lived in localities with <2500 residents were considered to live in a rural area. In China, we use a binary variable that classifies areas as rural versus urban as defined by the National Bureau of Statistics in China based on area level factors including population density. In India, rural/urban dwelling was captured using a binary indicator for community size of more or less than 5000 inhabitants. These classifications are based on country-specific definitions used in each country to accurately distinguish rural versus urban areas in each country's unique context.

2.5. Statistical analysis

We evaluated how use of polluting cooking fuels related with cognitive function in each study using ordinary least squares (OLS) multivariable linear regression. In our primary analyses, the outcome variable was the general cognitive function factor score estimated using the common items across studies (Immediate Recall, Delayed Recall, Orientation, and Constructional Praxis) and the independent variable of interest was household use of polluting cooking fuels. All other variables were controlled for as potential confounders because we hypothesized that they are common causes of both polluting fuel use as well as cognitive functioning. We constructed models in a staged fashion to test the sensitivity of findings to different levels of adjustment for confounders. In Model 1, we adjusted for basic demographic characteristics (age, gender, rural/urban, and marital status). In Models 2 and 3, we added SES markers by adding education in Model 2, and household wealth, per-capita consumption, and indicators of poor housing in Model 3. Descriptive results are weighted using sampling weights provided by each study. Regression models are unweighted. Regressions for CHARLS data clustered standard errors at the community level whereas MHAS and LASI models clustered standard errors at the household level as studies surveyed both spouses in each selected household if respondents were married, leading to non-independence of observations within each household.

To make the magnitude of the association between polluting cooking fuel use and cognitive function easier to interpret we also scaled the parameter estimates for polluting cooking fuel use on cognitive function in terms of cognitive differences between people of differing years of age. This is because age is closely related with cognitive function as cognitive abilities tend to decline with older age in late-life (Institute of

Medicine, 2015). This was accomplished by dividing the parameter estimate for polluting cooking fuel use by the parameter estimate for age, in each study, in the fully adjusted models (Model 3). We note that exposure to polluting cooking fuel may be time-varying and cumulative yet our estimates of the equivalent additional years of age associated with polluting fuel use is based on contrasts between people of different ages rather than the same person over time. Nevertheless, the conversion is useful to give perspective to the magnitude of the effect of polluting cooking fuel use on cognition.

We conducted multiple sensitivity analyses. First, we tested models using factor scores based on all available cognitive tasks in each study as outcomes. Second, we considered multiple fuels used in households in LASI and CHARLS. Third, following prior studies that have reported stronger effects of polluting cooking fuel use for adults age 65+ (Ji et al., 2021; Luo et al., 2021) and women (Chen et al., 2021; Ji et al., 2021; Luo et al., 2021), we tested whether being 65 or older or female modified the observed associations across countries using interactions between age group/gender and polluting cooking fuel use and estimating models stratified by age group and gender. Fourth, in LASI, we were able to evaluate associations with polluting fuels by ventilation type and cooking location (i.e., clean cooking fuel versus using polluting fuels indoors without ventilation, using polluting fuels indoors with ventilation [such as traditional/electric chimney, exhaust fan, or cooking near open widows/doors], and using polluting fuel outdoors). We were also able to investigate associations with polluting fuels by stove type (i.e., clean cooking fuel versus polluting fuels in an improved cookstove, polluting fuels in a traditional chullah, or polluting fuels in an open fire).

3. Results

3.1. Descriptive results

We report descriptive results showing the demographic and socioeconomic characteristics of each sample by reported primary cooking fuel in Table 1. The percentage of respondents in households that relied on polluting cooking fuels was substantial and differed across countries with 11.7% of respondents in Mexico, 46.6% of respondents in India, and 47.5% of respondents in China living in households that used polluting fuels for cooking. Descriptive results also demonstrated that, across studies, respondents who relied on polluting cooking fuels performed worse across all cognitive tasks compared to their counterparts utilizing clean fuels for cooking. Disparities in cognitive function were also accompanied by considerably different demographic and economic characteristics. We obtained a series of expected results in that, across the three countries, respondents in households that used polluting cooking fuels were more likely to have lower levels of education, be in a

Table 1
Descriptive Characteristics of Adults age 50+ in India, Mexico, and China by Primary Cooking Fuel.

	Longitudinal Aging Study in India				Mexican Health and Aging Study				China Health and Retirement Longitudinal Study			
	Clean Cooking Fuel (n = 26,993)		Polluting Cooking Fuel (n = 23,539)		Clean Cooking Fuel (n = 11,378)		Polluting Cooking Fuel (n = 1505)		Clean Cooking Fuel (n = 6779)		Polluting Cooking Fuel (n = 6134)	
Cognitive Function	N	%	N	%	N	%	N	%	N	%	N	%
Orientation (Mean, SD)	2.2	1.1	1.6	1.1	2.5	0.8	2.1	1.0	2.5	1.0	2.0	1.2
Immediate Recall (Mean, SD)	5.2	1.8	4.6	1.7	4.0	1.4	3.2	1.3	4.3	1.8	3.6	1.8
Delayed Recall (Mean, SD)	4.1	1.9	3.4	1.7	4.2	2.1	3.6	2.2	3.4	2.0	2.7	2.0
Constructional Praxis (Mean, SD)	0.5	0.5	0.3	0.4	5.6	1.0	5.1	1.4	0.7	0.4	0.5	0.5
Standardized Common Tasks	0.1	1.0	−0.5	0.9	0.1	0.9	−0.5	1.0	0.2	0.8	−0.2	0.8
Standardized All Tasks	0.1	1.0	−0.4	0.9	0.2	1.0	−0.7	0.9	0.2	0.8	−0.2	0.8
Demographics												
Age (Mean, SD)	63.0	9.6	63.5	9.2	66.5	9.5	66.1	9.5	62.0	9.0	63.5	8.6
Female	14,281	52.7	12,540	53.6	6630	56.7	810	53.2	3447	50.6	3165	51.6
No Education	9985	39.0	15,022	68.1	1531	12.4	579	39.4	1448	19.7	2280	37.5
Low Education	4923	17.5	4438	17.4	3211	25.8	657	43.7	1108	14.7	1336	21.7
Mid Education	4795	16.7	2649	9.4	2613	22.6	192	12.5	2962	44.0	2168	35.3
High Education	7290	26.8	1430	5.0	4023	39.2	77	4.4	1261	21.6	350	5.5
Marital Status												
Married/Partnered	19,586	71.7	16,945	71.0	7517	66.3	1106	72.3	5841	84.8	5270	84.3
Widowed	6742	26.4	6049	27.2	2154	15.8	264	18.5	832	13.2	758	13.7
Other (Divorced/Separated/Never Married)	665	1.9	545	1.8	1707	17.9	135	9.2	106	2.0	106	2.0
Household Wealth Quartile												
1st Quartile (Lowest)	4301	16.9	7912	33.7	2476	21.8	620	38.9	1041	16.0	2000	31.7
2nd Quartile	4893	18.5	7673	34.5	2828	23.6	414	31.3	1301	15.9	1985	32.0
3rd Quartile	7186	26.9	5522	23.1	3067	29.2	224	15.1	1872	25.2	1452	23.8
4th Quartile (Highest)	10,613	37.6	2432	8.8	3007	25.5	247	14.7	2565	43.0	697	12.6
Per Capita Consumption Quartiles												
1st Quartile (Lowest)	3957	17.1	8982	39.6	2168	17.0	758	51.2	1024	12.4	2213	35.7
2nd Quartile	6223	24.2	6585	28.4	1979	17.2	383	25.0	1482	19.9	1779	28.5
3rd Quartile	7637	26.3	4802	19.8	3274	28.0	299	19.9	1849	25.7	1379	22.6
4th Quartile (Highest)	9176	32.4	3170	12.3	3957	37.8	65	3.9	2424	42.0	763	13.2
Rural/Urban												
More Urban	14,950	51.3	2533	7.1	9924	86.6	461	27.1	3834	65.6	1198	20.8
Number of Indicators of Poor Housing												
0	16,398	58.5	6876	21.9	9625	84.2	314	17.5	3755	63.7	791	14.6
1	7678	29.2	8020	33.5	1472	13.3	722	49.0	2012	24.6	2416	39.9
2+	2917	12.3	8643	44.6	281	2.6	469	33.5	1012	11.7	2927	45.5

Note: Source: authors' own calculation using data from the 2017–2019 LASI, 2015 MHAS, and 2013 CHARLS. "Low Education" was defined as 1–5 years in all studies. "Mid Education" was defined as 6 years in MHAS/CHARLS and 6–9 years in LASI. "High Education" is 7+ years in MHAS/CHARLS and 10+ in LASI. More urban is defined as a locality with more than 2500 residents in MHAS and more than 5000 in LASI whereas rural/urban classifications in CHARLS are based on definitions from the National Bureau of Statistics in China incorporating area level factors including population density.

lower quartile of household wealth, be in a lower quartile of per capita consumption, and have more indicators of poor housing quality when compared to respondents in households using clean cooking fuels. Across countries, respondents who used polluting cooking fuel were more likely to live in rural areas.

3.2. Regression results: polluting cooking fuel

Regression results are provided in Table 2. We focus our attention first on India and find, in Model 1, that using polluting (versus clean) cooking fuels was associated with poorer cognitive function with an association equivalent to scoring 0.36 standard deviations lower on our summary cognitive function measure (95% Confidence Interval (CI): −0.384, −0.344), when we only adjusted for basic demographic characteristics (age, sex, rural/urban dwelling, and marital status). When education was added in Model 2 and wealth, consumption, and indicators of poor housing were added in Model 3, the parameter estimate for polluting cooking fuels weakened, but was still related with reduced cognition (Model 2: β = −0.171, 95% CI: −0.189, −0.153, Model 3: β = −0.115, 95% CI: −0.135, −0.095). The fully adjusted association between polluting cooking fuel use and cognition was equivalent to differences in cognitive function observed between individuals 5.5 years of age apart in India.

Regression results were qualitatively similar in Mexico. Before adding SES markers (Model 1), polluting (versus clean) cooking fuel use was associated with 0.48 standard deviations poorer cognitive function (95% CI: −0.540, −0.418). Adjustment for SES in Models 2 and 3 resulted in weaker parameter estimates, which were (β = −0.224, 95% CI: −0.281, −0.167) when education was added and (β = −0.111, 95% CI: −0.172, −0.050) when wealth, per-capita consumption, and indicators of poor housing were added. Results for the use of polluting cooking fuel from our fully adjusted model were equivalent to

Table 2

Ordinary least squares regression of cognitive function among older adults age 50+ in India, Mexico, and China using only tasks common across studies.

	Longitudinal Aging Study in India (LASI)			Mexican Health and Aging Study (MHAS)			China Health and Retirement Longitudinal Study (CHARLS)		
	Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)	Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)	Model 1 β (SE)	Model 2 β (SE)	Model 3 β (SE)
Cooking Fuel (Ref: Clean)									
Polluting Cooking Fuel	−0.364***	−0.171***	−0.115***	−0.479***	−0.224***	−0.111***	−0.221***	−0.106***	−0.052***
	(0.010)	(0.009)	(0.010)	(0.031)	(0.029)	(0.031)	(0.018)	(0.016)	(0.016)
Urban									
More Urban Area	0.418***	0.196***	0.178***	0.287***	0.114***	0.076***	0.378***	0.197***	0.148***
	(0.011)	(0.010)	(0.010)	(0.024)	(0.022)	(0.022)	(0.021)	(0.017)	(0.017)
Basic Demographics									
Age	−0.025***	−0.020***	−0.021***	−0.047***	−0.034***	−0.034***	−0.026***	−0.016***	−0.016***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Female	−0.448***	−0.174***	−0.192***	0.070***	0.146***	0.139***	−0.244***	−0.001	−0.007
	(0.007)	(0.007)	(0.007)	(0.015)	(0.014)	(0.014)	(0.016)	(0.017)	(0.016)
Marital Status (Ref: Married/Partnered)									
Widowed	−0.214***	−0.129***	−0.118***	−0.125***	−0.100***	−0.072***	−0.140***	−0.074***	−0.073***
	(0.011)	(0.010)	(0.010)	(0.024)	(0.022)	(0.022)	(0.031)	(0.025)	(0.024)
Divorced/Separated/Never Married	−0.095**	−0.094***	−0.083***	−0.031	−0.063**	−0.022	−0.121**	−0.110**	−0.103*
	(0.029)	(0.025)	(0.025)	(0.022)	(0.020)	(0.020)	(0.051)	(0.054)	(0.058)
Education (Ref: No education)									
Low Education		0.504***	0.473***		0.591***	0.560***		0.455***	0.444***
		(0.010)	(0.010)		(0.026)	(0.026)		(0.021)	(0.021)
Mid Education		0.840***	0.796***		0.819***	0.770***		0.791***	0.767***
		(0.011)	(0.011)		(0.027)	(0.027)		(0.021)	(0.020)
High Education		1.166***	1.098***		1.168***	1.073***		1.093***	1.038***
		(0.012)	(0.012)		(0.027)	(0.028)		(0.029)	(0.028)
Wealth Quartile (Ref: Q1)									
Wealth Q2			0.033**			0.013			0.039*
			(0.011)			(0.021)			(0.020)
Wealth Q3			0.061***			0.061**			0.059***
			(0.012)			(0.021)			(0.023)
Wealth Q4 (Highest)			0.080***			0.070**			0.065**
			(0.012)			(0.021)			(0.029)
Consumption Quartile (Ref: Q1)									
Per Capita Cons Q2			−0.003			0.089***			0.072***
			(0.011)			(0.023)			(0.019)
Per Capita Cons Q3			0.028*			0.092***			0.118***
			(0.012)			(0.022)			(0.020)
Per Capita Cons Q4 (Highest)			0.044***			0.157***			0.184***
			(0.012)			(0.023)			(0.025)
Number of Indicators of Poor Housing (Ref: 0)									
1			−0.073***			−0.114***			−0.030
			(0.010)			(0.023)			(0.020)
2+			−0.173***			−0.205***			−0.051**
			(0.011)			(0.038)			(0.021)

Note: Source: authors' own calculation using data from the 2017-2019 LASI, 2015 MHAS, and 2013 CHARLS. "Low Education" was defined as 1-5 years in all studies. β indicates parameter estimate. SE indicates standard error. * denotes $p < 0.05$. ** denotes $p < 0.01$, *** denotes $p < 0.001$. "Mid Education" was defined as 6 years in MHAS/CHARLS and 6-9 years in LASI. "High Education" is 7+ years in MHAS/CHARLS and 10+ in LASI. More urban is defined as a locality with more than 2500 residents in MHAS and more than 5000 in LASI whereas rural/urban classifications in CHARLS are based on definitions from the National Bureau of Statistics in China incorporating area level factors including population density. Sample sizes in LASI, MHAS, and CHARLS are 50,532, 12,883, and 12,913, respectively.

differences in cognitive function observed between individuals 3.3 years of age apart in Mexico.

Patterns of results were consistent in China. In Model 1, polluting cooking fuel use was associated with a 0.22 standard deviations lower cognitive score (95% CI: −0.256, −0.186). Although parameter estimates were diminished somewhat by adjustment for SES in Models 2 and 3, polluting cooking fuel use was related with poorer cognitive function across models. The parameter estimates for polluting cooking fuel use was (β = −0.052, 95% CI: −0.083, −0.021) in the fully adjusted model (Model 3), which is equivalent to differences in cognitive functioning of people 3.3 years of age apart in China.

To compare associations across countries, we plot the parameter estimates for polluting cooking fuel use (from Table 2) with 95% confidence intervals by Model and country in Fig. 1 to compare the size of parameter estimates across countries. This illustrates that although parameter estimates for polluting cooking fuel use exhibit large differences when only basic demographic characteristics are controlled (Model 1), the parameter estimates become more similar with adjustments for SES. In the final model, the largest associations between polluting cooking fuel use and cognition were observed in India, followed by Mexico, and then China, with large overlap of the confidence intervals across countries.

3.3. Sensitivity analyses

We conducted multiple sensitivity analyses. First, to determine whether polluting cooking fuel use was related with cognitive function even when a broader battery of cognitive tests were used, we re-estimated models using the summary cognitive score calculated using all cognitive tasks available in each study (results shown in Supplemental Table 1). These results were largely consistent with those reported in Table 2 where only the four tasks common to all studies were used. In fully adjusted models (Model 3), using a polluting cooking fuel (compared to a clean cooking fuel) was associated with poorer cognitive function in India (β = −0.113, 95% CI: −0.131, −0.095), Mexico (β = −0.168, 95% CI: −0.217, −0.119), and China (β = −0.052, 95% CI: −0.083, −0.021) when all available cognitive tasks were used to create the standardized summary score.

The second set of sensitivity analyses involved considering other polluting fuels used in households to assess HAP. As mentioned above, these questions were only available for LASI and CHARLS. Thus, results for this section refer to India and China. These results are provided in Supplemental Table 2. The pattern of findings when considering multiple household fuels was largely consistent with those based only on polluting cooking fuels. After adjustment for all SES markers (Model 3), the parameter estimates were (β = −0.169, 95% CI: −0.189, −0.149) and (β = −0.077, 95% CI: −0.118, −0.036) in India and China, respectively.

Third, we investigated whether parameter estimates for polluting fuel use differed by gender and age groups across countries. Across countries, interactions between gender and polluting cooking fuel use were strong and suggested consistently larger parameter estimates for women. Interactions between polluting cooking fuel use and age were not present in Mexico but were found in India and China, but in opposite directions. Specifically, polluting cooking fuel use parameter estimates were larger for the group age 65+ in China but were larger for the group below age 65 in India. Supplemental Fig. 1 presents the associations stratified by age and gender.

Fourth, when investigating differences in cognitive function by cooking location and ventilation in the LASI, we find the largest reductions in cognition among those using polluting cooking fuel when there was no ventilation (n = 6312, β = −0.146, 95% CI: −0.173, −0.119) or using polluting fuels outdoors (n = 3172, β = −0.149, 95% CI: −0.182, −0.116) compared to those using clean cooking fuels with smaller reductions from cooking indoor with ventilation (n = 14,054, β = −0.097, 95% CI: −0.117, −0.077). Changing the reference group showed that cooking indoors with ventilation related with slightly better cognition compared to those using no ventilation (β = 0.048, 95% CI: 0.023, 0.073) suggesting a benefit of cooking with ventilation. For differences by stove type, compared to those cooking with clean fuels, those cooking with polluting fuels in a traditional chullah (n = 18,810, β = −0.117, 95% CI: −0.137, −0.097) or an open fire (n = 3896, β = −0.131, 95% CI: −0.162, −0.100) showed lower cognitive function. However, no significant differences in cognition were observed between clean fuel users and those cooking with polluting fuels in an improved cookstove (n = 827, β = −0.037, 95% CI: −0.098, 0.024). Changing the reference group showed that using polluting cooking fuels in an improved cookstove was associated with significantly better cognition (β = 0.093, 95% CI: 0.026, 0.160) compared to using polluting fuels in an open fire, suggesting a benefit of using improved cookstoves. Full results from these sensitivity analyses are provided in Supplemental Table 3.

We conducted additional tests to determine whether associations between polluting cooking fuel use and poorer cognition were robust to adjustment for daily/weekly use of incense and insect repellents (mosquito coils, liquid vaporizers, and fast cards), which may also expose residents to household pollution, in the LASI where this information was available. However, parameter estimates for polluting cooking fuel use were virtually unchanged when adjusting for these exposures and are thus not reported.

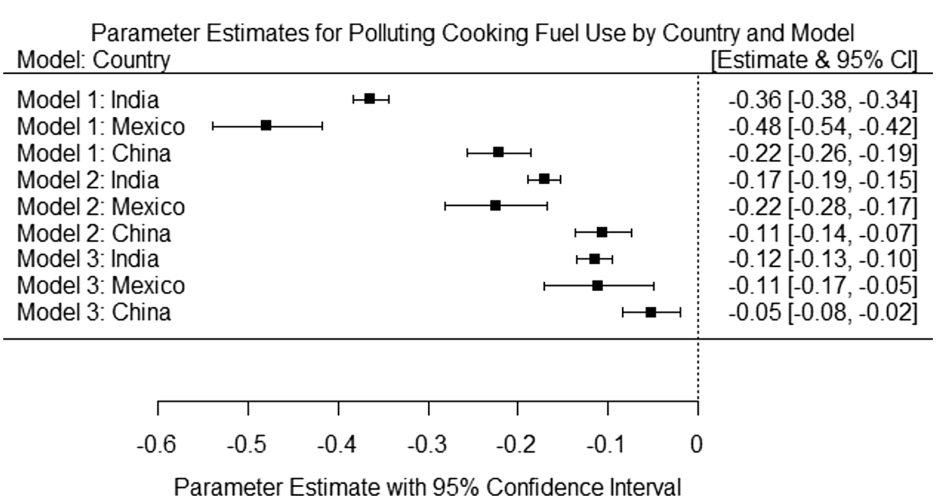

Fig. 1. *Adjusted Mean Difference in Cognitive Functioning in Standard Deviations for those Using Polluting Cooking Fuel versus those Using Clean Cooking Fuel with 95% Confidence Intervals for India, Mexico, and China.* Source: Authors' own calculations using data from the Longitudinal Aging Study in India, Mexican Health and Aging Study, and China Health and Retirement Longitudinal Study. Model 1 adjusts for age, sex, marital status, rural/urban dwelling. Model 2 adds educational attainment. Model 3 adds household wealth quartile, per-capita consumption quartile, and indicators of poor housing.

4. Conclusions

Using a sample of 76,328 older adults including over 30,000 individuals who relied on polluting cooking fuels, we found that using polluting cooking fuels was related with poorer cognitive function relative to individuals who relied primarily on clean cooking fuels. These associations were consistent across three nationally representative, population-based studies of older adults in India, Mexico, and China using harmonized measures of cognitive functioning and polluting cooking fuel use. This association was not explained by poorer SES, rurality, or lower educational attainment among users of polluting cooking fuels. Overall, the observed deficits in cognition associated with household use of polluting cooking fuel across all countries were meaningful, equivalent to differences in cognitive functioning that we would expect between individuals 3.3–5.5 years of age apart in our models. Importantly, these deficits were consistently larger among women who likely do most of the cooking across these countries. We also found in secondary analyses that associations between polluting cooking fuel use and poorer cognition may possibly be blunted by using ventilation and improved cooking technology.

This research has important public health implications as the combustion of biomass fuels results in very high exposure to fine and ultrafine particulate matter air pollution and nearly 3 billion individuals across the globe rely on these fuels for heating and cooking (WHO, 2018). This is problematic since the particles generated during combustion are so small that they are able to circumvent the blood-brain barrier and travel directly into the brain via the olfactory bulb (Costa et al., 2014; Elder et al., 2006; Kreyling, 2016). Once in the brain, these particles can damage neurons and cause sustained inflammation in the brain, which is a contributor to neurodegeneration (Sartori et al., 2012). Even those particles that do not directly travel to the brain can trigger oxidative stress, inflammation, and vascular injury throughout the body, the resulting clinical consequences of which may ultimately lead to cognitive impairment.

Our results are consistent with the mechanisms and findings of associations between ambient air pollution, cognitive impairment, and dementia (Ailshire and Crimmins, 2014; Gatto et al., 2014; Kulick et al., 2020a, 2020b; Oudin et al., 2016; Power et al., 2018, 2011; Ranft et al., 2009; Salinas-Rodríguez et al., 2018; Tonne et al., 2014; Weuve et al., 2012; Yu et al., 2020). Although little research has been conducted on HAP and cognition, our findings are consistent with prior studies that have found polluting cooking fuel use to be associated with poorer cognitive function in Mexico (Saenz, 2021; Saenz et al., 2018b), China (Cao et al., 2021; Chen et al., 2021; Cong et al., 2021; Du et al., 2021; Ji et al., 2021; Luo et al., 2021, 2021; Qiu et al., 2019), and in India (Krishnamoorthy et al., 2018; Rani et al., 2021). This work adds to these prior studies, however, by newly including a nationally representative study of older adults from all states in India and approaching this research at an international scale using harmonized data from nationally representative cohorts across three different countries around the globe. This has allowed us to directly compare the observed associations between countries. Our work also contributes to the literature more generally by using direct measures of cognition from three well-characterized cohorts as compared to relying on administrative data sources that can be unreliable in their outcome measures and information on key confounders.

Despite differences in the geographic environments and types of fuels used across the three countries we studied, we found that household polluting fuel use (whether proxied through cooking fuels or multiple fuels used in households) was consistently associated with impairments in cognition across all countries. This consistency was found in spite of the fact that the types of polluting fuels used for domestic energy differ across countries, with the use of dung remaining prevalent in parts of India (Office of the Registrar General & Census Commissioner, India, 2011) and coal use being common in rural China (Li et al., 2011; Zhang and Smith, 2007). Some differences in the magnitude of this association are plausibly explained by differences in median diameters of particles, concentrations of metals, and/or concentration of polycyclic aromatic hydrocarbons from different biomass fuels (including wood and coal) (Jin et al., 2016). Other explanations might also include different ventilation types, time spent cooking, or methods of cooking that may change the extent of exposure during cooking and other population characteristics such as diet quality and genetic factors that could confer protection from exposures. Although we were unable to examine all these factors across studies, data from India did suggest that using polluting fuels with ventilation was associated with smaller reductions in cognition than in unventilated spaces and that cooking with polluting fuels in an improved cookstove may reduce effects of polluting cooking fuel use on cognitive function. Despite the various ways in which countries may differ, the findings of similar associations across national studies adds important information to evidence supporting a potential causal association between household polluting cooking fuel use and cognition.

Another compelling finding of this study is that factors such as gender and age may be important determinants of how HAP may impact cognitive function. Consistent with prior studies (Chen et al., 2021; Ji et al., 2021; Luo et al., 2021; Qiu et al., 2019), we found that women's cognition suffered more from polluting cooking fuel use across all three countries. Although prior studies have reported significant associations between polluting cooking fuel use and specific cognitive abilities for both men and women (Qiu et al., 2019; Saenz, 2021; Saenz et al., 2018b), the current analysis focusing on *general* cognitive ability suggested that in China and Mexico significant effects of polluting cooking fuel use on cognitive function were limited to women. This is not surprising because, across regions of the world, women tend to be tasked with cooking and spend more time cooking than their male counterparts (Energy Sector Management Assistance Program [ESMAP] and Global Alliance for Clean Cookstoves [GACC], 2015) leading to relatively higher exposure to pollution related to cooking fuels and health effects for women (Sehgal et al., 2014). Although our findings are consistent with work finding larger effects of polluting fuel use on adults age 65+ in China (Ji et al., 2021; Luo et al., 2021), our results suggest this may not be universal as larger effects were observed for those *under* age 65 in India. Reasons underlying these differences may be complex, including differential mortality selection given differences in life expectancy (World Health Organization, 2020) and cultural expectations on cooking responsibilities.

In studying these three distinct nations, we also found that using polluting cooking fuels was not distributed equally within populations but often these patterns were similar across countries. For example, we found that respondents who resided in rural areas were more likely to rely primarily on a polluting cooking fuel compared to those in urban areas. This is significant given that several studies have suggested that adults in rural areas tend to have less favorable cognitive outcomes when compared to their urban-dwelling counterparts (Robbins et al., 2019), and this has been observed in Mexico (Saenz et al., 2018a), China (Jia et al., 2014), and India (Xu et al., 2018). The harmful effects on cognitive function from HAP from polluting cooking fuels observed in this analysis may help to explain disparities in cognitive function across rural and urban areas. Future studies should seek to test and quantify how exposure to pollutants inside the home may explain rural-urban disparities in cognitive function in low- and middle-income countries.

There are limitations to the current analysis. Although we investigated both polluting cooking fuels and other polluting fuels used in the house, using self-reported cooking fuels as a proxy for HAP may not fully capture the extent of one's exposure. It is common for households to practice "stove stacking", regularly using solid fuel stoves alongside clean cookstoves (ESMAP and GACC, 2015). Polluting fuels as secondary fuel sources are important sources of pollution but the studies we analyzed did not collect data specific to secondary *cooking* fuels. Other exposures such as incense, insect repellents, and wood-fired baths (Endo et al., 2000; Thompson et al., 2011) may also be important sources of

HAP in certain regions of the world. However, sensitivity analyses in the LASI suggested that associations with polluting cooking fuel were robust to adjustment for incense and insect repellents. Ambient air pollution from industrial or other sources may also correlate with HAP exposures. Future work should assess whether multiple fuels are used for cooking, conduct comprehensive questionnaires on other household practices that may increase pollution in the home, and assess for community level industrialization and outdoor air pollution measures.

Another limitation was that we excluded study participants missing on variables of interest. Although we could include the majority of age-eligible participants in our analyses (85.5% in China to 96.4% in India), excluded respondents were more likely to be older, not married, urban dwellers, and male in all studies and their exclusion could bias our parameter estimates. Additionally, although MHAS and CHARLS have completed multiple waves, LASI has only completed one. This limits us to cross-sectional designs to ensure consistent methodologies across studies where polluting fuel use and cognition data were collected contemporaneously. This is limiting because individuals switch cooking fuels over time and changes from polluting to clean cooking fuels are more common than the reverse (Cong et al., 2021; Saenz, 2021). Many individuals currently using clean cooking fuels may have used polluting fuels earlier, leading to exposure in the group we define as "unexposed." This would likely bias cross-sectional estimates towards the null. Alternatively, poorer cognitive function may affect one's ability to consider costs and benefits of switching to clean fuels and impair one's ability to effectively switch to cleaner fuels, which would bias our estimates away from the null. Thus, future studies should consider cooking fuels used throughout life to understand how differences in degree of exposure to HAP throughout life impacts cognition. Lastly, information on cooking location, ventilation, and stove type was only available in LASI preventing an in-depth look into how cooking practices affect cognition internationally.

These results have substantial implications for the health of older adults at a global level. A considerable proportion of global aging projected to occur from 2010 to 2050 will be in low- and middle-income countries (LMICs), including in Latin America, India, and China (WHO, 2011). This will be accompanied by large expansions in the number of people with dementia in LMICs, which is projected to increase from 27.3 million in 2015 to 89.3 million in 2050. This means that by 2050, 68% of people with dementia will be in LMICs (Alzheimer's Disease International, 2015). The expansion of the population of older adults and dementia in LMICs indicates the need to identify the relevant exposures specific to LMICs that may put individuals at risk for poor cognitive outcomes. Although using polluting cooking fuels was related with poorer cognitive outcomes equivalent to several additional years of age, using polluting cooking fuels is a *modifiable* factor. Policy efforts should focus on shifting households to improved cookstoves and cleaner cooking fuels. This could be accomplished through educational programs providing information on potential health consequences of HAP, subsidy programs to reduce the economic barriers to accessing clean cookstoves and fuels, and infrastructural improvements to improve the availability of clean cooking fuels in rural areas of LMICs.

CRediT authorship contribution statement

Joseph L. Saenz: Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Sara D. Adar:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Yuan Zhang:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Jenny Wilkens:** Conceptualization, Methodology, Formal analysis, Writing - original draft, Writing - review & editing. **Aparajita Chattopadhyay:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Jinkook Lee:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing. **Rebeca Wong:** Conceptualization, Methodology, Writing - original draft, Writing - review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Indicators of poor housing quality

Dwelling materials. In the LASI, interviewers made assessments of whether the roof, wall, and floor were made of temporary materials. If any of component of the structure (roof, wall, or floor) was considered to be temporary, the household was considered to have poor dwelling materials. In the MHAS, respondents who reported having a dirt floor, cardboard laminate ceiling, or asbestos or metal laminate walls were classified as having poor dwelling materials. In the CHARLS, respondents in households where the structure was made of wood/bamboo/grass, woolen felt, sheet iron, cave dwelling, tent, or adobe were classified as having poor dwelling materials.

Sanitary services. Poor sanitary services were captured in the LASI as having no facility, using a flush or pour flush toilet that does not flush to a piped sewer system, septic tank, or pit latrine, sharing toilet facilities with another household, or other sanitary facilities besides flush/pour flush toilet, pit latrine, or composting toilet. In the MHAS respondents were classified as having poor sanitary facilities if they used a bucket with water, reported not needing water, or did not having a sanitary facility. In the CHARLS respondents were classified as having poor sanitary facilities if they reported having no toilet or a non-flushing toilet.

Electricity. Our indicator of not having electricity was based on report of not having electricity in the LASI and the CHARLS. However, as the MHAS did not ask whether the household had access to electricity, we inferred whether the household had electricity by the respondents' reports of whether they had a refrigerator, television, washing machine, internet, or computer. Respondents who reported having any of these items were assumed to have electricity while those reported having none of the items were assumed not to have electricity.

Water source. Having a poor source of water in the LASI was classified as using a tanker, cart with small tank, surface water, bottled/pouch water, or water from another source (not piped, from well, or fresh water), or having a water source greater than a thirty minute round trip. In the MHAS households who got water from a lake, river, stream, or other piped water excluding piped water in the home or water from outside of house but from the land were classified as having a poor source of water. In CHARLS, respondents with no running water were classified as having a poor source of water.

Crowding. Overcrowding in all studies was measured as having greater than 2.5 persons per room (calculated as total number of persons in the household divided by total number of rooms). LASI considers bedrooms, living rooms, dining rooms, drawing rooms, servant's rooms, and halls to be rooms, whereas bathrooms, balconies, passages, and kitchens were not counted as rooms. The MHAS and CHARLS counted rooms similarly.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envint.2021.106722.

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