Section: Pathology

Systematic Review Article

INDOOR AIR POLLUTION AND INTRINSIC CAPACITY AMONG ADULTS AGED ≥45 YEARS IN INDIA: A SYSTEMATIC REVIEW

Jeevapriya Ravi[1], Vijaiyalakshmi Praveen[2], Sree Raksha Chokkalingam[3], Saranya Y[4], Sreenupriya R[5], Arun Murugan S[6]

[1]*Senior Assistant Professor, Department of Community Medicine, Government Medical College, Omandurar Government Estate, India.*
[2]*Assistant Professor, Department of Community Medicine, Government Medical College, Omandurar, Government Estate, India.*
[3]*CRMI, Government Medical College, Omandurar Government Estate, India.*
[4]*CRMI, Government Medical College, Omandurar Government Estate, India.*
[5]*CRMI, Government Medical College, Omandurar Government Estate, India.*
[6]*Head of the Department, Department of Community Medicine, Government Medical College, Omandurar Government Estate, India.*

Received : *10/03/2026*
Received in revised form : *20/04/2026*
Accepted : *08/05/2026*

Corresponding Author:
Dr. Sree Raksha Chokkalingam,
CRMI, Government Medical College, Omandurar Government Estate, India.
Email: sreesharmi4@gmail.com

DOI: 10.70034/ijmedph.2026.2.320

Source of Support: Nil,
Conflict of Interest: None declared

Int J Med Pub Health
2026; 16 (2); 1911-1920

ABSTRACT

Background: India bears a massive global burden of indoor air pollution (IAP), driven by sustained reliance on solid cooking fuels across the country. Due to the current global energy crisis, this number is predicted to be raising steadily in the future. Although cardiorespiratory consequences due to IAP are well-characterised, its impact on intrinsic capacity (IC), the WHO-defined composite of cognitive, psychological, locomotor, sensory, and vitality function, remains unsynthesised in the Indian context. This systematic review aimed to critically appraise the association between IAP exposure and all five IC domains among adults aged ≥45 years in India.

Materials and Methods: We included all studies enrolling adults aged ≥45 years residing in India, with various IAP exposure and outcomes mapped to at least one WHO IC domain. PubMed and Google Scholar were searched systematically with the last search being conducted on February 12, 2026. Risk of bias was assessed independently using the Newcastle-Ottawa Scale (NOS) with studies categorised as low, moderate, or high quality. Given substantial heterogeneity in IC outcome measurements, quantitative meta-analysis was not performed. A structured narrative synthesis with direction-of-effect assessment was undertaken.

Results: Thirteen studies all rated high in methodological quality met the inclusion criteria collectively incorporating upto 72,250 participants. In the cognitive domain, polluting fuel use was associated with significantly lower cognitive performance. In the psychological domain, odds of depression were higher among polluting fuel users. In the sensory domain, unclean fuel use was associated with a higher visual impairment which affected women more than men . In the vitality domain, solid fuel use was associated with 10% higher odds of frailty. Evidence for the locomotion domain was limited to one non-significant finding.

Conclusion: IAP exposure is consistently associated with multiple intrinsic capacity domains among older adults in India, with the strongest evidence in cognition and psychological capacity. The cognitive burden is equivalent to an estimated 6 years of accelerated biological ageing. These findings position clean fuel policy, kitchen ventilation, and IC-integrated geriatric screening as urgent public health priority.

Keywords: Aging, Air Pollution, Indoor; Cognitive Dysfunction; Depression; Healthy Aging; Systematic Review

INTRODUCTION

Indoor air pollution (IAP) is a leading health risk in middle-income countries, India being one of the largest contributors of global burdens due to continued dependence on polluting fuels for household uses.[1-3] Although clean fuel measures have expanded access to liquefied petroleum gas(LPG), sustained exposure to solid fuels like wood, dung, crop residue, coal, and kerosene is still an imminent burden in rural and socio economically backward and underprivileged populations in India.[2,4]

The health consequences of indoor air pollution have been documented extensively for respiratory and cardiovascular diseases.[1,2] However, evidence suggests that exposure to indoor air pollution may contribute to accelerated functional decline across mental and physical domains in older population.[5-8]

The World Health Organization (WHO) has introduced the concept of intrinsic capacity (IC) to capture the physical and psychological competence of an individual. Intrinsic capacity comprises of five domains: cognition, psychological capacity, locomotion, vitality, and sensory function serving as a potent indicator for assessing healthy ageing. Decline in these five domains are indicators of disability, disease, dependency, and mortality.[9-11]

India is experiencing a swift demographical shift, with an increasing number of elderly population aged 45 years and above.[12] Therefore, identifying modifiable environmental factors on intrinsic capacity is the key for fostering healthier ageing patterns. While many observational studies have found and stated links between household air pollution and specific outcomes like cognitive decline, depression, frailty, and sensory loss,[5-8] these findings are scattered and have not been comprehensively integrated using the intrinsic capacity framework.

This systematic review aims to synthesize and critically appraise evidence on the association between indoor air pollution and intrinsic capacity domains among older population aged more than 45 years in India.

MATERIALS AND METHODS

This systematic review was reported according to the PRISMA 2020 guidelines.[13] A detailed protocol specifying objectives, eligibility criteria, and analytical methods was registered in the PROSPERO systematic review registration site. Registration: CRD420251244801.

Eligibility criteria was defined using the modified PECO framework as mentioned below:

- Studies including adults aged ≥45 years in India. Multi-country studies were eligible if India-specific effect estimates could be extracted.
- All studies that are assessing indoor air pollution, including:

Solid/unclean cooking fuels (biomass, firewood, dung, crop residue, coal)
Kerosene use
Cooking fuel type
Kitchen ventilation
Separate kitchen
Stove type was included.

- Studies that assessed either Composite Intrinsic capacity or outcomes corresponding to WHO intrinsic capacity domains as mentioned below were included:

Locomotion - gait speed, grip strength, physical activity, phenotype-based frailty index (adapted Fried criteria), Frailty status.
Sensory - Cataract assessment- LOCS III grading, sensory capacity score.
Cognition - COGNITO Battery (Computerized cognitive testing), HMSE, Composite standardised cognitive performance score, Adapted Health and Retirement Study (HRS) cognition battery, Composite Cognitive Index.
Psychological - CES-D-10, CIDI-based algorithm.
Vitality - Sleep problem index, Vitality domain score.

This review does not have any comparators. Studies merely stating awareness without objective exposure measurements were excluded. Studies that only dealt with outdoor air pollution were excluded.

Studies were required to report adjusted effect estimates (e.g., odds ratios [OR], risk ratios [RR], regression coefficients [β]) with corresponding measures of precision (95% confidence intervals or standard errors).

Both randomized and non-randomized study types were included. Observational epidemiological studies, including Prospective or retrospective cohort studies, Case–control studies, Cross-sectional analytical studies and Experimental studies including Randomised control trials were included in the screening.

A systematic search was conducted across PubMed and Google Scholar. In short, the search strategy contained the terms Indoor air pollution, intrinsic capacity, cognition, vitality, locomotion, sensory, depression and India. The full search strategy and a more detailed description of the eligibility criteria is available at the PROSPERO trial registration site. The date of the last search was February 12, 2026.

All records identified through database searches were imported into a reference management system and duplicates were removed. Abstract and title screening was performed independently by 2 of us (S.R.C. and S.Y.) according to the predefined eligibility criteria. Any discrepancy was resolved by a third reviewer(S.R.). We attempted to identify further studies from the reference lists of the included articles.

Full text screening of studies was performed by three of the reviewers (S.Y.,S.R.C,S.R) and any questions or doubts were discussed with at least one other reviewer (M.R.J). Reasons for exclusion at full-text stage were documented. Fig.1 is a PRISMA flow diagram summarizing the study selection process.

Data were extracted using a structured, piloted extraction Excell spread sheet by two of us (S.Y., S.R.C.) and all data were validated at least twice by a third reviewer (S.R.). Extracted variables included:

Study identifiers (author, year, location within India)
Sample size
Demographic information
Inclusion/exclusion criteria highlights
2 Socioeconomic indicators
Comorbidities or special population characteristics
Exposure definition and measurement
Intrinsic capacity domain assessed
Outcome measurement tool
Fully adjusted effect estimates and 95% confidence intervals
P value
Direction of effect.

The same is presented in the tables 1 and 2.

Where both composite intrinsic capacity and domain-specific estimates were reported, data were extracted separately.

Risk of bias was assessed using the Newcastle Ottawa scale for Analytical Cross-Sectional Studies,[14] and presented in Table 7. Studies were categorized as low, moderate, or high risk of bias.

For binary outcomes (e.g., depression, cognitive impairment, frailty), adjusted odds ratios (ORs) were extracted. For continuous outcomes (e.g., cognitive score), adjusted regression coefficients (β) were extracted. When necessary, standard errors were derived from reported confidence intervals.

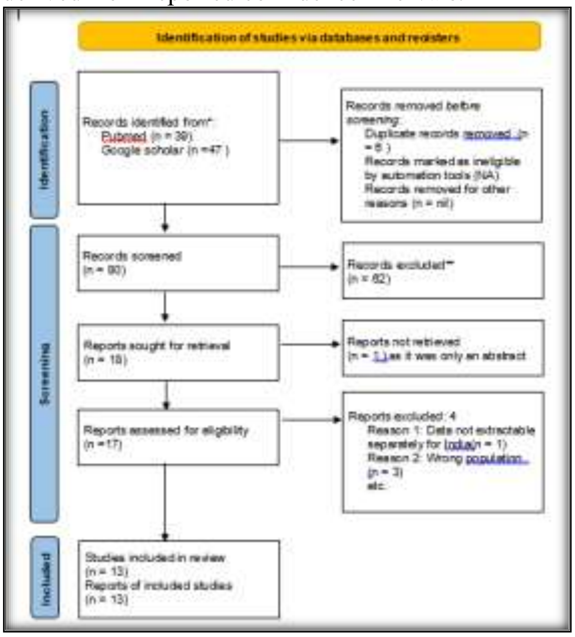

Figure 1: ***Prisma Flow Chart***

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RESULTS

Thirteen studies conducted in India met the inclusion criteria. Twelve were cross-sectional and one incorporated longitudinal components. Most studies were based on nationally representative datasets and sampling, including LASI and SAGE. Sample sizes ranged from 2,441 to more than 70,000 participants.

Exposure was primarily defined as use of polluting or solid cooking fuels compared with clean fuels; some studies additionally incorporated composite housing indicators reflective of indoor air pollution.

Outcomes were mapped to the five WHO intrinsic capacity (IC) domains: cognition, psychological capacity, sensory capacity, locomotion, vitality, and composite IC.

Effect measures varied across studies and included adjusted odds ratios (OR), linear regression β coefficients, and average marginal effects (AME). Given heterogeneity in outcome scaling and effect metrics, quantitative meta-analysis was not undertaken. A structured narrative synthesis and direction-of-effect assessment were performed.

Risk of bias was assessed and checked using the Newcastle-Ottawa Scale adapted for cross-sectional study design.[14] All included studies were rated as high methodological quality (scores 7–9 out of 9). Most studies demonstrated nationally representative datasets, validated outcome measures, and multivariable adjustment. The predominance of cross-sectional study designs limits causal interpretation, as temporality between indoor air pollution exposure and decline in intrinsic capacity cannot be definitively established.

Composite Intrinsic Capacity: One nationally representative study evaluated a composite intrinsic capacity index encompassing all five domains.[1,11] Polluting fuel exposure was associated with higher odds of intrinsic capacity deficit (OR 1.062; 95% CI 1.047-1.078).[15] Although modest in magnitude, the estimate was precise and statistically robust.

Cognitive Domain: Seven studies evaluated the association between indoor air pollution exposure and cognitive outcomes in India.[16-22] Outcomes were reported as continuous measures, including standardized z scores, 0-43 composite scores, or standardized global cognition indices. All studies reported multivariable adjusted estimates. One study, Saha 2024,[17] reported mean scores for overall cognition but regression coefficients were reported for each exposure of air pollution that was considered in the said study such as: separate kitchen, sanitation, and electricity.

Across all seven studies, exposure to polluting fuels was associated with lower cognitive performance. Adjusted β coefficients ranged from - 0.11 to -2.07, depending on scale and exposure category.

In an analysis of LASI Wave-1 data, exposure to polluting cooking fuels was discussed elaborately. Association of composite cognitive scores with each charcoal/lignite/coal use, wood/shrub use and dung cake use was calculated. The same was adjusted for socio-demographic and behavioural factors (adjusted β -2.07 for charcoal/coal; -1.11 for wood; p<0.001; -0.89 for dung cake) (Jana et al., 2022).[18]

One study additionally examined domain-specific cognitive subcomponents. Polluting fuel use was associated with lower performance in visuospatial ability (β = -0.28; p = 0.013) and executive function (β = -0.25; p = 0.019). Associations for memory, language, and attention were negative but did not consistently reach statistical significance (Mitra et al.,2025).[19]

In all studies, the direction of association was adverse (lower cognitive performance among polluting fuel users). No study reported a protective association.

Despite heterogeneity in cognitive scales and exposure classification, direction-of-effect consistently indicated a negative association across all studies. Effect magnitudes varied substantially depending on outcome scale (standardized z-scores versus raw composite scales), but adverse associations predominated.

Given differences in cognitive measurement instruments and scaling approaches, pooled effect estimation was not appropriate and hence was not performed. A Structured narrative synthesis was then undertaken and demonstrated uniform adverse directionality.

Psychological Domain : Five studies evaluated depressive symptoms and major depressive episodes using validated questionnaires (e.g., CES-D-10, CIDI-SF).[16,22,23,24] Outcomes were reported as binary (odds ratio) and standardized continuous scores. Odds ratios ranged from 1.09 to 2.06 across studies and regression coefficients ranged from 0.038 to 0.186. One study had reported a positive association with sleep problems and depression but a negative association with cognition (β = 0.038; β = 0.186; β = - 0.381).[22]

Sensory Domain: Two studies assessed sensory outcomes including cataract, visual impairment, and standardized sensory scores. Ravilla 2016 reported the association between cataract and biomass fuel usage as 0.98 for men and 1.18 for women.[25] But as the confidence interval ranged from 0.84 to 1.14 in men it is deemed to be statistically insignificant. Islam 2022 reported the outcome as AME = 3.22pp.[26]

Vitality Domain: One study assessed vitality-related outcomes.[27] Polluting fuel exposure was associated with both Reduced vitality score (β = - 0.008) and Increased odds of frailty (OR 1.10; 95% CI 1.04-1.16). This indicated statistically significant adverse associations.

Locomotion Domain : One study examined slow gait speed. The adjusted OR was 1.52 (95% CI 0.88 - 2.61), which did not reach statistical significance. Evidence for locomotion was limited.[28]

Across domains, direction-of-effect consistency was high, particularly in cognitive and psychological domains. Heterogeneity was observed in outcome measurement and effect metrics, but adverse associations predominated. No study reported protective effects of polluting fuel exposure.

Table 1: Study Characteristics

Study (Author, Year)	Sample Size (Total/Arms)	Age (Mean ± SD or Range)	Gender (% Female)	Setting (% Rural)	Inclusion/Exclusion Criteria	Socioeconomic Indicators	Comorbidities/ Special Characteristics
Smith, 2023 SAGE Wave 1 (India, ≥65 years)	Total: 2,441 Polluting: 1,936 Clean: 505	71.6 ± 10.0 years	48%	70.5%	Inc: Community-dwelling adults aged ≥65. Exc: Institutionalized and homeless.	Education (82.4% ≤ primary), Wealth quintiles	BMI, Disability (ADL limitations)
Ravilla, 2016 India Eye Study (North & South India, ≥60 years)	Total: 5,871 Biomass: 65%	Men: 70.1 ± 6.8 Women: 67.9 ± 6.4	48%	71.1–74.6%	Inc: Randomly sampled clusters; people ≥60 years. Exc: Non-participants (slightly older/more female).	SES index (caste, land, rooms), Education	BMI, Diabetes, Vitamin C deficiency, Malnutrition
Islam, 2022 LASI Wave 1 (National, ≥45 years)	Total: 53,438 Polluting: 23,281 Clean: 30,157	Mean: 60.1 years Range: ≥45 years	53.7%	68.8%	Inc: Non-institutionalized aged ≥45. Exc: <45 years, non-response on vision/fuel.	MPCE quintiles, Education, Caste, Occupation	Tobacco use, Persons per room
Jin, 2022 LASI Wave 1 (National, ≥60 years)	Total: 29,789 Polluting: 14,203 Clean: 15,586	68.7 ± 7.4 years	52.1%	66.3%	Inc: Adults aged ≥60. Exc: <60 years, missing fuel/mental health data.	Economic status (MPCE), Education, Caste, Religion	BMI, Chronic diseases, Sleep disorder
Rani, 2024 LASI Wave 1 (National, ≥50 years)	Total: 50,206 Polluting: 23,448 Clean: 26,758	Range: ≥50 years (38.5% are 50–59)	53.0%	70.3%	Inc: Adults aged ≥50. Exc: Missing outcome or fuel data.	MPCE quintiles, Education, Work status, Caste	BMI, Multimorbidity (≥2 chronic diseases)
Saha, 2024 LASI Wave 1 (National, ≥45 years)	Total: 35,059 Arms: NR	Range: ≥45 years (55.2% are 45–59)	35.2%	65.2%	Inc: Middle-aged and older adults aged ≥45. Exc: NR specifically.	Education, Housing type (Kutcha/Pucca), Sanitation, Electricity	Sleeping problems, Self-rated health

Shaw, 2024 LASI Wave 1 (National, ≥45 years)	Total: 72,250 Arms: NR	Mean: 58.57 years Range: ≥45 years	58.0%	68.2%	Inc: Representative non-institutionalized aged ≥45. Exc: NR specifically.	MPCE quintiles, Schooling (Mean 4.06 years), Caste	Depression, Sleep problems
Halder, 2025 LASI Wave 1 (National, ≥45 years)	Total: 55,572 Frail: 9,609	Range: ≥45 years (45–59 & ≥60)	53.3%	NR	Inc: Adults aged ≥45. Exc: <45, missing grip/walk speed, BMI outliers.	Education, MPCE quintile, Health insurance, Occupation	Tobacco abuse, Alcohol abuse
Jana, 2022 LASI Wave 1 (National, ≥45 years)	Total: 63,883 Solid: 28,486 Clean: 35,397	Range: ≥45 years (41.4% are 60+)	57.1%	63.9%	Inc: Adults aged ≥45 and spouses. Exc: NR specifically.	MPCE quintiles, Education, Caste, Religion	Physical activity, Yoga engagement
Li, 2022 SAGE Wave 1 (India subset, ≥50 years)	Total: 6,276 Arms: NR	63.31 ± 9.57 years	54.0%	50.7%	Inc: Adults aged ≥50. Exc: Missing depression or key covariates.	Annual household income level, Education	BMI, Diabetes, Hypertension
Mitra, 2025 CBR-SANSCOG (Rural Karnataka, ≥45 years)	Total: 4,145 Polluting: 1,665 Clean: 2,480	57.2 ± 9.05 years	43.7%	100% (Rural Taluk)	Inc: Resident ≥5 years, aged ≥45. Exc: Dementia, psychiatric/terminal illness, sensory/locomotor disability.	Annual income, Education years, Job skill level	BMI, Depression, Hypertension, Diabetes, Dyslipidaemia
Saenz, 2021 LASI Wave 1 (India subset, ≥50 years)	Total: 50,532 Polluting: 23,539 Clean: 26,993	Mean: 63.0–63.5 years Range: ≥50 years	~53.0%	48.7–93.0% (Arm dependent)	Inc: Adults aged ≥50. Exc: Missing fuel or cognitive tasks.	Education, Wealth quartiles, Consumption, Housing quality	NR
Shen, 2024 LASI Wave 1 (India subset, ≥60 years)	Total: 30,981 Polluting: 14,728 Clean: 16,253	Mean: 68.9 years Range: ≥60 years	52.0%	45.9–89.3% (Arm dependent)	Inc: Adults aged ≥60. Exc: Missing demographics or fuel information.	Education level, Per-capita consumption	BMI, Multimorbidity (≥2 diseases)

Abbreviations: NR = Not Reported; MPCE = Monthly Per Capita Consumption Expenditure; BMI = Body Mass Index; ADL = Activities of Daily Living; SES = Socioeconomic Status; Inc = Inclusion criteria; Exc = Exclusion criteria; LASI = Longitudinal Ageing Study in India; SAGE = WHO Study on Global AGEing and Adult Health; CBR-SANSCOG = Community-Based Research study in rural Karnataka.

Note: All "National" studies for India primarily utilize the LASI Wave 1 (2017–18) or WHO SAGE Wave 1 (2007–10) datasets. Sample sizes represent complete cases after exclusions. Polluting fuels include biomass, wood, dung, crop residue, kerosene, and coal. Clean fuels include LPG, natural gas, and electricity.

Cognitive Domain

Table 2: Association between indoor air pollution and cognitive function among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Jin 2022	29,789	Solid vs clean cooking fuel	Global cognitive impairment	β	-0.63	-0.79	-0.47	<0.001
Saha 2024	35,059	IAP vs no IAP	Composite cognitive score (exposed mean)	Mean	25.35	25.22	25.48	NR
		No separate kitchen	Cognitive score	β	-0.64	-0.90	-0.39	<0.001
		No electricity	Cognitive score	β	-0.97	-1.34	-0.61	<0.001
		No sanitation	Cognitive score	β	-0.81	-1.07	-0.55	<0.001
Jana 2022	63,883	Charcoal/lignite/coal vs clean	LASI composite (0-43)	β	-2.07	-2.37	-1.77	<0.001
		Wood/shrub vs clean	LASI composite (0-43)	β	-1.11	-1.21	-1.00	<0.001
		Dung cake vs clean	LASI composite (0-43)	β	-0.89	-1.12	-0.67	<0.001
		Other solid fuels vs clean	LASI composite (0-43)	β	-1.22	-1.51	-0.92	<0.001
Mitra 2025	4,145	Polluting vs clean fuel	Global cognition (z-score)	β	-0.28	-0.44	-0.11	0.002
			Visuospatial ability	β	-0.28	-0.48	-0.08	0.013
			Executive function	β	-0.25	-0.44	-0.07	0.019
			HMSE	β	-0.09	-0.28	0.09	0.448

Saenz 2021	50,532	Polluting vs clean cooking fuel	Composite cognitive (z-score)	β	-0.115	-0.135	-0.095	<0.001
Shen 2024	30,981	Polluting vs clean cooking fuel	Cognitive composite (z-score)	β	-0.262	-0.30	-0.22	<0.001
Shaw 2024	72,250	IAP composite index	LASI composite (0-43)	β	-0.381	-0.453	-0.309	<0.001

Abbreviations: β = standardized regression coefficient; CI = confidence interval; IAP = indoor air pollution; LASI = Longitudinal Ageing Study in India; HMSE = Hindi Mental State Examination; NR = not reported. All models fully adjusted for sociodemographic and health covariates.

Psychological Domain

Table 3: Association between indoor air pollution and depression/psychological capacity among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Jin 2022	29,789	Solid vs clean cooking fuel	Depressive symptoms (CES-D-10)	OR	1.09	1.03	1.16	<0.05
Rani 2024	50,206	Solid vs clean cooking fuel	Major depression (CIDI-SF)	OR	1.35	1.24	1.48	<0.001
Li 2022	6,276	Polluting vs clean cooking fuel	Major depressive episode (CIDI)	OR	2.06	1.44	2.94	<0.001
Shaw 2024	72,250	IAP composite index	Depression (CES-D)	β	0.186	0.162	0.210	<0.001
		IAP composite index	Sleep problems	β	0.038	0.022	0.054	<0.001

Abbreviations: OR = odds ratio; β = standardized regression coefficient; CI = confidence interval; CES-D = Center for Epidemiologic Studies Depression Scale; CIDI = Composite International Diagnostic Interview; CIDI-SF = CIDI-Short Form; IAP = indoor air pollution. All models fully adjusted.

Sensory Domain

Table 4: Association between indoor air pollution and sensory function among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Ravilla 2016	5,871	Biomass vs clean fuel	Cataract (men)	OR	0.98	0.84	1.14	0.82
		Biomass vs clean fuel	Cataract (women)	OR	1.18	1.02	1.36	0.02
Islam 2022	53,438	Unclean vs clean fuel	Visual impairment (logMAR)	AME	3.2 pp	1.4	5.0	<0.001

Abbreviations: OR = odds ratio; AME = average marginal effect; CI = confidence interval; pp = percentage points; logMAR = logarithm of the minimum angle of resolution. All models fully adjusted.

Vitality Domain

Table 5: Association between indoor air pollution and vitality/frailty among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Halder 2025	55,572	Solid vs clean cooking fuel	Frailty (Fried phenotype, ages 45-59)	OR	1.10	1.04	1.16	0.001

Abbreviations: OR = odds ratio; CI = confidence interval. Fried phenotype = validated 5-component frailty measure (weakness, slowness, exhaustion, low activity, weight loss). Model fully adjusted.

Locomotion Domain

Association between indoor air pollution and locomotor function among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Smith 2023	2,441	Unclean vs clean cooking fuel	Slow gait speed (4m walk test)	OR	1.52	0.88	2.61	NS

Abbreviations: OR = odds ratio; CI = confidence interval; NS = not statistically significant (p>0.05). Slow gait speed defined as <0.8 m/s over 4-meter walk test.

Composite Intrinsic Capacity

Table 6: Association between indoor air pollution and composite intrinsic capacity among adults aged ≥45 years in India

Study (Year)	Sample Size	Exposure	Outcome	Effect Type	Effect Size	95% CI Lower	95% CI Upper	P-value
Shen 2024	30,981	Polluting vs clean cooking fuel	IC deficit (composite 5 domains)	OR	1.062	1.047	1.078	<0.001

Abbreviations: OR = odds ratio; CI = confidence interval; IC = intrinsic capacity. Composite IC deficit defined per WHO framework (integration of cognitive, psychological, sensory, locomotor, and vitality domains). Model fully adjusted.
Note: All effect estimates are from fully adjusted models controlling for age, sex, residence, education, socioeconomic status, and relevant health covariates. LASI = Longitudinal Ageing Study in India; SAGE = WHO Study on Global AGEing and Adult Health; CBR-SANSCOG = Community-Based Research study in rural Karnataka.

Table 7: Risk of Bias Assessment (Newcastle-Ottawa Scale)

Study ID	Selection (Max 5★)	Comparability (Max 1★)	Outcome (Max 3★)	Total	Quality
Islam, 2022	★★★★★	★	★★★	9/9	High
Halder P, 2025	★★★★★	★	★★★	9/9	High
Smith, 2023	★★★★	★	★★★	8/9	High
Ravilla, 2016	★★★★	★	★★★	8/9	High
Mitra, 2025	★★★★★	★	★★★	9/9	High
Shen, 2024	★★★★	★	★★	7/9	High
Jin, 2022	★★★★★	★	★★	8/9	High
Rani, 2024	★★★★★	★	★★	8/9	High
Saha, 2024	★★★★★	★	★★	8/9	High
Shaw, 2024	★★★★★	★	★★	8/9	High
Jana, 2022	★★★★★	★	★★	8/9	High
Li, 2022	★★★★	★	★★	7/9	High
Saenz, 2021	★★★★	★	★★	7/9	High

Scoring Logic (per NOS.pdf): Selection (Max 5★: Representativeness, Sample Size, Non-response, Validated Tool); Comparability (Max 1★: Multivariable Analysis); Outcome (Max 3★: Objective Assessment, Statistical Test) = Total 9★.

DISCUSSION

This systematic review provides the first comprehensive synthesis of evidence linking indoor air pollution to intrinsic capacity across its five WHO defined domains: cognitive, psychological, locomotor, sensory, and vitality among adults aged ≥45 years in India. Across the 13 included studies, IAP exposure was consistently associated with significant deterioration in multiple IC domains the highest being in cognition and psychological domains.[16-28]

Cognitive domain: The cognitive domain yielded the most consistent evidence across the included studies. Saenz et al,[20] using the LASI dataset, indicated that 5.5–6 years of early cognitive ageing occurred in the population exposed when compared to the unexposed after full socioeconomic adjustment. Jana et al,[18] also performed subgroup analysis for each fuel type. This revealed the steepest cognitive penalty for charcoal or coal use, followed by wood/shrub, dung cake, and other solid fuels indicating a dose response effect that strengthens causal inference. Shen et al,[21] and Jin et al,[16] corroborated these findings in a sub-sample of older adults aged ≥60 years further adding evidence to a consistent cognitive decline among this population. Crucially, Mitra et al,[19] a cross-sectional study which extracted baseline data from CBR-SANSCOG, a prospective cohort study from rural Karnataka, replicated these associations using a validated neuropsychological battery, reporting significant deficits in global cognition and executive function but not in memory, language, or attention domains after full covariate adjustment. Domain-specific analysis highlighted that visuospatial and executive deficits may be early sensitive markers of IAP-related neurological harm.[19]

Shaw et al. made a distinctive contribution by modelling depression and sleep disturbance as sequential mediators of the IAP cognition pathway. IAP had a significant direct effect on cognition while also significantly predicting depression and sleep problems, which in turn independently impaired cognitive scores. The total indirect effect through these mediators was β = -0.056, accounting for only 12.8% of the overall IAP–cognition association signifying that 87.2% of the association operates through direct pathways independent of these measured mediators.[22] This mediation architecture is biologically credible: particulate matter activates the hypothalamic-pituitary-adrenal (HPA) axis, elevates cortisol secretion, and causes neuroinflammation, each of which constitutes an established pathway to both depression and accelerated neurocognitive ageing.[29,30,31]

Psychological domain: The psychological domain also demonstrated clear and consistent associations across multiple studies. Rani and Astha,[23] reported a 35% increase in the odds of major depression (CIDI-SF) associated with unclean cooking fuel use in the fully adjusted model. Particularly alarming was the finding that indoor use of unclean fuel without any adequate ventilation conferred the highest depression risk, reinforcing ventilation as a modifiable, low-cost intervention target. Li et al,[24] using WHO SAGE Wave-1 India data, reported an even larger odds ratio for major depressive episode among users of polluting fuel. However, this difference may reflect variations in the CIDI diagnostic threshold relative to the CES-D scale used by other studies. Jin et al,[16] likewise found a 9% increase in depressive symptom odds among LASI respondents aged ≥60 years. These convergent findings position IAP as an overlooked environmental determinant of late-life depression in India.[32]

Vitality domain: With respect to the vitality domain encompassing physical energy, nutritional status, and frailty, Halder et al,[27] provided the first Indian evidence linking solid fuel use to frailty (Fried phenotype). They reported an adjusted odds of frailty 10% higher for solid fuel users aged 45–59 years. Shen et al,[21] corroborated this finding through standardised vitality scores, reporting a significant negative association with polluting fuel use.

Sensory domain: The sensory domain, although less extensively studied, provided notable evidence. Islam et al,[26] demonstrated using LASI Wave-1 national data that unclean fuel users had a 3.2 percentage-point greater absolute probability of visual impairment. This disparity is a clinically significant gap in the already existing massive burden of avoidable blindness in India. Ravilla et al,[25] in the India Eye Study found that biomass fuel use was significantly associated with cataract in women but not in men. This sex-specific pattern may stem from differential cumulative IAP exposure through cooking roles. Shen et al,[21] further reported a standardised sensory capacity decrement in the Indian sub-sample.

Locomotion domain: The locomotion domain yielded the most limited evidence among the five intrinsic capacity domains examined in this review. Only a single study directly assessed a locomotor outcome in relation to indoor air pollution exposure among older Indian adults. Smith et al,[28] analysed WHO SAGE Wave-1 India data and reported a non-significant association between unclean cooking fuel use and slow gait speed. Although the effect estimate suggested a 52% increase in the odds of slow gait among unclean fuel users, the confidence interval crossed the null, precluding definitive conclusions. The relatively small sample size and cross-sectional design further constrain interpretation, as the study lacked statistical power to detect modest-to-moderate effects and could not establish temporality.

Composite Intrinsic capacity: At the level of composite IC, Shen et al,[21] reported a statistically significant association between polluting cooking fuel use and IC deficit in the India sub-sample of LASI Wave-1. Although the effect size appears modest in absolute terms, this estimate reflects impairment across the composite index. The convergence of domain-specific findings with this composite estimate validates the IC framework as a holistic, actionable lens for assessing the public health impact of IAP in ageing populations.[1,17]

Women demonstrated the largest IAP-associated cognitive and psychological deficits across studies. This trend likely emerges from the gendered patterns of domestic labour in India, whereby women assume primary cooking responsibilities.[33,34] Rural residents consistently showed worse outcomes across studies, primarily due to their reliance on solid biomass fuels, which exceed 90% in some states, as well as poor kitchen infrastructure and limited access to clean fuel subsidies.[23,35] Saenz et al,[20] specifically demonstrated that cooking without ventilation exacerbated cognitive deficits, while use of improved cookstoves attenuated the cognitive penalty. Adults with no formal schooling, the poorest wealth quintiles, and those from Scheduled Caste/Tribe communities consistently showed the steepest IAP-related IC decrements, reflecting the convergence of environmental and socioeconomic disadvantage in shaping cognitive ageing in India.[18,16,27]

The biological mechanisms behind IAP related IC impairment are multifactorial and mutually reinforcing. Particulate matter from solid fuel combustion can migrate to brain tissue through the olfactory route, triggering neuroinflammation mediated by TNF-α, interleukin-1β, and reactive oxygen species.[36,37] Sustained neuroinflammation can lead to synaptic dysfunction, tau hyperphosphorylation, and amyloid-β deposition, all crucial to the pathological processes involved in Alzheimer's disease and related dementias.[38] Pollutants from combustion also activate the HPA axis, elevating circulating cortisol, which exerts neurotoxic effects on hippocampal volume and episodic memory.[30,31] Epigenetic changes including methylation of circadian CLOCK genes provides a plausible explanation for IAP exposure affecting sleep and its role in pathogenesis of mood disorders.[39] For sensory outcomes, combustion generated oxidative radicals, damage lens and retinal pigment epithelium, contributing to cataract formation and macular degeneration.[40] For vitality and frailty, chronic inflammation from repeated IAP exposure accelerates sarcopenia and reduces mitochondrial efficiency.[41,42]

All 13 included studies were assessed using the Newcastle-Ottawa Scale and demonstrated high methodological quality, with scores ranging from 7 to 9 out of 9. Ten studies received high scores for including large, nationally representative samples and validated measures for both exposure and outcome, alongside thorough adjustments for socioeconomic and health related factors. The use of harmonized LASI Wave-1 data across majority of studies represents a major strength, enabling high comparability of estimates. However, it simultaneously introduces cross-study dependence, as many estimates are derived from overlapping or identical underlying cohorts. This dependence should be considered when interpreting the apparent consistency across studies, as it may reflect shared data. Furthermore, all included studies used cross-sectional designs, which limit temporality.[43,44]

The public health implications of these findings are profound. India's Pradhan Mantri Ujjwala Yojana (PMUY) scheme has distributed over 90 million free LPG connections to below poverty line households since 2016. However, sustained use remains low, particularly in rural areas, due to ongoing fuel affordability and traditional cooking practices.[45,46] Recent geopolitical disruptions have compounded these challenges, as the ongoing conflict in the Middle East has severely constrained LPG imports—nearly 60% of India's domestic LPG is imported, with 90% originating from the Middle East region—causing supply shortages, black market price surges, and a documented reversion to firewood and coal among vulnerable urban and rural households. Evidence from the present review suggests that even partial mitigation of IAP exposure through better ventilation, improved cookstoves, or transitioning to LPG could yield measurable gains in cognitive and psychological IC domains. Integrating IC-based health assessments into national programmes such as the National Programme for Health Care of Elderly (NPHCE) could further enable earlier identification and intervention in high-risk individuals.

Limitations: Several limitations of this review merit acknowledgment. First, the preponderance of cross-sectional evidence constrains causal inference. Second, all included studies relied on self-reported or household-level proxy measures of IAP exposure rather than objective Particulate Matter monitoring, likely introducing exposure misclassification. Third, the substantial heterogeneity in cognitive assessment methods spanning composite indices, standardized continuous measures, dichotomous outcomes, and comprehensive neuropsychological test batteries prohibited statistical pooling of effect estimates, thereby constraining the review to a systematic review alone. Fourth, the focus on national LASI data constrains generalizability to tribal, and peri urban populations which are underrepresented in the survey. Fifth, the absence of ambient air pollution data across all studies leaves outdoor to indoor pollution contamination as an uncontrolled confounder.

Future recommendations

These limitations point to a clear research agenda. Future studies should employ longitudinal designs with objective monitoring of IAP exposure, standardized IC assessment protocols aligned with WHO guidance, and targeted sub-group analyses for historically marginalized communities.[1,49]

CONCLUSION

IAP exposure is consistently and adversely associated with multiple intrinsic capacity domains among older adults in India, with the strongest evidence in cognition and psychological capacity. In the sensory, vitality and locomotion domains, although only a few studies were incorporated, all conclusively indicated a negative impact. These findings position clean fuel policy, kitchen ventilation, and IC-integrated geriatric screening as urgent, intersecting public health priorities.

REFERENCES

1. World Health Organization. WHO guidelines for indoor air quality: household fuel combustion. Geneva: World Health Organization; 2014.
2. GBD 2019 Risk Factors Collaborators. Global burden of 87 risk factors in 204 countries and territories, 1990–2019: a systematic analysis. Lancet. 2020;396(10258):1223–49.
3. Balakrishnan K, Ghosh S, Ganguli B, Sambandam S, Bruce N, Barnes DF, et al. State and national household concentrations of PM2.5 from solid cookfuel use in India. Environ Health Perspect. 2013;121(4):428–34.
4. Government of India. National Family Health Survey (NFHS-5), 2019–21: India Fact Sheet. Mumbai: International Institute for Population Sciences; 2021.
5. Amegah AK, Jaakkola JJ. Household air pollution and the sustainable development goals. Bull World Health Organ. 2016;94(3):215–21.
6. Oudin A, Forsberg B, Adolfsson AN, Lind N, Modig L, Nordin M, et al. Traffic-related air pollution and dementia incidence. Environ Health Perspect. 2016;124(3):306–12.
7. Pun VC, Manjourides J, Suh H. Association of ambient air pollution with depressive and anxiety symptoms in older adults. Environ Health Perspect. 2017;125(3):342–8.
8. Smith KR, Bruce N, Balakrishnan K, Adair-Rohani H, Balmes J, Chafe Z, et al. Millions dead: household air pollution in the global burden of disease study 2010. Annu Rev Public Health. 2014;35:185–206.
9. World Health Organization. World report on ageing and health. Geneva: World Health Organization; 2015.
10. Beard JR, Officer A, de Carvalho IA, Sadana R, Pot AM, Michel JP, et al. The World report on ageing and health: a policy framework for healthy ageing. Lancet. 2016;387(10033):2145–54.
11. Cesari M, Araujo de Carvalho I, Thiyagarajan JA, Cooper C, Martin FC, Reginster JY, et al. Evidence for the domains supporting intrinsic capacity. J Gerontol A Biol Sci Med Sci. 2018;73(12):1653–60.
12. United Nations, Department of Economic and Social Affairs, Population Division. World Population Ageing 2019. New York: United Nations; 2019.
13. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: updated guideline for reporting systematic reviews. BMJ. 2021;372:n71.
14. Wells GA, Shea B, O'Connell D, Peterson J, Welch V, Losos M, et al. The Newcastle–Ottawa Scale (NOS) for assessing the quality of nonrandomised studies in meta-analyses. Ottawa: Ottawa Hospital Research Institute; 2014.
15. Shen J, Shi H, Zhang J, Meng X, Zhang C, Kang Y. Household polluting cooking fuels and intrinsic capacity among older population: A harmonized nationwide analysis in India and China. Sci Total Environ. 2024;912:169031. doi:10.1016/j.scitotenv.2023.169031.
16. Jin Y, Zhou X, Deng L, et al. Association between the domestic use of solid cooking fuel and increased prevalence

of depression and cognitive impairment in a big developing country. Front Public Health. 2022;10:1038573.
17. Saha S, et al. A study about the impact of indoor air pollution on cognitive function among middle-aged and older adult people in India. Arch Public Health. 2024;82(1):57.
18. Jana A, Varghese JS, Naik G. Household air pollution and cognitive health among Indian older adults: evidence from LASI. Environ Res. 2022;214:113880.
19. Mitra S, Sagiraju M, Pradhan H, et al. The cognitive toll of household air pollution: cross–sectional associations between polluting cooking fuel use, cognitive functions and brain MRI in a rural aging population from Karnataka, India. Lancet Reg Health Southeast Asia. 2025;39:100624.
20. Saenz JL, Adar SD, Zhang YS, et al. Household use of polluting cooking fuels and late-life cognitive function: a harmonized analysis of India, Mexico, and China. Environ Int. 2021;156:106722.
21. Shen J, Shi H, Zhang J, et al. Household polluting cooking fuels and intrinsic capacity among older population: a harmonized nationwide analysis in India and China. Sci Total Environ. 2024;912:169031.
22. Shaw S, Kundu S, Chattopadhyay A, Rao S. Indoor air pollution and cognitive function among older adults in India: a multiple mediation approach through depression and sleep disorders. BMC Geriatr. 2024;24(1):81.
23. Rani R, Astha. Association between household air pollution due to unclean fuel use and depression among older adults in India. Indian J Psychiatry. 2024;66(9):814–822.
24. Li X, Guo Y, Xiao J, et al. The effect of polluting cooking fuels on depression among older adults in six low- and middle-income countries. Sci Total Environ. 2022;838:155690.
25. Ravilla TD, Gupta S, Ravindran RD, et al. Use of cooking fuels and cataract in a population-based study: the India Eye Disease Study. Environ Health Perspect. 2016;124(12):1857–1862.
26. Islam S, Upadhyay AK, Mohanty SK, et al. Use of unclean cooking fuels and visual impairment of older adults in India: a nationally representative population-based study. Environ Int. 2022;165:107302.
27. Halder P, Tiwari J, Mamgai A, Pal S. Association of frailty with indoor air pollution among older adults and elderly population in India. Arch Public Health. 2025;83(1):131.
28. Smith L, et al. Unclean cooking fuel use and slow gait speed among older adults from 6 countries. J Gerontol A Biol Sci Med Sci. 2023;78(12):2318-2324.
29. Brockmeyer S, D'Angiulli A. How air pollution alters brain development: the role of neuroinflammation. Transl Neurosci. 2016;7(1):24–30. doi:10.1515/tnsci-2016-0005
30. Varghese FP, Brown ES. The hypothalamic-pituitary-adrenal axis in major depressive disorder: A brief primer for primary care physicians. Prim Care Companion J Clin Psychiatry. 2001;3(4):151–155.
31. Qin DD, Rizak J, Feng XL, et al. Prolonged secretion of cortisol as a possible mechanism underlying stress and depressive behaviour. Sci Rep. 2016;6:30187. doi:10.1038/srep30187
32. Perianayagam A, Prina M, Selvamani Y, et al. Sub-national patterns and correlates of depression among adults aged 45 years and older: Findings from Wave 1 of the Longitudinal Ageing Study in India. Lancet Psychiatry. 2022;9(8):645–659. doi:10.1016/S2215-0366(22)00138-1
33. Choudhuri P, Desai S. Gender inequalities and household fuel choice in India. J Clean Prod. 2020;265:121487. doi:10.1016/j.jclepro.2020.121487
34. Chen C, Zhu Q, Huang Y, et al. Sex differences in the effects of indoor solid fuel use on cognitive function in elderly Chinese: A longitudinal study. Environ Int. 2021;155:106611.
35. Pandey A, Brauer M, Cropper ML, et al. Health and economic impact of air pollution in the states of India: The Global Burden of Disease Study 2019. Lancet Planet Health. 2021;5(1):e25–e38. doi:10.1016/S2542-5196(20)30298-9
36. Brockmeyer S, D'Angiulli A. How air pollution alters brain development: the role of neuroinflammation. Transl Neurosci. 2016;7(1):24–30. doi:10.1515/tnsci-2016-0005
37. Peeples L. How air pollution threatens brain health. Proc Natl Acad Sci USA. 2020;117(25):13856–13860. doi:10.1073/pnas.2008940117
38. Schikowski T, Altug H. The role of air pollution in cognitive impairment and decline. Neurochem Int. 2020;136:104708. doi:10.1016/j.neuint.2020.104708
39. Buoli M, Grassi S, Caldiroli A, et al. Is there a link between air pollution and mental disorders? Environ Int. 2018;118:154–168. doi:10.1016/j.envint.2018.05.044
40. Cacciottolo M, Wang X, Driscoll I, et al. Particulate air pollutants, APOE alleles and their contributions to cognitive impairment in older women and to amyloidogenesis in experimental models. Transl Psychiatry. 2017;7(1):e1022. doi:10.1038/tp.2016.280
41. Guo M, Du C, Li B, et al. Reducing particulates in indoor air can improve the circulation and cardiorespiratory health of old people: a randomized, double-blind crossover trial of air filtration. Sci Total Environ. 2021;798:149248. doi:10.1016/j.scitotenv.2021.149248
42. Arokiasamy P, Uttamacharya U, Jain K, et al. The impact of multimorbidity on adult physical and mental health in low- and middle-income countries: what does the Study on Global Ageing and Adult Health (SAGE) reveal? BMC Med. 2015;13:1–16. doi:10.1186/s12916-015-0287-6
43. Qiu H, Zhu Z, Zhong N, et al. Household biomass fuel use and cognitive decline among older adults in China: Evidence from CHARLS. Environ Pollut. 2019;254:113029.
44. Li N, Song Q, Su W, et al. Exposure to indoor air pollution from solid fuel and its effect on depression: A systematic review and meta-analysis. Environ Sci Pollut Res. 2022;29(33):49553–49567. doi:10.1007/s11356-022-19596-w
45. Roy K. Transition to cooking with clean fuels in rural households of India: Studying the effect of policy and other factors. Energy Sustain Dev. 2024;80:101456.
46. Ranjan R, Singh S. Household cooking fuel patterns in rural India: Pre- and post-Pradhan Mantri Ujjwala Yojana. Indian J Hum Dev. 2020;14(3):518–526.
47. Perianayagam A, Bloom D, Lee J, et al. Cohort profile: The Longitudinal Ageing Study in India (LASI). Int J Epidemiol. 2022;51(1):e167–e176. doi:10.1093/ije/dyab213
48. Liao W, Liu X, Kang N, et al. Effect modification of kitchen ventilation on the associations of solid fuel use and long-duration cooking with the increased prevalence of depressive and anxiety symptoms: The Henan Rural Cohort Study. Indoor Air. 2022;32(1):e13016.
49. Liang F, Yang X, Liu F, Li J, Xiao Q. Long-term exposure to ambient fine particulate matter and incidence of major depressive disorder: A longitudinal cohort study in China. Sci Total Environ. 2021;795:148806.