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Research Article

Carbon Monoxide Exposure and Risk of Cognitive Impairment Among Cooks in Africa

Ryan McCord,[1] Stephanie Parsons,[2] Ashley S. Bittner,[2] Charles B. L. Jumbe,[3] Gillian Kabwe,[4] Joseph Pedit,[5] Nancy Serenje,[6] Andrew P. Grieshop,[2] and Pamela Jagger[5,7]

[1]*Sanford School of Public Policy, Nicholas School of the Environment, Duke University, Durham, North Carolina, USA*
[2]*Department of Civil, Construction and Environmental Engineering, North Carolina State University, Raleigh, North Carolina, USA*
[3]*Centre for Agricultural Research and Development, Lilongwe University of Agriculture and Natural Resources, Bunda, Lilongwe, Malawi*
[4]*Copperbelt University, Kitwe, Zambia*
[5]*Carolina Population Center, University of North Carolina at Chapel Hill, Chapel Hill, North Carolina, USA*
[6]*Centre for Environment, Energy, And Engineering Zambia, Lusaka, Zambia*
[7]*School for Environment and Sustainability, University of Michigan, Ann Arbor, Michigan, USA*

Correspondence should be addressed to Ryan McCord; ryan.mccord@duke.edu

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We use air pollution exposure measurements and household survey data from four studies conducted across three countries in sub-Saharan Africa (SSA) to analyze the association between carbon monoxide (CO) exposure from cooking with biomass and indicators of cognitive impairment. While there is strong evidence on the relationship between ambient air pollution exposure and cognitive impairment from studies in high-income countries, relatively little research has focused on household air pollution (HAP) in low-income country settings where risks of HAP exposure are high. This study is the first to our knowledge to focus on the association between HAP exposure (specifically CO exposure) and cognitive impairment across diverse settings in SSA. We use 24-hour measurements of primary cooks' exposure to CO across four study sites: urban Zambia ($n = 493$); urban Malawi ($n = 130$); rural Malawi ($n = 102$); and urban Rwanda ($n = 2,576$). We model the estimated percent carboxyhemoglobin (%COHb) of cooks and map values to a toxicological profile for risk of cognitive impairment. We find that across all study settings, cooks' average %COHb levels are below levels of daily concern, but that cooks who use charcoal for preparing greater than 40% of meals are more likely to spend additional time at higher levels of risk. For the urban Zambia sample, we compare %COHb and frequency of charcoal use to a series of cognitive test scores and find no consistent relationships between %COHb and cognitive test scores. High levels of daily CO exposure from cooks across SSA highlight the potential for longer-term negative cognitive (and other) health outcomes motivating additional research and efforts to characterize and mitigate risk.

1. Introduction

Globally, approximately 9 million deaths per year are attributable to air pollution exposure [1]. Air pollution (both household and ambient) is a major threat to health and well-being, particularly in low- and middle-income countries (LMIC) [1]. While exposure to household air pollution (HAP) from cooking, heating, and lighting is expected to decline as households transition to cleaner, more efficient fuels, the absolute number of people with high levels of air pollution exposure is projected to increase in sub-Saharan Africa (SSA) due to rapid population growth, limited investment in regulations and policies aimed to reduce air pollution monitoring, and the slow rate of energy transitions [2–5]. In

Africa, air pollution is likely to remain a major risk factor for the burden of disease for decades to come [1, 3, 6, 7].

Air pollution is recognized by the World Health Organization (WHO) as one of the five major risk factors for noncommunicable diseases including neurodegenerative diseases like dementia and Alzheimer's [1, 8]. Between 2015 and 2050, the number of people living with dementia in SSA will increase by 257%, largely due to an aging population experiencing higher rates of cognitive impairment [9]. Cognitive function is critical for daily life and plays an important role in making complex decisions, such as budgeting and spending [10, 11]. Cognitive impairment is characterized by difficulty focusing, making decisions, remembering, or learning new things [12, 13] and can lead to decreased social welfare, diminished capacity for decision-making, lower levels of human capital, and eventually to debilitating health conditions including dementia and Alzheimer's [14–16]. While several factors are associated with cognitive impairment and decline [17], there has been increasing focus on the role of exposure to air pollution [18–24]. Understanding the relationship between air pollution and cognitive function helps to characterize the costs of exposure to air pollution from a health perspective, as well as in terms of lost productivity and human capital development.

A growing body of epidemiological research has established the association between air pollution and cognitive functioning and the potential mechanisms underlying that relationship [25–28]. Acute cognitive impairment is commonly associated with exposure to carbon monoxide (CO) [29–35] and fine particulate matter ($PM_{2.5}$), especially from ambient sources [18–20]. In this analysis, we focus primarily on exposure to CO and include additional analysis of exposure to $PM_{2.5}$. CO is emitted by both indoor and outdoor sources, but in African cities, burning charcoal for cooking and heating represents a large share of exposure [36–39]. Exposure to CO is associated with negative respiratory and cardiovascular outcomes [40, 41], and it can also cause severe neurologic symptoms including confusion, dizziness, and short-term memory loss due to the hypoxemia caused by CO binding to hemoglobin instead of oxygen [31, 33, 42]. Adverse effects of CO exposure are expected in people without other risk factors when the concentration of CO in the blood reaches 4% [43].

In this study, we focus on CO exposure and frequency of charcoal used for household cooking to explore observable impacts of CO exposure on cognitive function as well as the potential impacts (e.g., expected time spent with cognitive impairment based on level of CO exposure) in rural and urban settings. In rural settings, CO is mainly associated with the use of firewood and other biomass fuels for cooking, while in urban settings, the use of charcoal for cooking and heating is a major source of CO exposure [36–39]. Relatively more of the emissions from charcoal-burning stoves are CO (compared to $PM_{2.5}$ and other pollutants) in both laboratory and field settings [37–39, 44].

Our study makes several contributions to the literature. First, we use data from multiple LMIC settings to explore the association between CO exposure and risk of cognitive impairment as measured by established toxicological profiles for CO exposure among adult cooks in SSA. Even though 92% of air pollution-related health and economic losses occur in LMICs [1], most studies focus on high-income country settings [21–24, 45]. Studies that have focused on LMICs, specifically in SSA countries, find that exposure to ambient air pollution has consequences for early childhood cognitive development and is associated with lower IQ scores [3, 46].

Second, we focus on household (vs. ambient) air pollution exposures. Focusing solely on exposure to ambient air pollution in LMICs overlooks an important source of exposure generated by the burning of biomass fuels for cooking and heating [47]. Across several LMIC settings, cooking and/or heating with biomass has been associated with lower cognitive test scores among adult populations in India [48, 49], Mexico [15, 19], and China [50–53]. Shupler et al. and Jagger et al. discuss cognitive health/well-being outcomes in the context of HAP exposures, but we know of no studies focused on the relationship between HAP and cognitive impairment in African settings, where cooking with biomass and charcoal are ubiquitous [54, 55].

Lastly, we use directly measured CO exposure in our analysis. Most studies, particularly those focused on HAP, use proxy measures of exposure by relying on information about a household's primary cooking fuel and related information on cooking practices that could affect levels of HAP exposure. In general, those who use biomass for cooking or heating are treated as "exposed" to HAP, and those who use clean fuels (e.g., liquified petroleum gas or electricity) are considered not exposed to HAP.

We aim to understand the potential impact of cooking with charcoal by exploring modeled percent carboxyhemoglobin (%COHb) levels (the most used biomarker for exposure to CO [56]) across different populations of charcoal users in the context of established toxicological profiles for CO exposure. Additionally, for a subset of households from Zambia, we test whether there is a relationship between modeled %COHb values and cognitive test scores within a population that relies heavily on charcoal for cooking.

2. Methods

2.1. Study Design and Context. We use data from four independent research efforts led by the same core research team and involving similar protocols for the collection of personal exposure to HAP, sociodemographic, and health outcome data (Table 1). In each of the four studies, almost all cooking was with biomass. As a result, each of the studies included a subsample of respondents who underwent 24-h CO monitoring. Our sample includes a randomly sampled subset of primary cooks from each of the four studies, all of whom participated in CO monitoring. Urban Malawi data were collected in 2014 from a case-control study focused on the association between HAP and tuberculosis conducted in five neighborhoods in low-income, high-density suburbs of Lilongwe [57] ($n = 130$). Data from urban Rwanda were collected as a part of a randomized controlled trial conducted between 2015 and 2020, exploring the impact of a household

Table 1: Summary of data sources and study settings.

Setting	Year(s) of data collection	CO sample size	Percent meals cooked with charcoal[a]	Cognitive tests administered?
Urban Malawi	2014	130	71.55%	No
Urban Rwanda	2015; 2016; 2019	2576 (pooled)[b]	73.82%	No
Urban Zambia	2019	493	82.60%	Yes
Rural Malawi	2013	102	1.52%	No

[a]Recall data from meals cooked over the past 3 days.
[b]All data pooled across three waves of data collection.

cooking intervention (biomass pellets and microgasifier cookstoves) on health and well-being in Gisenyi, Rwanda's second largest city [55, 58] ($n = 2{,}576$ pooled from 2015, 2016, and 2019 rounds of data collection). Data were collected in urban Zambia during the first wave of a quasi-experimental evaluation exploring the impact of two household cooking interventions (improved charcoal stoves; biomass pellets and micro-gasifier cookstoves) in four low to middle-income neighborhoods in Lusaka [59] ($n = 493$). Data from rural Malawi were collected from Liwonde and Kasungu Districts in 2013, adding a fourth wave to a 400-household panel that focused specifically on household cooking and fuel use [60–62] ($n = 102$).

Charcoal is the primary cooking fuel used by households in Lilongwe, Malawi (89%); Gisenyi, Rwanda (67%); and Lusaka, Zambia (80%) [63–65]. In rural Malawi, 7.5% of households use charcoal as their primary cooking fuel [63] with the majority using fuelwood.

We include a rural setting to illustrate the differences between fuelwood and charcoal-dominated cooking systems and because rates of charcoal use are rapidly increasing in rural areas throughout Africa (e.g., in Malawi, the use of charcoal has more than tripled since 2010 [66]). We pool data from the four studies for our analysis except when we focus on cognitive test scores, which we only have from urban Zambia.

2.2. Data Collection

2.2.1. Personal Exposure Measurement. In all studies, primary cooks (e.g., the person who cooks most meals in the household) wore a CO monitor (Lascar Electronics, model EL-USB-CO) to measure and record CO concentration (ppm) every minute for a 24-h monitoring period. These monitors measure 0–300 ppm CO and have an accuracy of ±5 ppm CO. The CO monitors recorded exposure to CO from cooking as well as any other activities during that period. Using a full 24-h period encompasses daily patterns of household cooks and accounts for intraindividual variability throughout the day. Primary cooks wore the data loggers on lanyards or clips that were pinned onto their lapels, situating them near their breathing zone, and were asked only to remove monitors when bathing or sleeping. Monitors were calibrated once before and once after each field campaign; raw data was corrected with monitor-specific calibration factors (calibration detailed in SI1). For each cook, we calculated 24-h average CO exposure, the average from the 1-h period with the highest level of CO exposure (referred to as 1-h maximum), and the average from the first hour of data collection (referred to as first-hour CO).

In our analysis of the relationship between HAP exposure and cognitive test scores among cooks in urban Zambia, we conduct secondary analyses using $PM_{2.5}$ exposure data. A random subset of the primary cooks in Zambia who received CO data loggers also received $PM_{2.5}$ monitors ($n = 33$). Cooks wore RTI MicroPEMs along with EL-USB-CO data loggers for the 24-h period. Participants wore both monitors in a bag positioned close to the breathing zone. MicroPEMs include a 25 mm Teflon filter and pump for gravimetric analysis of 24-h average $PM_{2.5}$ exposure and a nephelometer, which measures real-time light scattering of $PM_{2.5}$ [67]. To avoid overloading the filter and to ensure battery life for the test duration, MicroPEMs alternated on and off every 30 seconds, collecting data every 10 seconds when turned on. Six filter blanks were collected throughout the deployment campaign for quality assurance. Real-time $PM_{2.5}$ concentrations were corrected using the 24-h average from the filter measurement for each deployment.

2.2.2. Cognitive Testing. The same randomly selected subset of primary cooks in our Zambia study who underwent CO monitoring participated in a series of cognitive tests immediately before the 24-h monitoring period. Ideally, we would have conducted these tests at the end of the monitoring period, but this was not possible due to fieldwork logistics. Due to incomplete or missing data, we used a sample of $n = 451$ cognitive tests matched with CO exposure data. The missingness ($n = 42$ missing) is due to a fairly even split between errors in survey entry causing the cognitive module to be skipped or due to an incomplete (< 24-h) monitoring period for CO, which can happen if the monitors were picked up too early. We only retain data from households where we have complete data for both the cognitive testing module and 24 hours of CO monitoring data. We find no systematic differences between the missing and nonmissing households, so we retain only complete observations for this portion of the analysis.

The cognitive exercises were selected from a larger battery of neuropsychological screening tests designed to assess the neurological impact of CO toxicity in the absence of diagnostic tools [68]. This tool has been tested and validated to detect neurological impairment after acute CO exposure [68, 69]. The specific tests we selected for use in this study have been used and validated in other LMIC settings [14, 15, 18, 19, 48–53] (Table 2). While we do not expect the tests to provide a comprehensive assessment of cognitive function, they are useful insofar as they provide information on

Table 2: Description of cognitive tests.

Cognitive tests	Description	Possible scores	Examples of similar tests used in relevant studies
Orientation task	Recall current day, month, and year	0–3	[15, 18, 19, 48, 50, 52, 53]
Immediate word recall	Repeat as many words as possible from a ten-word list	0–10	[14, 15, 19, 48, 49, 51–53]
Forward digit span	Repeat strings of numbers of increasing length in the same order as they are read	0–8	[18, 49, 52]
Backward digit span	Repeat strings of numbers of increasing length in reverse order as they are read	0–8	[18, 19, 48–50, 52]
Delayed word recall	Repeat as many words as possible from the original ten-word list after completing digit span tests	0–10	[15, 18, 19, 48, 49, 51–53]

how cognitive tests are (or are not) correlated with CO exposure at the levels experienced by cooks in these settings.

The tests include an orientation task in which the respondent attempts to recall the current day, month, and year (possible score, 0–3); an immediate word recall in which the respondent repeats as many words as possible from a list of ten words (possible score, 0–10); a forward digit span test in which the respondent repeats strings of numbers of increasing length in the same order as they are read out (possible score, 0–8); a backward digit span test in which the respondent repeats strings of numbers of increasing length in the opposite order as they are read out (possible score, 0–7); and, after the two digit span tests, a delayed word recall in which the respondent is asked to repeat the words from the original list after some time focused on other tasks (possible score, 0–10). The word lists used for the two recall tasks require certain characteristics. They need to be easily recognizable by people regardless of education level, have only one meaning, and translate to one distinct word in the primary local language, Nyanja. Before the lists were finalized, we conducted focus groups with Lusaka residents to confirm that all the words met the criteria and made changes as necessary (see SI2 for a full description of the protocol). Usually, an individual's raw score from a neurological test is translated to a standardized score based on normative data for the population. However, normative data are not available for this population, so we used raw scores in our analysis [70].

2.2.3. Sociodemographic and Health Data. In all four study sites, the study teams administered a structured household questionnaire to the person with the most knowledge about household cooking. We use specific responses/data from the household survey to parameterize our %COHb estimates and as controls in our analysis of the relationship between %COHb and cognitive test scores. The questionnaires were translated to the relevant local language (Chichewa for Malawi, Kinyarwanda for Rwanda, and Nyanja and Bemba for Zambia). While there were minor differences between questionnaires in the different studies, all included modules on household demographics, income, assets, household expenditures, descriptions of the household and its facilities, and cooking practices, including stoves and fuels used and cooking environments. We collected individual-level data for the primary cook in each household including age, sex, education level, and smoking history. We collected anthropometric measurements for primary cooks including height and weight (no weight data were collected in urban Zambia). Primary cook weight was measured using a scale placed on a board for stability to the nearest 0.05 kg. Height was measured using a stadiometer. Amputations and pregnancy status of cooks were noted if applicable. All measurements were carried out by trained staff.

2.3. Analysis. The toxicological profile of CO is a framework for specific descriptions of adverse effects of exposure to CO [43] (Table 3). We present our findings using this framework and refer to these five levels in our analysis. Percent COHb is a more accurate representation of CO toxicity than CO exposure because it is a direct indicator of internal dose and controls for the age, sex, and weight of study participants, factors which affect the way the body processes exposure to CO [56].

2.3.1. %COHb Estimation. In the absence of the ability to draw blood to directly measure %COHb, we used 24-h exposure measurements and physiological parameters (age, gender, and weight) to estimate %COHb values in primary cooks using an established model framework. We use the Coburn-Forster-Kane (CFK) equation, the most widely used and validated approach to estimate %COHb levels in the blood [71, 72]. The estimate uses the following equations:

$$\frac{d\%[\mathrm{COHb}]}{\mathrm{dt}} = \mathrm{C}_0 - \mathrm{C}_1 \frac{\%[\mathrm{COHb}]}{100 - \%[\mathrm{COHb}]} \tag{1}$$

where

$$C_0 = \frac{100}{[\mathrm{THb}]_0}\left(\frac{V_{\mathrm{CO}}}{V_b} + \frac{P_{\mathrm{ICO}}}{\mathrm{BV}_b}\right) \tag{2}$$

$$C_1 = \frac{100\left(1 + kP_{\mathrm{CO}_2}\right)}{k[\mathrm{THb}]_0\mathrm{MBV}_b} \tag{3}$$

$$B = \frac{1}{D_{\mathrm{LCO}}} + \frac{P_B - P_{\mathrm{H_2O}}}{V_A} \tag{4}$$

where $\%[\mathrm{COHb}]$ is the concentration of COHb in blood in mL CO per mL of blood ([COHb]) as a percent of reduced

Table 3: Levels correlating %COHb ranges to adverse health effects.

Level	%COHb range	Associated effect
0	< 1.5%	No effect (endogenous production, naturally produced within the body)
1	1.5%–4%	Enhanced myocardial ischemia and increased risk of arrhythmias in coronary artery disease patients, exacerbation of asthma
2	4%–20%	Neurobehavioral/cognitive changes (sensorimotor performance, altered time discrimination, impaired learning ability, and attention level) Current smokers average a %COHb value at this level (4.3%)
3	20%–50%	Neurological impairment (headaches, dizziness, drowsiness, weakness, nausea, confusion, and forgetfulness)
4	> 50%	High risk of death

Source: Wilbur et al. [43].

hemoglobin concentration ([RHb]) in blood. [THb]0 = [RHb] + [COHb] + [oxyhemoglobin]. V_{CO} is the endogenous CO production rate. V_b is the blood volume. P_{ICO} is the pressure of inspired CO in air saturated with water vapor at body temperature. k is the equilibrium constant for reaction O_2 + RHb = O_2RHb. P_{CO2} is the mean pulmonary capillary O_2 pressure. M is the Haldane coefficient. D_{LCO} is the pulmonary CO diffusion rate. P_B is the barometric pressure. P_{H2O} is the vapor pressure of water at body temperature. V_A is the alveolar ventilation.

Equation (1) cannot be solved explicitly since [COHb] and $[THb]_0$ are dependent, so a fourth-order Taylor's series expansion is applied [73]. Excluding P_B, P_{H2O}, and P_{ICO}, the remaining variables are physiological parameters and were calculated using relationships with age, gender, and weight. Because weight data were not obtained for the urban Zambia subsample, we randomly assigned each cook a weight from a nationally representative distribution by gender using data from the 2017 STEPS Survey by WHO Africa [74]. To ensure the STEPS data was appropriate for Zambia, we compared %COHb estimations using Malawi 2017 STEPS Survey data [75] and actual weight data collected in the Malawi subsamples and found no significant differences between %COHb estimations calculated with each weight source (SI3a). Therefore, we concluded, in the absence of actual weight data for our Zambia subsample, it was appropriate to use the Zambia STEPS data.

Any other variables not collected in the survey or calculated from survey data were determined from a distribution of literature values. Values were randomly assigned to each participant for $[THb]_0$, V_{CO}, energy conversion factor (ECF), and if menstruating (female only). For expended energy, participants were assigned "light exertion" during sleeping hours, 11 pm–7 am, and then randomly assigned light, medium, or heavy exertion for each hour during awake hours. The time step was 1 h, and the previous hour's %COHb value was used as the initial %COHb for that time step. The initial %COHb value for the first hour of the simulation was estimated as 0.3% ([76]; see SI Section 2 for more details). We deemed a 1-h time step appropriate for this analysis because a primary application of the CFK equation by the US EPA, the Air Pollution Exposure Model (APEX 5.2), uses a 1-h time resolution default for pollutant concentration input [77]. The input constants and distributions are described in Table 4. From the hourly %COHb values for each primary cook, we use the first-hour average (i.e., the %COHb value for the hour after they received the monitor), 24-h average, and 1-h maximum %COHb values for further analysis. The first-hour average was included since the cognitive tests were given at the start of the 24-h monitoring period, thus the first hour is the closest measurement in time to when the tests were performed. SI3b details additional assumptions and validation checks we used in our %COHb modeling.

2.3.2. Mapping %COHb of Cooks Onto the Toxicological Profile for CO. To understand the potential impact of cooks' exposure to CO, we map cooks from all four datasets onto the toxicological profile for CO (Table 3). We further consider the role of cooking with charcoal on %COHb level by grouping cooks based on the share of meals they cooked using charcoal. This variable was calculated using a cooking diary from each survey where cooks reported the primary stove used for each meal during the past 3 days. The number of meals cooked with charcoal was divided by the total meals cooked, and then cooks were grouped into one of the five following charcoal share categories: 0%–20%; 20%–40%; 40%–60%; 60%–80%; 80%–100%. We ran one-way analysis of variance (ANOVA) tests to determine whether the differences in %COHb are significant between data sets (Zambia vs. Rwanda vs. urban Malawi vs. rural Malawi) and levels of charcoal usage. To assess these differences a second way, we regressed log-transformed %COHb on charcoal level, controlling for cooking location and data sources with standard errors clustered based on the study site. Cooking location was categorized as indoor if most of the cooking was done in an enclosed space (e.g., kitchen inside the house; kitchen outside the house; bedroom; other room in the house) and as outdoor if cooking was done in any outdoor or sheltered area (e.g., outdoors and veranda).

We then calculate the share of time each cook spent in each level of the toxicological profile over the 24-h monitoring period. We use ANOVA tests and regressions to determine whether cooks spent more hours at levels 2 and 3 of the toxicological profile as their share of charcoal use increased.

Table 4: %COHb input constants and distributions of parameters.

(a)

Constants	Value	Basis/reference
M	218	(Rodkey et al., 1969) [78]
k	0.32	(EPA, 2010) [72]
P_{H2O} (torr)	47	(EPA, 2010) [72]
Duration (min)	60	Exposure levels averaged over 1 h
Expended energy (kcal min^{-1})		(EPA, 2010) [72]
Light exertion	2.39	
Medium exertion	5.97	
Heavy exertion	9.55	

(b)

Parameters	Min	Mean	Std. Dev.	Max	Distribution	Basis/reference
Age (years)		33.40	14.79		Normal	Collected from survey
Weight (lbs.)		142	33.21		Normal	Collected from survey; WHO, 2017a (Zambia) [74]
Elevation (ft)	2,509			4,859		Setting specific
Hb (g mL blood^{-1})						
Female	12			16	Uniform	(Billett, 1990) [79]
Male	14			18	Uniform	
Energy conversion factor (L O_2 kcal^{-1})	0.20			0.21	Uniform	(EPA, 2010) [72]

2.3.3. Cognitive Testing Analysis. We analyzed the effect of increasing %COHb levels on cognitive test scores among the subsample of cooks from urban Zambia. Each cognitive score was modeled individually using multivariate linear regressions. Analyzing each score individually allows us to understand whether CO exposure has a broad association with cognitive decline or if it only affects certain tasks. Covariates included log-adjusted household expenditures per capita (converted to USD) as well as gender, age, and education of the primary cook. We used log-transformed %COHb levels from the first hour of deployment as our primary explanatory variable. We also conducted analyses using log-transformed 24-h average %COHb.

To compare to other studies, which typically use proxy measures for exposure, we explore the effect of the share of meals cooked with charcoal. In the models that use share of meals cooked with charcoal, we include time spent cooking in the past 24 h and cooking location as covariates. We also explored relationships between cognitive test scores and $PM_{2.5}$ exposure in the small subset with those measures. In our models with $PM_{2.5}$ exposure as the independent variable, we use the same set of covariates listed above.

2.4. Human Subject Approvals. Procedures for each study were approved by the Institutional Review Board at the University of North Carolina at Chapel Hill (12-1247 rural Malawi; 13-1270 urban Malawi; 14-0735 Rwanda; 19-0061 Zambia). All participants provided written informed consent to participate. We also received approval from the appropriate local ethics boards in each country. In rural Malawi, oversight was provided by the University of North Carolina through a Federal Wide Assurance agreement, in urban Malawi, the Malawi National Health Sciences Research Committee (Protocol Number 1190); in Rwanda, the Rwanda National Ethics Committee and National Institute of Statistics (No. 447/RNEC/2014); and in Zambia, the reviewing body is the Humanities and Social Science Research Ethics Committee at the University of Zambia (2019-MAY-012).

3. Results

3.1. Mapping %COHb Onto Toxicological Profile for CO. Overall, %COHb values were highly variable, due to large interindividual variability in exposure and physiological parameters. One-hour maximum %COHb values ranged from 0.3% to 51%. We present descriptive statistics of variables used in the %COHb mapping exercise for the pooled dataset (Table 5) and show the 24-h average and 1-h maximum %COHb values separated by subsample overlayed on the corresponding levels from the toxicological profile of CO (Figure 1). Daily average %COHb estimates were below levels of major concern for the general population, that is, those without preexisting heart or lung conditions. However, rates of preexisting conditions in SSA (e.g., hypertension and rheumatic heart disease) are higher than in high-income countries [80, 81]. The highest average %COHb (for both 24-h average and 1-h maximum) was in the Zambian sample, where 83% of meals were cooked on charcoal stoves. In urban samples, approximately three-quarters of meals

Table 5: Descriptive statistics of all households.

	Urban Malawi n = 130		Urban Rwanda n = 2576		Urban Zambia n = 102		Rural Malawi n = 493		All households n = 3301	
	Mean (sd)	Max	Mean (sd)	Max	Mean (sd)	Max	Mean (sd)	Max	Mean (sd)	Max
%COHb (24-h avg)	1.25 (1.08)	5.04	1.21 (1.52)	16.96	2.62 (2.07)	11.84	0.63 (0.70)	6.88	1.41 (1.66)	16.96
%COHb (1-h max)	4.19 (4.59)	24.38	3.92 (5.40)	50.91	8.44 (7.04)	44.13	1.66 (1.66)	15.11	4.53 (5.82)	50.91
Hours spent at %COHb toxicological levels (out of 24 hours)										
	# hours	% hours	# hours	% hours	# hours	% hours	# hours	% hours	# hours	% hours
Time at Level 0	19.00	79.17	19.44	81.00	14.16	59.00	22.43	93.46	18.73	78.04
Time at Level 1	3.29	13.71	2.98	12.42	4.79	19.96	1.39	5.79	3.21	13.38
Time at Level 2	1.68	7.00	1.51	6.29	4.91	20.46	0.18	0.18	1.98	8.25
Time at Level 3	0.02	0.08	0.07	0.29	0.14	0.58	0.00	0.00	0.07	0.29
Time at Level 4	0.00	0.00	0.0004	0.00	0.00	0.00	0.00	0.00	0.0003	0.00
	# cooks	% cooks	# cooks	% cooks	# cooks	% cooks	# cooks	% cooks	# cooks	% cooks
Charcoal share level										
0%–20%	13	10.00	396	15.37	34	6.90	101	99.02	544	16.48
20%–40%	11	8.46	174	6.75	25	5.07	0	0.00	210	6.36
40%–60%	8	6.15	132	5.12	24	4.87	0	0.00	164	4.97
60%–80%	28	21.54	204	7.92	65	13.18	0	0.00	297	9.00
80%–100%	70	53.85	1670	64.83	345	69.98	1	0.98	2086	63.19
Cooking location										
Indoor	40	30.77	2023	78.53	382	77.48	84	82.35	2529	76.61
Outdoor	90	69.23	553	21.47	111	22.52	18	17.65	772	23.39

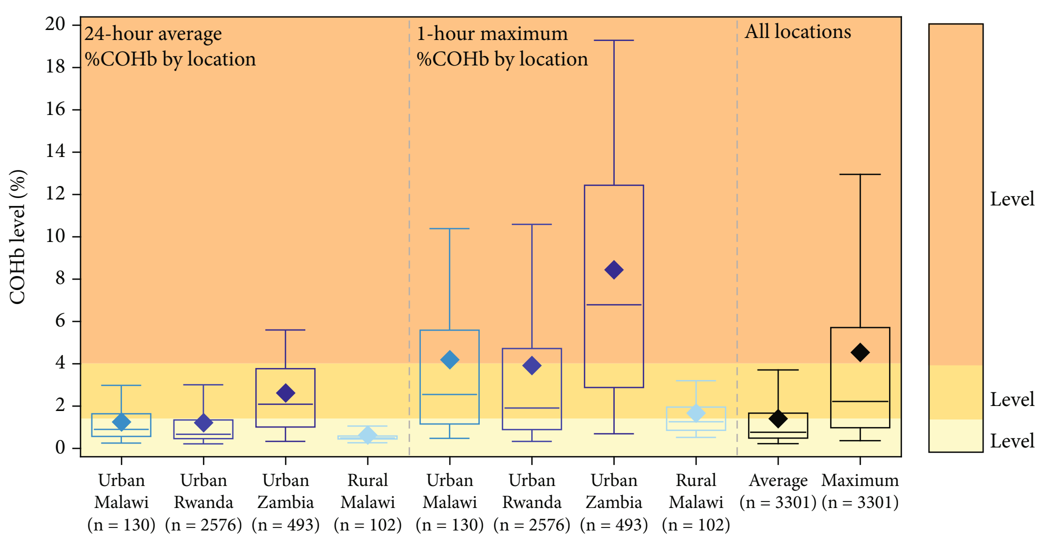

Figure 1: Mapping of %COHb 24-h average and 1-h maximum onto toxicological profile levels based on study location. Background shading denotes the %COHb ranges for each level (Table 1) for reference. Each box represents the interquartile range (25th to 75th percentiles), the middle line represents the median, whiskers represent the 9th and 91st percentiles, and the diamond represents average of each distribution.

were cooked with charcoal across our full sample. In rural Malawi, this figure was only 1.5%, which is expected given that firewood is the dominant fuel in rural Malawi. In all settings except urban Malawi, most households cooked indoors. We found significant differences between %COHb levels across all groups, except between urban Malawi and Rwanda, which suggests that there is consistent intersite variability in CO exposure. Results from the ANOVA for differences between study settings are in the supporting information (Table SI4).

We analyzed where cooks fall on the neurotoxicological profile stratified by the share of meals cooked on a charcoal stove (Figure 2). There was a general upward trend in %COHb both for the 24-h average and 1-h max values as the share of charcoal use increases. The average cook using charcoal for more than 40% of meals fell into Level 1 of the toxicological profile where risks are increased for people with preexisting conditions. The average cook using less than 40% was in Level 0, where risks are negligible. One-hour maximum %COHb measurements showed that cooks using charcoal for greater than 40% of meals were categorized, on average, into Level 2 (results from the ANOVA for differences between charcoal use levels are in the supporting information, Table SI5a). This suggests that moving from 0%–20% to 20%–40% charcoal use did not significantly increase the 24-h average or 1-h maximum %COHb. There also were no significant differences within the three individual groups using greater than 40% charcoal (40%–60% charcoal use vs. 60%–80% vs. 80%–100%). However, cooks using charcoal for 40% or more of their meals cooked did have significantly higher %COHb levels than those using less than 40%. This result held when we control for cooking location and study setting (Table SI5b).

Instead of considering where the average cook falls on the toxicological profile, we combined all data and considered the share of time cooks were spending at each level in a 24-h period (Figure 3). Here, we stratified by percent of meals cooked with charcoal and cooking location. The share of time is defined as the number of hours spent at the given level as a fraction of the total 24 h for all 3301 cooks included in the study (79,224 total hours). We find that cooks spent most of their time at Level 0 (averaging 18.7 h per day across the full sample). They spent an average of 3.2 h at Level 1 and 2 h at Level 2 where risks of impairment become more pronounced.

We see a general upward trend in time spent at higher levels of risk as the share of charcoal use increases. When we consider charcoal share as a continuous variable, we find a significant increase in time spent in Levels 1, 2, 3, and 4 as cooks increase their share of charcoal (Table SI6). When we split the variable into categories, we again find that the important cutoff is cooking 40% or greater of meals with charcoal; there is significantly higher time spent in Levels 1, 2, and 3 for cooks using greater than 40% charcoal compared to those using less than 40%. Across all levels of charcoal use, indoor cooking was associated with higher percentages of time spent in higher toxicological profile levels for indoor cooking, but these differences were not statistically significant.

3.2. Cognitive Testing in Urban Zambia. Given that there is potential for cooks in high charcoal-using settings to spend substantial time with %COHb levels in ranges where cognitive impairment may be observed (e.g., $>4\%$ COHb), we explored whether we detect impairment using cognitive tests. The majority of primary cooks included in this sample were women (92%) who were cooking indoors (87.4%) and nonsmokers (98%). The average first hour %COHb score was 1.6% (std dev 2.5). The average 1-h maximum %COHb estimate was 8.2% (std dev 6.93). (Table 6).

Each test is scored individually with a range of 0–10 for the word recall tests and 0–8 for the digit spans. Cooks scored an average of five on the immediate word recall and scored significantly lower (average of four) on the delayed recall, which is the expected result. Similarly, cooks scored significantly higher on the forward digit span (average of 3.7) compared to the backward digit span (1.9).

Figure 4 shows the results of the regressions that test the relationship between various HAP measures and each of the cognitive test scores using coefficient plots. We show results both for a simple bivariate regression between each HAP measure and the respective cognitive test score as well as the estimates after adjusting for household expenditures per capita and gender, age, and education of the primary cook. While the results indicate that among cooks with higher %COHb, cognitive scores are lower, this relationship is not statistically significant. The first-hour %COHb (log-transformed) is our preferred measure. These estimates are the most precise but are not significantly different from zero, except for in the forward digit span. We also tested the relationship between 24-h average %COHb (log-transformed) and test scores. These results look very similar to the first-hour %COHb except for in the digit span tests where the point estimates are negative and approaching statistical significance.

Since the cutoff point of 40% charcoal use emerged as an important indicator of higher %COHb in the first part of our analysis, we also created a binary variable for whether a household cooks more than 40% of its meals with charcoal and used this as an additional independent variable in our models. We saw significant declines in both digit span test scores in the bivariate models, but this effect was not robust after adding covariates. Lastly, given that many other studies have focused on the role of $PM_{2.5}$, we tested this relationship as well with our considerably smaller ($n = 33$) subset of households in which we collected $PM_{2.5}$ exposure data. While we saw the largest negative point estimates when using log-transformed $PM_{2.5}$, these estimates are very noisy, due to the very small sample size.

The full regression results for the relationship between the first hour %COHb and the cognitive test scores including covariates are presented in (Table SI7). Higher levels of education are consistently and significantly associated with increased cognitive test scores. We also see some indications of a negative relationship between the age of the primary cook and test scores with significantly lower scores on both the immediate and delayed word recalls. None of the other covariates has a consistent relationship with test scores across models.

4. Discussion

While there are only a few studies that provide field-based measurements of %COHb in similar settings, our modeled estimates are on average lower than others reported in the literature [82, 83]. We find 24-h average values of 1.4% across all our study settings (1-h max of 4.5%). Samples from Malawi [82] and India [83] where %COHb was directly measured from blood draws found values of 5.8% and

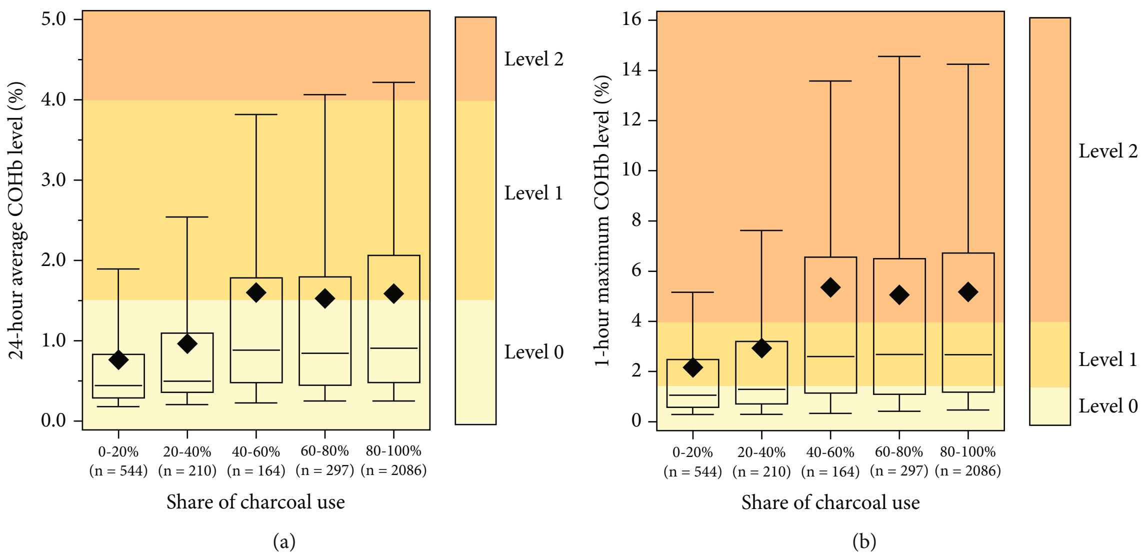

FIGURE 2: Mapping of %COHb (a) 24-h average and (b) 1-h maximum onto toxicological profile levels based on the share of meals cooked with charcoal (all locations). Background shading denotes the %COHb ranges for each level (Table 1) for reference. Each box represents the interquartile range (25th to 75th percentiles), the middle line represents the median, whiskers represent the 9th and 91st percentiles, and the diamond represents average of each distribution.

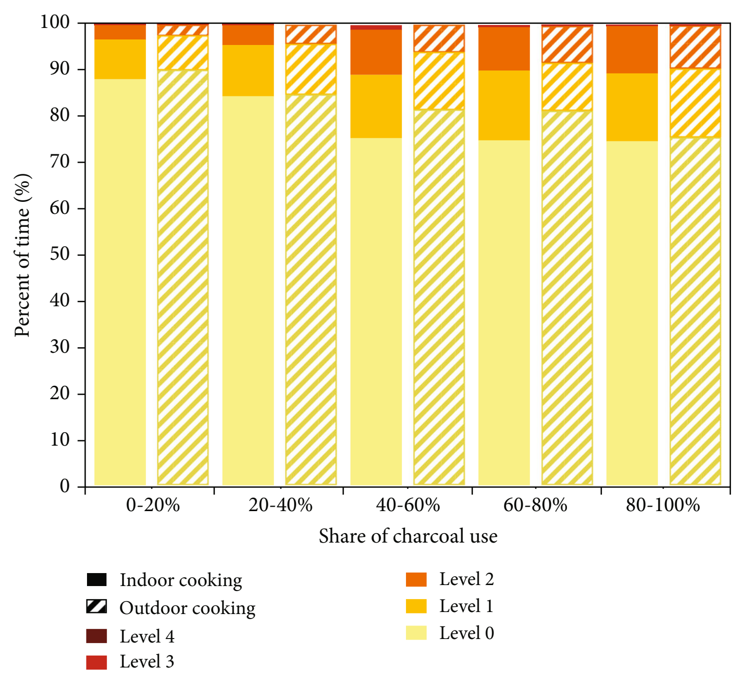

FIGURE 3: Share of time spent at toxicological profile levels based on %COHb stratified by share of meals cooked with charcoal and whether predominately indoor or outdoor cooking. Less than 1% of time was spent at Level 4 for all charcoal share groups.

15.7%, respectively, among biomass users. We consider the estimate from India to be less comparable given the high levels of overall pollution relative to the locations in our study. We do see values lower than the more comparable study in Malawi, but even if our %COHb estimates are in fact lower than actual levels, we use the same method to estimate %COHb levels in all settings, so we expect the relative rankings (e.g., higher %COHb in one cook compared to the next) to be accurate. Additionally, if we are underestimating %COHb, this would mean that we are understating the potential cognitive symptoms and daily impairment cooks might be facing. We note that there may be other factors that could affect the CO exposure of a cook such as background levels of ambient air pollution, use of other polluting cooking fuels (e.g., fuelwood, crop residues, and dung), and polluting lighting fuels (e.g., kerosene) [57]. However, 24-h CO exposure in our urban sites averaged 7.7 ppm, greater than the WHO 24-h indoor air quality guideline of 6 ppm

Table 6: Descriptive characteristics and CO exposure of primary cooks in four Lusaka compounds ($n = 451$).

	Frequency	%
Cognitive testing		
Day/date recall		
Date recalled correctly	399	88.47
Day of week recalled correctly	426	94.46
Self-rated memory		
Excellent	63	14.00
Very good	71	15.74
Good	175	38.80
Fair	120	26.61
Poor	22	4.88
Immediate word recall (mean, std dev, and max)	5.03	(1.47)
Delayed word recall (mean, std dev, and max)	3.96	(1.66)
Digit span forward (mean, std dev, and max)	3.74	(1.25)
Digit span backwards (mean, std dev, and max)	1.90	(1.04)
Carbon monoxide exposure		
CO exposure 24 h avg (mean, std dev, and max)	15.23	(14.09)
%COHb 24 h avg (mean, std dev, and max)	2.56	(2.08)
%COHb 1 h max (mean, std dev, and max)	8.19	(6.93)
%COHb first hour (mean, std dev, and max)	1.57	(2.48)
Location and sociodemographic variables		
Neighborhood		
Matero	14	3.10
Kalingalinga	163	36.14
Kamanga	82	18.18
Ng'ombe	192	42.57
Share of meals cooked with charcoal	82.88	(29.16)
Cooking location		
In household	349	87.38
Outdoors	102	22.62
Gender		
Male	35	7.761
Female	416	92.24
Age (mean, std dev, and max)	33.12	(12.59)
Highest grade (mean, std dev, and max)	8.70	(3.34)
Household expenditures per capita (mean, std dev, and max)	462.06	(450.52)
High blood pressure		
No	351	77.83
Yes	100	22.17
Smoking status		
No	442	98.00
Yes	9	2.00

[84]. Thus, CO exposure these cooks experienced was not insignificant and could have longer term impacts on the cognitive health of our study population.

We find areas of concordance and difference between our findings and the larger literature linking air pollution exposure and cognitive function. For example, several studies have found that long-term use of polluting cooking and lighting fuels in areas where background levels of ambient air pollution are high is associated with a decline in cognitive test scores [15, 19, 48–53]. By relying on biomass as a proximate measure of HAP exposure, these studies are unable to attribute cognitive decline specifically to exposure to any specific pollutant, nor are they able to disentangle the acute vs. chronic exposure effects. We focus on the effect of acute exposure to CO (and $PM_{2.5}$ in a small subsample) on cognitive test scores. While we do not see significant associations between estimated %COHb and scores across the full range of our cognitive tests, we do see negative (and significant in some model specifications) lower scores on the forward and backwards digit spans among cooks with higher %COHb in unadjusted models. Digit spans are an example of an attention task, which is a category of cognitive test that has been consistently associated with cognitive decline as air pollution exposure increases [15, 18, 85, 86]. Other types of tests, including word recall have smaller and less consistent declines in scores, consistent with our findings [14, 51, 87].

It is possible that the levels of CO exposure in our sample were not high enough to affect test scores beyond the attention task. Cognitive impairment from acute CO exposure is well established at %COHb levels above 20% [29–31], but none of the 24-h average %COHb levels estimated for our sample was above 20%, and only 7% of the measurements averaged above 20% in any given hour during the 24-h period. However, a study by Amitai et al. on CO exposure and cognitive function found declines in attention task scores even with %COHb levels ranging from 1% to 11% [69]. It is also possible that there was simply not enough variation in our %COHb levels. Recently published studies on the relationship between HAP and cognition consistently find decreased cognitive test scores for biomass fuel users. However, these studies use large, nationally representative datasets that include significant numbers of people using clean fuels (e.g., electricity or liquified petroleum gas) as the reference group in their analysis [48–51]. The fact that cooking with clean fuels was uncommon in our Zambian study population and that our sample size was relatively small may contribute to our inconclusive findings relative to larger studies.

There are several limitations of our study. First, CO exposure measurements were only collected for a 24-h period. We note that it would have been preferred to have cognitive data from the end of the monitoring period. A 24-h monitoring period was selected to encompass the maximum participants; however, a longer measurement period, such as 48 or 72 h would likely be more representative of average personal exposure. Since we were unable to measure %COHb directly, we estimated it using the CFK equation [71]. Many inputs used in the equation are population-level distributions; however, many factors such as race,

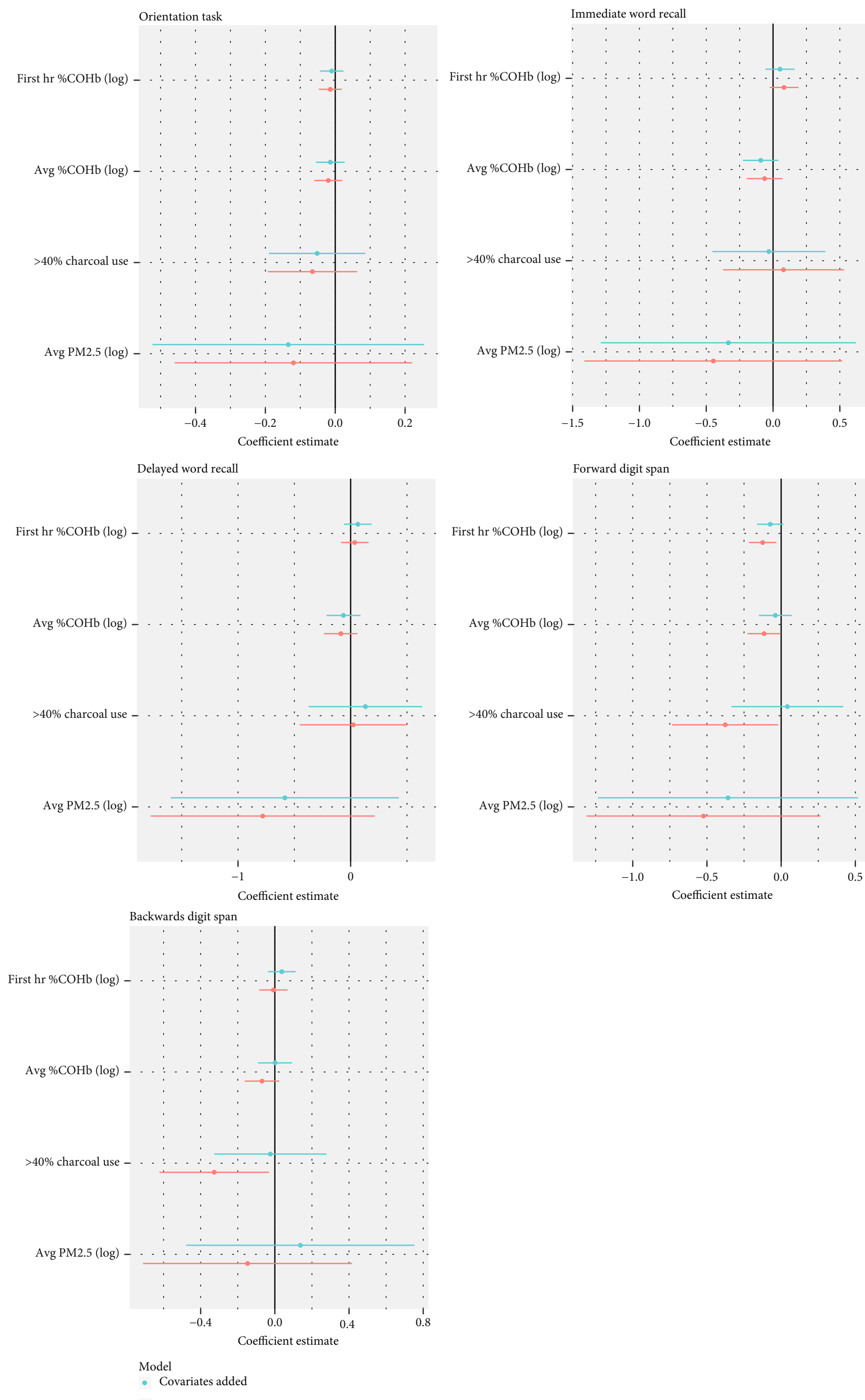

Figure 4: Coefficient plots of %COHb, > 40% charcoal usage, and $PM_{2.5}$ exposure with cognitive test scores.

whether the respondent is pregnant, and health conditions of the respondent, such as anemia, can also influence these parameters and were not directly accounted for [71, 72]. The CFK equation also relies on measured parameters of the respondent, including the age, gender, weight, and exercise level, that are uncertain. In the Zambia subsample, age and gender data were collected, but weight and exercise level were based on published population-level distributions, adding uncertainty to the estimates produced by the equation. Second, administering cognitive testing in an LMIC setting with an enumeration team new to the protocol could have introduced some measurement errors. The enumeration team underwent extensive training, and we pretested the protocol before starting data collection. We find expected relationships in our data, such as that cooks scored significantly higher on the forward compared to the backwards digit span and the immediate versus delayed recall. We also see a consistent, positive relationship between the education of the test taker and their scores, which has been observed in other studies of HAP and cognitive test scores [15]. Together, we believe these factors suggest that the tests were carried out correctly and consistently, limiting bias in our dependent variable. Additionally, we make every effort to use different versions of the CO exposure variables to best capture the likely levels of exposure of respondents at the time of cooking. Lastly, we note that recent studies find that exposure to $PM_{2.5}$, emitted from burning biomass, is associated with a decline in cognitive test scores [86, 88]. We do attempt to explore the relationship between cognitive scores and $PM_{2.5}$ in our study, but the sample size for this analysis was very small ($n = 33$), which could explain why our results are inconclusive.

5. Conclusion

This study estimates the extent to which household cooking is associated with the risk of cognitive impairment due to exposure to elevated CO levels for cooks living in Southern and East Africa. Additionally, for a subsample of cooks from Lusaka, Zambia, we test the relationship between estimated %COHb levels and a series of neurocognitive tests. While we find that cooks across all settings are exposed to levels of CO associated with daily risk for neurocognitive impairment, we do not find consistent negative relationships between %COHb and cognitive test scores in Zambia.

Our results add to a growing body of literature [18–24], exploring a relationship between HAP exposure and cognitive function, which has implications for daily life function and decision-making. While it seems increasingly clear that biomass users in LMICs are at greater risk for cognitive impairment due to lack of access to modern energy services, our study highlights a need for further exploration of the heterogeneity within biomass users. Even after adopting clean cooking technologies and fuels, the use of biomass fuels persists with households stacking clean and dirty fuels to meet their household energy needs [88–90]. Given that stove-stacking (using multiple stove/fuel combinations) is a common practice even in places where cleaner cooking fuels are widely used, the frequency of biomass use should also be accounted for in future studies. We find that an increased share of meals cooked with charcoal (regardless of what other fuels are used for the rest of meals) is associated with increased %COHb levels and the associated implications for cognitive function. This study is the first to our knowledge that explores this relationship in SSA, where the use of biomass for cooking remains almost universal, and given urbanization trends, where the use of charcoal for cooking is likely to increase considerably in the coming decades [91].

Although differences in cognition as measured with a set of standard cognitive tests were not detectable across the relatively slight variation in %COHb values estimated for our study population, these high levels of daily exposure to CO signify the potential for longer term negative health outcomes, especially given the high rates of chronic illness in this population (e.g., hypertension) This calls for identifying strategies to mitigate long-term potential risks of cognitive impairment especially among those that depend on charcoal for cooking. To more specifically target efforts to reduce the risk of cognitive impairment, this study could be repeated with a much broader range of fuel use and exposure levels from several pollutants to help clarify the relationship between HAP exposure and cognitive impairment. Our findings lay the groundwork for future research that attempts to continue to characterize the risks of HAP exposure in both the short- and long-term for cognitive health. We recommend that future studies attempt to disentangle the role of exposure to various pollutants and time scales, as well as whether even marginal reductions in biomass use in the short term might have long-term benefits for cognitive health.

Data Availability Statement

The data that support the findings in this study are not publicly available due to privacy restrictions. Data for each individual study that contributes to the overall findings in this paper will be made available upon reasonable request.

Conflicts of Interest

The authors declare no conflict of interest.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. SI1: 2-point linear calibration for each Lascar CO monitor; SI2: cognitive testing module administered to respondents from Zambia; SI3a: %COHb Monte Carlo estimations using Malawi STEPS weight data versus actual weight data; SI3b: assumptions and validation of %COHb estimation; SI4: ANOVA for differences in %COHb between study locations; SI5a: ANOVA for differences in %COHb between charcoal share levels; SI5b: regression estimates of % of meals cooked with charcoal on log-%COHb; SI6: regression estimates of proportion of time spent at each level on the CO toxicological profile based on percent of meals cooked with charcoal; SI7: regression estimates of first-hour log-%COHb on cognitive test scores. *(Supporting Information)*

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