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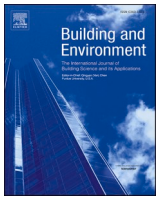

Reviewing the methodologies used to assess household $PM_{2.5}$ air pollution in sub-Saharan Africa

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ABSTRACT

Exposure to household air pollution (HAP) is a major global health issue in low- and middle-income countries, with exposure to fine particulate matter ($PM_{2.5}$) a major risk factor for a wide range of diseases. Sub-Saharan Africa (SSA) has unique contextual challenges for assessing HAP exposure, it is critical that learning from existing research is applied in future research. Reviews conducted to date have not considered in detail the methods applied when deploying $PM_{2.5}$ sensors to measure indoor air quality, nor did they focus on HAP. A review of HAP $PM_{2.5}$ measurement studies in SSA was conducted, focusing on measurement methods in order to understand how monitors have been deployed in the region. A search and extraction following PRISMA guidelines was applied. After exclusions, 51 papers were reviewed and information related to HAP sampling methods was extracted. Common themes in methodologies, assessing their effectiveness, and gaps in future research were highlighted. The findings highlight a considerable lack of research into HAP in the region where there is both an increasing population and an increase in the use of unclean fuels. A lack of standardisation in measurement practices was also identified. A key finding is the necessity for calibration of low-cost sensors against reference instruments within the region where they are deployed and calibrated against specific emission sources. This review provides recommendations to improving the accuracy and reliability of HAP measurement in SSA as well as key learnings for future larger-scale exposure and epidemiological studies to inform robust public health policy.

1. Introduction

Exposure to household air pollution (HAP) poses a major health threat and is among the top risk factors for morbidity and mortality. Approximately 3.5 million deaths are attributed to HAP exposure globally every year [1]. Of those deaths, approximately one third are due to pneumonia, 18 % from stroke, 27 % from ischaemic heart disease, 20 % from chronic obstructive pulmonary disease, and 8 % from lung cancer [2]. Other health impacts associated with HAP include low birth weight, acute lower respiratory tract infections, and anaemia, among others [3].

Combustion of biomass and dirty fuels such as coal, wood, dung, kerosene, crop residues etc. For heating and cooking are the largest contributors to HAP [4,5]. Incomplete and inefficient combustion of these energy sources produces harmful air pollution in indoor micro-environments in which people spend their time and also in the breathing zone of individuals. HAP comprises pollutants such as particular matter (PM), carbon monoxide (CO) oxides of nitrogen (NOx) and Volatile Organic Compounds (VOCs). $PM_{2.5}$ (PM with a diameter of 2.5 μm and smaller) are fine particles that can penetrate deeply into the lungs and may also pass into the bloodstream thereby affecting many organs in the body [6].

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Globally, approximately three billion people cook and heat their homes using open fires and stoves that generate HAP [2]. HAP is a public health concern in many low- and middle-income countries (LMICs) around the world and especially in SSA. Recent research suggests that HAP exposure in SSA was associated with under-five year old child mortality (Odds ratio (OR): 1.33; 95 % Confidence Interval (CI): 1.03–1.71) [7]. Children from households where cooking occurred inside the dwelling had a higher risk of mortality compared to households that cooked in a separate building (OR: 0.85; 95 % CI: 0.73–0.98) or outside (OR: 0.09; 95 % CI: 0.05–0.18) [7]. Children and women are both at high risk of HAP exposure given time spent in the dwelling and preparing family meals. Stoner et al. [8] have predicted an increase in the number of people cooking with polluting fuels in SSA which is estimated to exceed 1 billion people by 2025, emphasising the need to monitor HAP within the region.

Given the adverse health impacts associated with HAP, there has been growing research to measure HAP in dwellings to help inform interventions that aim to reduce and/or prevent HAP exposure. The relatively high costs of high/reference-grade air quality monitoring equipment at scale when monitoring HAP in numerous dwellings has led to the use of low-cost air pollution monitors. These monitors use sensors to detect and monitor specific air pollutants such as $PM_{2.5}$. Given the relative low-cost of these air quality sensors as well as the ease of their implementation and use, they are being used around the world to measure HAP (and ambient air pollution) especially in areas known to have high levels of HAP [9,10].

While low-cost air quality sensors have several benefits of use, there are challenges associated with their deployment, data quality and reliability, among others. A previous review assessed indoor air quality sensing technologies, mostly from studies conducted in the USA and found that the sensors showed moderate correlations with comparison (higher-grade) instruments and that the data from these sensors should be used with caution [10]. A second study reviewed the use of low-cost sensors for indoor air quality focusing on the features of the sensors and their application in different indoor settings [11]. Neither of these reviews considered in detail the methods applied by the researchers when deploying low-cost air quality sensors to measure indoor air quality, nor did they focus on HAP. We identified these gaps as an opportunity to draw together the literature for studies that used low-cost air quality sensors to measure HAP in SSA, a region known to have high HAP exposure levels, to interrogate the methods adopted in these studies to help inform the future use of low-cost sensors. Therefore, the aim of this review was to identify and describe the methods applied in studies conducted in SSA that measured HAP using low-cost sensors. Our objectives were to 1) describe the methodological characteristics (i.e., sampling time, location in the dwelling, sample size etc.) of studies conducted in SSA that used low-cost sensors to measure HAP; 2) to identify common themes pertaining to the methodologies; and 3) to highlight strengths, weaknesses and practical implications that were identified by the authors of the studies using sensors to measure HAP in dwellings in SSA.

2. Materials and methods

2.1. Search strategy

Databases that were searched included Web of Science Core Collection from Clarivate Analytics, PubMed from National Library of Medicine, and Scopus. Only research articles were included as document type; conference papers, letters, reviews, theses, case reports, and book chapters were excluded.

2.2. Inclusion/exclusion criteria

The search terms are provided in Table 1. While our focus was on HAP, we included 'indoor' in our original pre-screening search to avoid missing any studies conducted in dwellings that did not use the term HAP. Only articles published in English were included. No date filters were applied (the date of the final search was December 7, 2022, therefore only articles published up until that date was included). The geographical scope was SSA (see Table 1 for countries' names) and the HAP of interest was restricted to $PM_{2.5}$. The terms 'outdoor' and 'ambient' were not included within the search terms, however, they were not excluded to ensure that studies monitoring both HAP and ambient air quality were not excluded. This was done to include studies that monitored both HAP and outdoor air pollution. It was during the screening phase where HAP studies focusing on $PM_{2.5}$ in SSA were selected. Since the aim of this study was to understand what the methodological developments and gaps are in HAP monitoring within SSA with a view to applying the learning to future longitudinal studies specifically focused on HAP, any personal exposure monitoring studies that were found within the literature search were excluded. Only studies where a $PM_{2.5}$ monitor was installed in a room(s) within a dwelling were included.

Table 1
Search terms applied in the review.

Term 1	Term 2	Term 3	Term 4	Combination
Kenya OR Uganda OR Nigeria OR "South Africa" OR Tanzania OR Senegal OR Ghana OR Rwanda OR "Sub-Saharan Africa" OR "Sub Saharan Africa"	"Particulate Matter $_{2.5}$" OR $PM_{2.5}$ OR "fine particulate matter" or "fine particulate matter $_{2.5}$"	Epidemiolog[a] OR "Public health" OR Health OR Wellbeing OR "Well- being" OR "well being"	"Air pollut[a]" OR "air quality" OR "air quality sensor[a]" OR "air quality sensing" OR "Sensor[a]" OR "low cost sensor[a]" OR "low-cost sensor[a]" OR "air quality monitor[a]" OR monitor[a] OR sampl[a] OR "environmental pollution"	Term 1 AND Term 2 AND Term 3 AND Term 4

[a] Indicates that the search term has been truncated and the database search will look for variations on the word stem.

The screening criteria followed the Preferred Reporting Items for Systematic Reviews and Meta-analyses (PRISMA) for scoping reviews methodology [12]. All references for retrieved articles were uploaded into Endnote where deduplication was conducted. The first primary screening was intentionally broad. In the second round of review, four reviewers carried out a rigorous review of the retrieved articles divided among the four reviewers in order to determine which articles met the inclusion/exclusion criteria, with at least two reviewers assessing each article. The free-to-use software, Rayyan [13], was used to ensure the review was blinded and articles were only unblinded when two or more reviewers could not reconcile the inclusion or exclusion of an article and a third or fourth reviewer was brought in to assist in making the final decision. Articles in the second round were required to have original, experimental data and use a methodology that applied low-cost sensors for $PM_{2.5}$ measurement. Articles describing only ambient air quality measured using low-cost sensors were excluded. Eligible articles were then included for full-text review if the publication could be retrieved, after a final assessment of the retrieved publication's ability to cohere to the inclusion criteria, information was extracted from the final set of publications.

2.3. Data extraction charting

The required data for the review were captured in Microsoft Excel [14] spreadsheets using the following headings: study location, sample size (number of households), instrument range, sampling length, averaging, location of sensor in the dwelling, tabulated for presentation in summary format here. Additional information extracted are presented in supplementary material (Table S1 and Table S2) include; pollutants monitored, measurement type, study limitations identified by authors, measurement uncertainties, indoor pollution sources, month/season of measurements, correction method of data (if any), and calibration methods.

3. Results and discussion

Of the databases that were searched, 803 articles were identified. Duplicates (n = 313) were removed using the same process described by Bramer et al. [15]. The remaining 490 articles were screened, and their eligibility determined. Following the exclusion of articles that did not meet the inclusion criteria, 51 articles were then included in the review (Fig. 1).

Tables 2–4 show the information extracted from all of the articles that were included with the review, grouped by the technology used to monitor HAP $PM_{2.5}$. Additional information that was extracted is shown in Supplementary Table S1 and Table S2.

3.1. Geographical distribution of indoor air quality field campaigns

Our literature search showed that, within SSA, indoor air quality field campaigns clustered around East-, West- and Southern Africa (Fig. 2). The largest number of HAP monitoring field campaigns were conducted in Kenya and Nigeria (16 and 10, respectively). No studies were found that were conducted in Central Africa. The map shows that there are many countries within the region in which household $PM_{2.5}$ monitoring has not been reported in literature meeting the inclusion criteria.

This sparse geographical distribution and small number of indoor air quality monitoring studies highlights key gaps in locations where HAP needs to be examined further. There are large sections in central SSA where indoor air quality remains unexplored. A review on pollution monitoring in Africa (both ambient and indoor) by Agbo et al. [68] found information on only 27 of 54 African countries. Within the continent, there is a significant focus on ambient, outdoor air pollution, with the implementation of national ambient air quality standards across a small number of countries all be it with a limited amount of data [68]. However, there is little to no focus on indoor HAP monitoring. Certain countries have a number of initiatives for regulating and monitoring air pollution in general, however, it may not be considered a priority on a political agenda [69]. There is also a lack of awareness on the impacts of exposure to HAP on health in certain communities, an improved awareness can be used to drive policies and increase the need for HAP monitoring [69]. Finally, there are a number of challenges with regards to air pollution monitoring within low- and middle-income countries (LMICs) in comparison to countries with higher income. For example, in LMICs, the air quality monitoring strategies can be relatively new in comparison to countries with higher incomes, with a significant difference in investment, there can often be little access to electricity to power sensors, little or no laboratory access for calibrations and maintenance of sensors and little financial resources in LMICs [70].

Fig. 2 also shows populations of countries within SSA, (data collected from the World Bank [67]). When comparing the study locations of the retrieved HAP articles with population data, only seven of the ten most populous SSA countries have monitored HAP (albeit a small number of HAP field campaigns). Some countries, such as the DRC, which is the 4th most populated country in Africa, particularly need more monitoring. These countries generally use coal, wood and biomass burning as sources of fuel and heat in poorly ventilated dwellings with little access to cleaner stoves [8,71,72]. Stoner et al. [8] have estimated that with an increase in population within the SSA region, there is likely to be an increase in the use of polluting fuels for cooking and heating. A joint

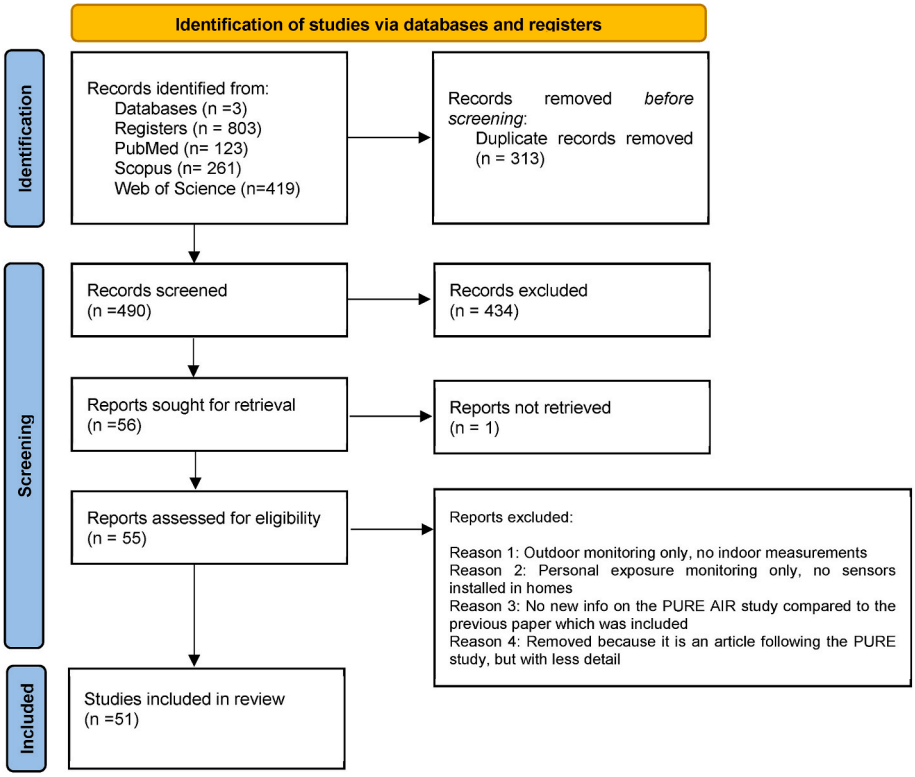

Fig. 1. PRISMA flow diagram adapted from Page et al. [12].

Table 2
Study characteristics of retrieved studies that used optical light scattering sensors (Optical Particle Counters) to measure HAP $PM_{2.5}$.

Authors	Study location	Number of homes	Range (ug m^{-3})	Sampling length	Averaging time	Location in the home
Afolabi et al. [16]	Nigeria	49	N/A	N/A	24-h	Indoor
Aigbokhaode and Isara [17]	Nigeria	62	1–250000000	30–60 min	5 min	Indoor
Ang'u et al. [18]	Kenya	42	N/A	65 min	N/A	Kitchen
de la Sota et al. [19]	Senegal	22	0-100, 000 (DustTrak DRX) 0–60, 000 (Indoor Air Pollution Meter 5000 Series)	24-h	1 min	1 m away from the emission source and 1.45 m above the ground
Eghomwanre et al. [20]	Nigeria	45	0–999	N/A	N/A	Sitting room
Gitau et al. [21]	Kenya	25	N/A	N/A	1 min	Kitchen
Giwa et al. [22]	Nigeria	75	0–500	62 min–147 min (depending on cooking time)		Kitchen centre, breathing height
Giwa et al. [23]	Nigeria	38	0–500	49 min–158 min	10 min	Kitchen
Hankey et al. [24]	Uganda	28	N/A	48 h	1 min	Kitchen
Iribagiza et al. [25]	Rwanda	90	N/A	16 weeks	24-h	Mounted to wall in cooking area
Iribagiza et al. [26]	Rwanda	2	N/A	14 days per household	2.5 min	Installed where the stove is used
Jelili et al. [27]	Nigeria	385	105,900 particles/L	4 weeks	45 min - 1hr	Living room
Jung and Huxham [28]	Kenya	28	1-150,000	15 min	1 min	Kitchen
Kajjoba et al. [29]	Kenya	6 (of 7)	0-1000	15 h	1 h	Indoor
Kansiime et al. [30]	Uganda	374	0–999	37 households measured per day	1 min	Cooking area and living space. 1.5 m away from windows and doors
Klasen et al. [31]	Peru, Nepal and Kenya	43 Kenya	1–400000	24-h	1 min	1.5 m off the floor and within 1 m of the cooking fire
Kumar et al. [32]	Bangladesh, India, China, Brazil, Egypt, Iraq, Ethiopia, Nigeria, Malawi, Tanzania, Kenya	60 (5 in each within Sub- Sahara Africa)	1.0–1000	7 days	1 min	Adult breathing height (1.5 m) above the floor and ~ 1.5 m away from the cook/stove
Lam et al. [33]	Kenya	20	(30–50) - ~25,000	4 days	4 days	Kitchen or bedroom
Muindi et al. [34]	Kenya	72 (sub-sample of 1058)	1 -150,000	On average 10.4 h (Viwandai), 11.8 h (Korogocho)	1 min	Indoor, primary cooking space
Nakora et al. [35]	Uganda	60 (10 from each village)	N/A	24-h (personal monitoring); continuous (cooking period monitoring)	N/A	1.5 m above the ground and 1 m from the point of cooking
Njenga et al. [36]	Kenya	5	N/A	Approximately 3 h, repeated for 25 days	1 min	Kitchen
Njenga et al. [37]	Kenya	5, (four tests in each household)	N/A	20 days	1 min	Kitchen
Ochieng et al. [38]	Kenya	49	1-150,000 (DustTrak 8520) 1–400,000 (DustTrak II 8530)	Approximately 1 day (ranged 16–22hr depending on battery life)	1 min, 1 h, approximately 1 day	Indoor, primary cooking space
Pennise et al. [39]	Ghana and Ethiopia	36 (Ghana) and 33 (Ethiopia)	NA	24-h (Ghana and two locations in Ethiopia), 48-h (one location in Ethiopia)	1 min	Kitchen
Tumwesige et al. [40]	Cameroon & Uganda	18 Cameroon, 17 Uganda	0–2000	1	1 min	Indoor, primary cooking space
Vinti and Vaccari [41]	Ghana	6 villages, 1 set of measurements indoors	0–2000	15 min - 1 h	N/A	Near kitchens

report from the Health Effects Institute [73] and the Institute for Health Metrics and Evolution has shown that, as of 2019, across the African continent, the three countries with the highest proportion of household cooking with solid fuels are; Central African Republic, South Sudan and Rwanda. However, we found that in two of these countries, there are no studies with measures of HAP $PM_{2.5}$ and only four HAP studies in Rwanda. Therefore, it is important to apply knowledge learnt in successful field campaigns to longitudinal studies across the region. Exposures need to be observed over time in large enough samples of the population to understand how these exposures are associated to different health outcomes; long term exposures are understood to be key for many disease areas [74]. Perhaps future research could be guided by prioritising study areas where the housing type and geographic location are representative of the largest populations. Longer term assessments would be needed to ensure this selection takes inequalities into account.

3.2. Study designs

Of the retrieved 51 studies, 19 were intervention studies. These studies involved monitoring HAP when comparing various

Table 3
Summary of the characteristics of retrieved references that used gravimetric samplers to measure HAP $PM_{2.5}$.

Authors	Study location	Number of homes	Sampling length	Averaging time	Location in the home
Johnson et al. [42]	Kenya, Uganda, Benin, Vietnam, India	Ranged from 5 to 39	N/A	N/A	Samples were collected directly above the stove
Liao et al. [43]	Guatemala, India, and Rwanda	40 Rwanda	24-h or 48-h	N/A	1 m away from the combustion zone of the primary cookstove
Mbazima et al. [44]	South Africa	30	7 days	24 h	Collected in sitting rooms where possible
Mutahi et al. [45]	Kenya	15 (urban); 9 (rural)	12-h	N/A	At approximately 1.5 m height from the ground
Muyanja et al. [46]	Uganda	88 (7 villages)	24-h	N/A	Kitchens
Piedrahita et al. [47]	Ghana	137 (microenvironments of 200 households)	1 or 2 days	24–48 h	Kitchen
Pilishvili et al. [48]	Kenya	45	Two weeks per stove. Measurements repeated three weeks later	48 h	Kitchen
Rose Eilenberg et al. [49]	China, Honduras, Uganda, India	Uganda 10	1 h to over 7 h	N/A	Indoor location where the stove is located
Shezi et al. [50]	South Africa	300	24 h	24 h	Living room or bedroom and/or cooking area
Shezi et al. [51]	South Africa	30	24 h, two samples collected in each home in each season	24 h	Preferably in a living room. In the absence of a living room, sampler was located in another room
Shezi et al. [52]	South Africa	300	24-h	1 min	Living room
Shupler et al. [53]	Bangladesh, Chile, China, Colombia, India, Pakistan, Tanzania, and Zimbabwe	5 communities Tanzania, 2 communities Zimbabwe	48 h	N/A	Kitchen
Sidibe et al. [54]	Mali	2	1.5 h–3 h, 40 samples collected	N/A	Living room and kitchen
Titcombe and Simcik [55]	Tanzania	4 households, 1 secondary school	Each site monitored for three separate days, spread out over duration of study	7–8 h	Kitchen
Van Vliet et al. [56]	Ghana	36	24 h	24 h	Kitchen
Wallach et al. [57]	Uganda	80	N/A	48 h	Living room
Zhou et al. [58]	Ghana and The Gambia	80 homes in Ghana, 203 homes in The Gambia	48 h (Ghana), 72 h (The Gambia)	N/A	Cooking area (1m height, 1m from stove)

Table 4
Summary of retrieved references in which studies used both light scattering and gravimetric techniques for measuring HAP $PM_{2.5}$.

Authors	Location	Number of homes	Range (ug m^{-3})	Sampling length	Averaging time	Location in the home
Coffey et al. [59]	Ghana	28 (rural); 32 (urban)	5.4–496	48-h	1 min	1 m from the most used cooking location
Dutta et al. [60]	Nigeria	N/A	N/A	72-h	1 min	General living area away from kitchen
Gumede and Savage [61]	South Africa	23	1–20000	24-h	10 min	Living room
Johnson et al. [62]	Kenya	100	N/A	24 h with light scattering and gravimetric monitor, 1–4 days in 28 homes with light scattering monitor	N/A	Kitchen and separate room, usually living room.
Oluwole et al. [63]	Nigeria	59	1–400000	1 h	15 min sampling averaged to 1 h	Kitchen
Oluwole et al. [64]	Nigeria	59	1–400000	1 h	1 min	Kitchen
Rosa et al. [65]	Rwanda	121 houses (61 in control group, 60 in intervention group)	N/A	24 h	1 min	1.5 m from ground, 1 m away from stove, 1.5 m from windows and doors
Yip et al. [66]	Kenya	45 homes from 2 villages	30–25000	2 days	48 h gravimetric. 1 min real time, averaged to 48 h	Kitchen

interventions, such as traditional and improved cook stoves, and use of clean and traditional fuels [17–19,21,24,36–40,42,43,47–49,63,66]. Two of these intervention studies involved testing emissions from traditional fuel-based sources of indoor lighting versus solar lamps [33,57].

Seven studies involved HAP monitoring during cooking, with the sampling strategy involving monitors being switched on before, during and after cooking [22,23,28,45,62,64]. One of the aforementioned studies also included the monitoring of emissions during the burning of incense as well as cooking [54].

The remaining studies monitored HAP via the installation of a light scattering $PM_{2.5}$ monitor or a gravimetric $PM_{2.5}$ collector within the

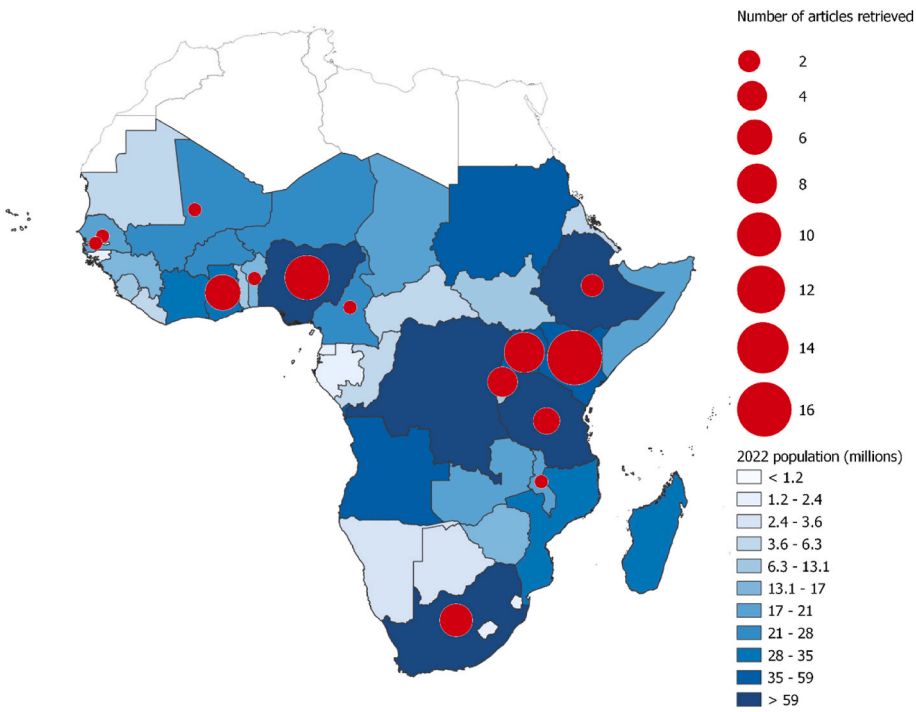

Fig. 2. Geographical locations of SSA HAP measurement field campaigns found within the literature search (red). 2022 populations of Sub- Saharan African countries (blue). Total population data collected from The World Bank [67] mid-year estimates. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

dwelling [16,20,25–27,29–32,34,35,41,44,46,50–53,55,56,58–61,65].

3.3. Common locations where the sensors/gravimetric monitors were installed in the home

Where stated within the studies, $PM_{2.5}$ monitoring primarily occurred within kitchens and living rooms (Tables 2–4) [18,20–24,27,28,36,37,39,44,46–48,52–57,60,61,63,64,66].

Lam et al. [33] monitored HAP in multiple rooms within the participants' kitchen and bedroom. Shezi et al. [50] and their subsequent study Shezi et al. [51] monitored $PM_{2.5}$ concentrations in living rooms, and if the participant's living room was not available, $PM_{2.5}$ was monitored within the bedroom and/or the cooking area.

Several studies have stated that HAP monitoring was conducted indoors within the primary cooking space [25,30,34,35,49,58,59], or within a specific length of a cookstove [19,26,31,32,38,40,41,43,65]. Four studies stated that HAP measurement was conducted within their studies, however, no details were given as to which room(s) specifically within the volunteers' dwellings were used for the measurements [16,17,29,45].

Studies by Johnson et al. [42] and Johnson et al. [62] used a measurement technique that was unique in comparison to the other studies. While most studies involved installing $PM_{2.5}$ (either light scattering or gravimetric) near to emission sources, Johnson et al. [42] and Johnson et al. [62] field campaigns measured $PM_{2.5}$ concentrations directly above an emission source (stove) using a sample inlet suspended above the emission plume, implying that the primary focus was stove emissions performance rather than indoor concentration levels.

3.4. Measurement corrections and calibrations

Many real time light scattering monitors use Optical Particle Counters (OPCs) for $PM_{2.5}$ monitoring and are laboratory calibrated with Arizona Road Dust [75–77], therefore for measurements made by OPCs, corrections should be made with gravimetric samples and real time monitors should be co-located with gravimetric $PM_{2.5}$ collection [78], as most of the particles emitted within these studies are from indoor combustion sources, and particles of different source/composition are known to have different optical properties and different densities [79–81]. Owing to the different optical properties of indoor emission sources, real time OPC measurements of indoor $PM_{2.5}$ require calibration to individual sources, and correction factors may need to be calculated for varying sources of indoor $PM_{2.5}$ [79,81]. Dacunto et al. [81] have previously monitored indoor concentrations and determined emission factors of $PM_{2.5}$ relating to various common indoor sources (i.e., cigarette smoke, incense, cooking, candles and fireplaces). They determined that calculated calibration factors for these sources were less than the factory calibration factors. This is particularly important because particular mass concentration has been (and continues to be) the key exposure variable; light scattering instruments do not provide direct measures of mass, and conversion to mass concentration requires assumptions of particle shape and density [82,83]. The other issue is that many of the lower cost sensors provide good linear response but require a reference and individual calibration coefficients [81,84]. Of the retrieved references, Lam et al. [33] calibrated their real time light scattering $PM_{2.5}$ monitors with pine wood smoke prior to deployment, however it is not stated within the article if calibration of the deployed monitors occurred against gravimetric or OPCs. Lam et al. [33] have also stated that the OPCs used for their field campaign had factors calculated for deployment within the volunteers' living areas and bedrooms. This was done by co-locating the monitors used with gravimetric $PM_{2.5}$ collectors and using correction factors based on previous studies.

Gravimetric measurement is the 'bench mark' as it is accurate and does not need as many corrections as real time [85,86], and larger concentrations can be measured in comparison to OPCs (within reason, as long as filters do not get clogged) [78,86], but gravimetric measurement is often expensive, as it requires conditioning of multiple filters, accurate and consistent flow rates and sensitive scales [31,86]. Small light scattering sensors can give real time measurements but require frequent calibration and can be less accurate. The data from low-cost sensors can vary greatly owing to missing data and measurement errors [87]. Datta et al. [87] have stated that out-of-sample R^2 of

low-cost monitors can vary between less than 1 % to over 75 % against the reference monitor, depending on the type of monitor. It is therefore important to know the precision and accuracy of the $PM_{2.5}$ measurements and where the collected data fits within these parameters.

In order to provide accurate measurements of HAP $PM_{2.5}$, any measurements that are intended to be conducted by OPCs, need to be calibrated against gravimetric measurements within the environment in which they intend to be used within the field. Calibration coefficients need to be calculated and applied to OPC measurements. Co-location of multiple real time monitors in the same location provides a good indication of the response and performance of monitors. If a co-location of multiple sensors can be conducted within the indoor sampling location, this is good, but a co-location alongside a reference instrument is preferred [87].

If field measurements are to be conducted by gravimetric measurements, blank filters need to be collected (this consists of collecting filters within the field in which there is no air sampled onto them), this allows for correction of the filed sample (the mass of $PM_{2.5}$ collected from the field sample is subtracted from the blank sample). Giordano et al. [88] and Zimmerman [89] have stated in further detail the process and systems needed to. calibrate low cost sensors including best practices and confounding factors in sensor calibrations.

Of the 51 articles that were retrieved, 37 stated either the correction or calibration method (Table 5). Several studies that used real time light scattering $PM_{2.5}$ monitors stated that co-location with gravimetric samplers were conducted [19,33,35,38,65,66]. With regards to studies conducted using gravimetric $PM_{2.5}$ measurements several articles collected laboratory or in home blank filters (in some cases both laboratory and in home blank filters were collected) [33,38,43–53,55,56,62]. Collection of blank filters allows for the correction of environmental conditions and improves the quality control and quality assurance of sample collection [90].

Background measurements (i.e., measurements taken within the monitoring location before a specific activity that generates $PM_{2.5}$) need to be taken with both gravimetric and real time monitors. If the sampler is located in kitchen, and samples are collected solely for the purpose of monitoring concentrations for the purpose of estimating emissions during cooking, then background measurements need to be taken before cooking. If household exposure is to be measured during daily activities, then the real time monitor needs to be switched on all the time, and gravimetric measurements need to be taken daily. Ang'u et al. [18] conducted measurements of $PM_{2.5}$ generated during cooking and collected background of $PM_{2.5}$ within the kitchen before cooking. This measurement of background $PM_{2.5}$ allowed for accurate measurements as $PM_{2.5}$ measured during the cooking episode will be subtracted from $PM_{2.5}$ present within the kitchen prior to cooking. In another study, Johnson et al. [62] measured $PM_{2.5}$ concentrations within kitchens prior to cooking, and subtracted $PM_{2.5}$ measured during cooking form that measured within the kitchen prior. Johnson et al. [62] also stated that if background concentrations exceeded 50 μg m^{-3} before cooking, the experiment was delayed until a lower background concentration was measured.

3.5. Strengths identified in the studies

Only a limited number of studies have directly identified their strengths. Zhou et al. [58] have stated that measuring in poor and affluent neighbourhoods allowed the authors to examine (to an extent) how HAP levels, composition and sources varied by socio-economic status (SES). They also measured $PM_{2.5}$ in household cooking areas and ambient sites which allowed them to compare the source contributions inside and outside homes. The use of a well-validated questionnaire was a strength identified by Shezi et al. [50] This questionnaire was said to allow for an assessment of HAP over several variables which generated substantial volume of data that was easy to use. This strength was also identified in later work by the same authors

Table 5
HAP measurement correction and calibration method as stated within the retrieved study.

Author	Measurement correction method	Calibration method
Aigbokhaode and Isara [17]	Not reported	Pre-calibrated before use
Ang'u et al. [18]	Background $PM_{2.5}$ before cooking. If $PM_{2.5}$ exceeded 25 μg m^{-3} before the tests, the sampling was then delayed until a lower background was measured. Measurements were made in the same kitchen for each fuel tested. Repeat measurements made for each cooking technology	Placed in "clean air" until zero readings attained
Coffey et al. [59]	Correction factors used to adjust sensor readings to gravimetric measurements. Relative humidity corrections found in existing optical PM sensing literature were applied to the particle coefficients to adjust for effects attributable to RH. Multilinear regression model was used to estimate the resulting particle coefficient adjusted for effects attributed to temperature, CO and CO_2 concentrations	Optical sensors calibrated against gravimetric samplers (co-location. Weekly flow rate calibrations, any pumps out of uncertainty removed from study. Filters were conditioned for 18–24 h. Filters left to equilibrate for 24 h before weighing. Filters weighed in triplicate and subtracted from the median blank filter. Filter mass less than 21 μg were (1.5 *x* SD of the blank) were regarded as below detection limit and replaced with 140 μg (10 *x* SD).
de la Sota et al. [19]	Co-location in a chosen kitchen for field validation, evaluating inter-instrument variability, sensitivity, and consistency. Comparison between IAP meter and DustTrak units carried out for quality control purposes, i.e. correction equations were not applied, given the differences between the test and field conditions.	IAP meter units were co-located with the DustTrak monitors (considered to be the internal reference) for the field-validation of the IAP meters
Eghomwanre et al. [20]	$PM_{2.5}$ measurements made at selected locations before proper readings. Measurements were taken every month in triplicate throughout sampling period	The samplers were calibrated following the guidelines of the before and after sampling
Giwa et al. [22]	Not reported	Self calibrating
Giwa et al. [23]	Not reported	Self calibrating
Iribagiza et al. [26]	Not reported	Re- calibrated before and after deployment in homes. Sensors calibrated in a chamber. Sensor installed in a sealed chamber, filtered air pumped into chamber and zero point measurements collected.
Johnson et al. [42]	Teflon filters weighed before and after sampling in a constant humidity and temperature room on an electronic microbalance with 0.1 μg resolution.	QA/QC checks, weekly scale checks with a standard weight. Pre-, post-; collection of field blanks, co-located measurements by partner research teams; daily review of collected survey data.
Johnson et al. [62]	Background levels measured in kitchen before and after cooking. Background concentrations subtracted from measured concentrations during cooking. If real time concentrations exceeded 50 μg m^{-3} before cooking, the experiment was delayed until	Not reported

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Table 5 (*continued*)

Author	Measurement correction method	Calibration method
	a lower background concentration was measured. Filters weighed in a temperature and humidity controlled room. Blank filters collected during study. Filters weighed before and after sampling, effects of handling corrected for by using the median mass on blank filters (20 blank filters collected). LoD was calculated as 7.8 μg (3 *x* SD blanks).	
Kansiime et al. [30]	Not reported	Laser sensor evaluated in lab and field against FEM GRIMM
Klasen et al. [31]	Calibrated to zero-air before deployment. Real-time measurements had to be conducted for at least 18 h to be included in the analysis. Relative humidity data used to adjust nephelometric PM concentrations. Nephelometric PM concentrations were converted to $PM_{2.5}$ gravimetric-equivalent concentrations using a previously validated equation.	Co-location with a gravimetric filter sampler in the field
Kumar et al. [32]	PM data is generally required to be corrected for the hygroscopic growth of particles at the RH higher than 85 % but the authors did not apply any corrections since the data were within the acceptable RH range.	Factory calibrated. Laboratory co-location measurements, using a nebuliser to simulate the high PM levels expected in a typical kitchen. Co-location measurements of PM levels were carried out against each other and also calibrated against a reference grade optical particle spectrometer (GRIMM model 11-C)
Lam et al. [33]	Field-based adjustment factors calculated for baseline and follow-up, from 48-h co-located gravimetric filter measurements taken in a subset of households. Kitchen correction factors estimated from previous studies and experiments. Pre-and post-sampling filter weights, and field and lab blank weights, determined in a temperature- and humidity-controlled environment	Monitors calibrated before deployment with pine wood smoke
Liao et al. [43]	Blank filter samples collected at each study site. Filters pre- and post-weighed in multiple labs. Filters conditioned for 24 h before weighing and post-weighed in the same lab in which they were pre-weighed. All filter weighing labs followed a similar protocol of temperature and humidity control. Two weight measurements were made for each filter, with third weight taken if the first two weights differed by more than 5 μg. Filters excluded when average flow rate deviated by more than 10 %, when sampling time deviated by more than 10 % of the full sampling	Pump flow rates calibrated prior to deployment. Weighing balance for filter samples was professionally calibrated annually

Table 5 (*continued*)

Author	Measurement correction method	Calibration method
	duration, and damaged filters holes or tears.	
Mbazima et al. [44]	Filter masses weighed before and after sampling. Blank filters collected. Flow rate of the sampler pump was checked before and after sampling with a rotameter	Gravimetric weighing was undertaken under controlled laboratory conditions
Muindi et al. [34]	Not reported	Calibration factor was determined, after co-location with gravitational personal monitor alongside the DustTrak (outdoor).
Mutahi et al. [45]	12-h integrated sample collected on a filter. $PM_{2.5}$ mass determined gravimetrically with a microbalance in relative humidity and temperature-controlled room. The mass difference of the filter before and after sampling is used to obtain particulate matter's mass. Mass concentration of $PM_{2.5}$ is then obtained by dividing the $PM_{2.5}$ mass by the volume of sampled air. Filters were weighed three times but on different days and the average mass was considered.	Clean filter was calibrated by coupling a mass flow meter and a rotameter to the sampler loaded with a filter and adjusting the pump's flow rate before and after the field campaign. Weighing balance for filter samples was professionally calibrated annually.
Muyanja et al. [46]	Filters conditioned in a temperature and humidity-controlled room for 48 h prior to weighing done prior and post sample collection. The mass difference of the filter before and after sampling is used to obtain particulate matter's mass. The concentration of $PM_{2.5}$ was calculated by dividing the change in filter weight by the volume of air sampled to give a final concentration in micrograms per cubic meter. Field blanks were used to account for potential bias in filter weight due to sampling methods.	Not reported
Nakora et al. [35]	Colocation with gravimetric samplers. Monitors zeroed in a Ziploc bag before and after deployment. Particle and temperature coefficients, with the results from zeroing, used in the data processing. Flow rates measured before and after sampling. Filters weighed and conditioned in a temperature and RH controlled room for 24 h. Filters weighed in triplicate.	Real-time measurements of $PM_{2.5}$ using the UCB-PATs monitors were adjusted based on gravimetric samples. They were calibrated with combustion aerosols of charcoal against gravimetric measurements of $PM_{2.5}$ in the laboratory before being used in the field.
Ochieng et al. [38]	Co-location with gravimetric measurements. Filters pre- and post-conditioned for 48-h before weighing in a temperature and humidity controlled environment in a laboratory. OPC measurements overestimated gravimetric measurements by approximately 5 times. Flow rates checked before and after sampling using a calibrated rotameter. Zero points	Not reported

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Table 5 (*continued*)

Author	Measurement correction method	Calibration method
	conducted before sampling in each household. Filters weighed in triplicate. Zero and span of the balance was checked after every batch of filters. Field blanks also collected	
Oluwole et al. [63]	Baseline procedures repeated 1 year later	Article states that measurements were conducted after calibration and equilibration, but does not state how the monitor was calibrated
Oluwole et al. [64]	Not reported	Article states that measurements were conducted after calibration and equilibration, but does not state how the monitor was calibrated
Pennise et al. [39]	Calibrated using wood smoke. OPC detector cleaned with isopropyl alcohol after every five uses.	Not reported
Piedrahita et al. [47]	Field blanks collected. Measurements subtracted from blanks.	Not reported
Rosa et al. [65]	24 h co- location of $PM_{2.5}$ monitor with gravimetric sampler within 30 homes. Field blanks collected, resulting in 5 μg of $PM_{2.5}$ subtracted from final filter mass. Linear regression of the PM2.5 monitor in comparison with the gravimetric measurement used to correct measurements	Flow rates of gravimetric sampler calibrated with rotameter before and after install in homes. Filters conditioned for 24 h in a temperature and relative humidity controlled environment
Rose Eilenberg et al. [49]	Clean handling procedures were used to minimize filter contamination. Repeat measurements and field blanks collected. Filters pre baked in air to remove excess carbon. Teflon filters weighed pre- and post-test after 24 h of conditioning in a temperature and relative humidity controlled environment to determine gravimetric PM2.5 mass	Not reported
Shezi et al. [51]	Filters weighed pre- and post sampling (accurate to 1 μg) in temperature and relative humidity controlled room. Mass balance calibrated prior to weighing. Laboratory and field blanks used to correct the mass of sampled filters. LoD was calculated using the mean of the standard deviation of 12 blank filters multiplied by three and dividing by the sample volume for 24 h	Not reported
Shezi et al. [52]	In homes where sampling instrument error occurred, or where sampling time was less than 90 % (21 h) of the required time, sampling was redone. Gravimetric analysis was used to determine $PM_{2.5}$ mass using a microbalance in temperature and relative humidity controlled laboratory. Filters conditioned for 24 h in the laboratory. QC achieved by weighing of blank filters. Laboratory and field blank filters were used to adjust the weight difference observed due to change in indoor climate of the weighing room and field handling of samples, respectively	The samplers were maintained and calibrated prior to data collection using the guidelines set by the manufacturer. The microbalance was calibrated prior to gravimetric analysis
Shezi et al. [50]	Sampling repeated in households when sampling error occurred or sampling time was <90 % of 24 h. Filters weighed and conditioned in a temperature and RH controlled environment for 24 h. Microbalance calibrated annually against standard weights. QC by repeat measurements (in 15 houses) and weighing blank filters. Blank filters used to adjust weight owing to change in indoor climate. LoD calculated using mean of mass change in 18 blank filters, multiplied by three and dividing by the sampling flow rate	Factory calibrated before study started
Shupler et al. [53]	Blank filters collected. Filters weighed before and after sampling. Maintained in a temperature and humidity controlled lab. QC conducted on mass balance by weighing 3 calibration weights. 5 reference filters weighed before weighing reference filters. Filters allowed to stabilise in environment before weighing. Each filter weighed in triplicate.	Not reported
Titcombe and Simcik [55]	Blank filters collected and used to correct for sampled filters. Travel blanks (blanks taken to country, but not sampled) and lab blanks (blank filters which remained in the analysis lab) used to correct sampled filters. Samplers flow meter was calibrated against a Gilibrator. Flow rates were measured before and after sampling where possible.	Not reported
Tumwesige et al. [40]	$PM_{2.5}$ concentrations were corrected by a factor of 0.295 (Jiang et al., 2011) to account for particle characteristics of combustion aerosol, including density, size distribution and index of refraction	Not reported
Van Vliet et al. [56]	Field blanks collected. Background measurements collected on filters. Filters weighed before and after sampling, conditioned in temperature and RH controlled environment for at least 24 h. Daily calibration of mass balance using calibration weights. Weighing of each filter conducted until two consecutive weights agreed within 2 μg of the average of three consecutive weights.	Not reported

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Table 5 (*continued*)

Author	Measurement correction method	Calibration method
	Pressure was measured during weighing steps to allow for pressure corrections.	
Wallach et al. [57]	Not reported	Filters weighed and conditioned in temperature and RH controlled environment for 48 h
Yip et al. [66]	Co-located samples of gravimetric and real-time $PM_{2.5}$ collected in the kitchen. Regression analysis between the mean 48-h $PM_{2.5}$ mass measured by the real time monitor and 48- hour $PM_{2.5}$ gravimetric samples conducted. For missing $PM_{2.5}$ gravimetric values, regression was used to estimate $PM_{2.5.}$ Field blanks collected. Filters weighed and conditioned in temperature and RH controlled environment for 24 h. Before weighing, 100 mg calibration weight and three lab blanks were weighed. Reproducibility of mass balance determined by reweighing the first filter in the previous batch. All filters weighed twice. If the second mass differed by $>$ 5 μg, the filters were weighed again. At the end of the weighing session, the filters were weighed again.	Pre- and post-calibrations were made by either a rotameter or a Dry Cal DC-Lite in the field. UCB- PATS calibrated against Dust Trak before field deployment
Zhou et al. [58]	Excluded $PM_{2.5}$ samples for which the monitor operated for less than 85 % of the measurement period or if there was evidence of broken air flow system. Blanks and duplicate collected in multiple homes Filters weighed and conditioned in temperature and RH controlled environment for 24 h. Filters weighed twice; if these two masses were not within 5 μg of one another, they were weighed a third time. The mean of the two masses within 5 μg of one another was used for calculating concentrations. Blanks and duplicate side-by-side measurements were collected in multiple homes.	Not reported

Shezi et al. [52]. Wallach et al. [57] stated several strengths within their study, including; that their study population was representative of the rural Ugandan population and grouping assignments that were balanced across age and SES. Wallach et al. [57] were able to make objective measurements of kerosene-based lighting usage and uptake of their intervention lighting using sensors rather than relying on a self-report system. Wallach et al. [57] also had a longitudinal study design (1-year) allowing the researchers to assess sustained impact of intervention.

A large variety of sampling techniques used in indoor exposure studies to quantify $PM_{2.5}$ concentrations makes it difficult to directly compare results because of a lack of standardisation in the methodology (e.g., location of sampler in the home, sampling duration, sampling interval). Kumar et al. [32] used a unified methodology to assess air pollution exposure which allowed for comparison across different locations and different populations and sub-groups. Oluwole et al. [63] stated that the community engagement and participatory approach used in their study design actively helped improve the knowledge and attitude of their participants with regards to reducing household exposure to biomass smoke. Muyanja et al. [46] highlighted that a large sample size with a longitudinal study design allowed them to adjust for seasonality. They also claimed that direct $PM_{2.5}$ measurements rather than using carbon monoxide as a proxy was a strength of the study. Klasen et al. [31] have tried to describe the relationship between CO and $PM_{2.5}$ as other authors have previously tried to use CO as a proxy for $PM_{2.5}$ concentrations, however, found low correlations between the two pollutants and stated that, based on the results in their study, indoor CO cannot be used as in indicator for $PM_{2.5}$.

The Shezi et al. [52] study had important socio-demographic, medical and obstetric variables already available which could be confounders when assessing the impact of indoor $PM_{2.5}$ on the outcome variable. Adjusting for important confounding variables such as diet, exercise and socioeconomic indicators would allow for assessment of health risks attributed to HAP. Other studies sought to measure indoor and outdoor $PM_{2.5}$[27,44,45]. Measurements of both indoor and outdoor pollutants can provide a useful insight into sources of pollutants and reduction measures. Furthermore, adverse health outcomes are due to the joint effects of both indoor and outdoor air pollution exposure and both regimes of $PM_{2.5}$ exposures help inform burden of disease assessments. Finally, Hankey et al. [24] used a matched-pair study design for measurements of indoor air quality. This design pre and post intervention HAP measurements using a clean stove as an intervention. This method allowed for paired statistical comparisons between intervention and non-intervention measurements accounts for intra-household variability, for example differences in house structure, size, income, individual behaviour, all of which can affect sources, composition of HAP and $PM_{2.5.}$

3.6. Limitations identified in the studies

Supplementary Table S 2 details the limitations for the retrieved 51 studies as reported by the authors. Small sample sizes were a key limitation identified in the majority of the references. Ten of the studies described their sample size as small [17,31,38,42,43,54,57,60,62,63]. Aigbokhaode and Isara [17] stating that although they had a sample size of 62 homes, the small sample size may impact their multivariate analysis. Ochieng et al. [38] conducted their study within 49 homes, however, as their study involves an intervention with a follow up period, they have stated that, owing to a loss in volunteers within the follow up period, estimations in reductions of HAP can be imprecise. The study conducted by Dutta et al. [60] had a primary focus on epidemiology, whilst the number of individual participants is stated, the number of homes in which HAP monitors were installed is not stated. Although, Dutta et al. [60] have specifically stated that the sample size within the study is small and a larger cohort is needed for their study. Sidibe et al. [54] conducted their study in two homes.

Johnson et al. [62] found that using many sensors made data management very difficult, and explained that a balance is needed between having a large enough sample size to collect accurate data and managing the data that is obtained. Logistical and financial constraints such as inaccessible (or hard to reach) participant locations, the need to reduce the number of visits to participant dwellings and the cost of transport can restrict a study design to small scale field campaigns. However, a balance is needed in having a large enough sample size in order to draw out robust and accurate conclusions from data whilst adjusting to constraints. Studies with small sample sizes in one location may not have the accuracy to represent HAP in another location. Tumwesige et al. [40], for example, have stated that the sample size within their intervention study was restricted as the cost of installing cleaner fuel sources reduced the sample size.

In order to improve accuracy and provide reliable results, repeat

measurements should ideally be made within each household [31]. However, there can often be practical, logistical and financial constraints that reduce the ability to make repeat measurements, for example travelling to sampling locations can be time consuming and expensive, budget constraints can reduce the of access to large numbers of sensors and the need to reduce the inconvenience of repeated visits to volunteer homes can restrict the number of repeat measurements that can be made. Zhou et al. [58] identified a limitation in their study whereby they did not have the resources to do repeat measurements.

Three studies; Lam et al. [33], Tumwesige et al. [40] and Shezi et al. [51] only sampled one community (e.g. urban/rural) which can lead to results that are not generalisable. This may be owing to logistical and financial constraints within the study, however, the conclusions that result from measurements made in one type of location cannot be applied to another location. In a study by Lam et al. [33] the kitchens were in a separate building away from the living and sleeping areas of the participants. While this was described as 'typical' of rural houses in that location, the same may not be true for other communities. Differences in volumes and sizes of households can make comparisons of HAP difficult, Tumwesige et al. [40] for example measured kitchen volumes of the volunteers within their HAP study, however, have found that, while the range in kitchen volumes represented real world conditions, the variability in kitchen volumes makes comparisons between households more challenging, as varying kitchen volumes will impact the dilution and ventilation rates of HAP [91,92]. Rosa et al. [65] have stated that they did not use random sampling and so the results shouldn't be seen as a representation of the larger population, it is therefore important to consider a standardised methodology in order to compare one set of HAP measurements to another. There are also variations between studies as to what is considered the main cooking location. Vinti and Vaccari [41] for example monitored $PM_{2.5}$ concentrations in six different villages, with each village having a cookstove in a different location. $PM_{2.5}$ was measured indoors close to a cookstove in one village, in a courtyard close to a rural stove in another village and within a semi-enclosed space close to a rural stove. It is therefore important that when conducting a longitudinal or cross-sectional study into HAP, consistency is maintained when defining where is the main cooking space.

Several of the retrieved articles were intervention studies. When designing intervention studies, for example, examining the effects of cleaner fuels in comparison to traditional fuels, it is important to use control groups, as control groups allow for accurate comparisons of measurements. In an intervention study, Oluwole et al. [63] stated that the control group was too small to test for significance. Liao et al. [43] and Oluwole et al. [64] both stated that they should have had a control group using clean cooking technologies to account for the possibility of selection bias and other confounders.

There were three studies that did not include, but suggested considering, the state of the indoor ventilation, namely Muyanja et al. [46], Klasen et al. [31] and Mbazima et al. [44], whether that be through air exchange measurements or by considering open windows, for example. Ideally for completeness and to improve the accuracy of measurements, ventilation and air exchange rates should be measured or modelled as ventilation can affect HAP concentrations of $PM_{2.5}$ [93–95].

Several studies did not state the fuel types used by the participants for cooking and heating [16,29,44,51,61], while Wallach et al. [57] obtained information on fuel types but did not take them into consideration in their analysis. Ang'u et al. [18] identified cases of fuel stacking (using multiple combinations of stoves and fuels within the same household) but only considered primary fuels in their study. Muyanja et al. [46] conducted integrated 24- hour measurements of in kitchen and living room $PM_{2.5}$ monitoring and stated that thermal monitors should have been used within their study to verify that stoves within kitchens, secondary stoves within homes, and kerosene lamps were used during the sampling period. If practical to do so during longitudinal monitoring of HAP, the cooking and heating fuel type used by the participant should be considered as different types of fuels that can generate varying concentrations and compositions of $PM_{2.5}$ [96,97]. Eriksson et al. [96] determined that fuels with a low energy density (such as dung) can generate particles on an order of magnitude more than fuels with a higher energy density such as coal.

Short sampling times were a common limitation among the retrieved studies. Periodic $PM_{2.5}$ sampling during cooking or controlled emission can be used to determine generalised $PM_{2.5}$ concentrations during short tests. However, in order to characterise exposure throughout a day, 24-hour measurements need to be made. Kansiime et al. [30] used a 1-min sampling time by taking 3 measurements within 3 min during a cooking event, while Vinti and Vaccari [41] used a 15-min sampling time. The authors identified that this was a limitation as it could not be reflective of true exposure over a 24-h period. One limitation identified by Muindi et al. [34] was the inability to sample for 24 h due to safety concerns for the instrumentation being left overnight within the household. Tumwesige et al. [40], Muyanja et al. [46] and Klasen et al. [31] used a sampling time of 24 h. Tumwesige et al. [40] identified behavioural changes as a potential limitation of this sampling time, while Klasen et al. [31] believed that the 24-h sampling time may not be representative of typical exposure levels in the household and have stated that measurements should be conducted longer than 24-h in order to be representative of household air pollution levels. Short sampling times are a result of a lack of access to continuous electricity [31]. This can be a key limitation in parts of SSA countries where access to power can be limited. Battery powered monitors can provide short term measurements, however there are practical limitations to using batteries.

Table 5 shows only the retrieved studies that stated the correction method, or calibration methods. By not stating the correction, or calibration method [16,21,24,25,27–29,36,37,41,54,61], it can be difficult to determine the accuracy of the measurements (either underestimating or overestimating HAP $PM_{2.5}$ concentrations), and it can also hinder the ability to repeat the measurements in further studies. Muindi et al. [34] stated that they did not correct for temperature and humidity which can affect $PM_{2.5}$ concentrations. Vinti and Vaccari [41] could not carry out calibrations or comparisons with other instruments using a standard operating procedure and thus stated that some of their measurements should be considered an approximate.

Finally, depending on meteorological conditions (and therefore season) and particle size, ambient outdoor pollutants can enter the indoor environment (Alonso-Blanco et al., 2023, [98,99]). However, the inability to monitor meteorological conditions has been identified as a limitation by Kansiime et al. [30] within their study. Where stated within the article, six of the studies only sampled during one season,[25,31,33,42–44]. This is despite differences in ambient air quality, meteorological differences across seasons, and changes in emission sources and rates of use over seasons; solid fuel burning for example increases in the winter for heating purposes [100–102]. De la Sota et al. [19], Kumar et al. [32] and Shezi et al. [52] stated that ambient air quality was not monitored in their respective studies irrespective of the potential of ambient pollutants entering into the indoor environment [99,103].

3.7. Practical implications and key messages for policymakers

This review focused on exposure to $PM_{2.5}$ because of its association with increased mortality and morbidity even at very low concentrations and the reasonable reliability of low-cost sensors to accurately measure $PM_{2·5}$. But there are also other indoor pollutants in addition to particulate matter, such as gaseous inorganic pollutants and volatile organic compounds that are damaging to health and must be monitored. With the increasing need to monitor HAP to drive policy, improve the understanding of the health impacts of poor air quality and increase awareness, the development of more accurate HAP monitors that can also be used for source apportionment is increasing [104–106].

This review highlights the need for constant dissemination of

calibration and correction methods within studies based within the SSA region. Whilst there may be practical reasons as to why instruments for HAP monitoring are not corrected or calibrated (for example owing to a lack of access to laboratories or a lack of funding) [70], calibrations, corrections of measurements and a traceability of QA/QC are crucial in providing accurate data that can be used to drive policy and change. Using data from inaccurate or poorly calibrated sensors to inform policy development or documents can have negative implications because uncertainties and errors can be unknown (World Meteorological Organization (WMO) et al., 2024). Giordano et al. [88] have stated that a lack of understanding in the challenges of using sensors and using sensor that have not been calibrated can lead to members of the public assuming that measurements can be higher than that measured using reference monitors. Countries with little infrastructure could assume (based on uncalibrated, or poorly calibrated data) that their ambient air quality is better or worse than the reality, leading to ineffective policy. The next step within the field of HAP within the SSA region is to develop a standardised method of monitoring that can be applied across a wide range of dwelling types and technologies. Calibrations and corrections need to be applied within the same environment that the HAP monitoring study is being conducted as calibrations in laboratory conditions can vary in comparison to the household environment [10].

The lack of access to regular consistent electricity has been highlighted as a key limitation to HAP monitoring within SSA. Availability of electricity is an important condition for powering low-cost sensors as the battery life for most devices is limited resulting in periods where concentrations of air pollution will not be measured. Power-related issues are a major practical challenge in many SSA countries and a potential barrier to air pollution data collection unless the situation of electricity supply is addressed. The use of low-cost sensors can be beneficial for use in SSA. Their relatively low costs and ease of use means that, lower cost equipment may allow researchers to conduct repeat measurements and feel more comfortable leaving equipment in households overnight and their limitations discussed can be overcome with reliable calibrations and co-location with reference instruments.

Behavioural changes in the home such as opening doors and windows, kitchen practices etc. May reduce HAP. However, ingress of air pollution from outdoors, consisting of both neighbourhood pollution and regional background $PM_{2.5}$, also affects HAP and therefore interventions aimed at reducing HAP should meaningfully address direct and indirect exposures to $PM_{2.5}$ rather than just at individual household level.

The clear lack of HAP measurements within the vast majority of SSA countries is a disadvantage to policy change and improving the air quality within the region [69]. Increased investment into HAP monitoring strategies within these counties where there is a lack of monitoring can be used to improve the awareness of the impacts of HAP on health.

Further research into the area of HAP can be enhanced with health and epidemiology studies, particularly in regions of SSA where HAP studies are lacking. By combining HAP with epidemiology studies, public awareness of the health impacts of poor HAP can be improved and can provide an impetus to change policy. Finally, there is a distinct lack of growth in HAP studies alongside the increasing population in SSA. To keep pace with the increasing population and increasing use of biomass and unclean fuel use, there needs to be an increase in policy change provided by evidence from HAP studies [69]. At this juncture, a more critical understanding and assessment is needed if results from HAP monitoring studies are to be used as evidence in policies.

4. Conclusions

This review summarises the current state of HAP in SSA. A clear and large geographical gap in HAP studies is evident in distribution of studies and highlights the growing need for HAP in a continent with a growing population and increasing use of biomass and unclean fuels for cooking and heating. We have identified inconsistencies in calibration and correction methods (if reported at all), and suggested that in order to drive policy changes, accurate traceable data needs to be presented to policy makers.

A number of HAP studies with the SSA region had common limitations, this can include (but is not limited too), small sample sizes, a lack or repeated measurements, and short measurement periods. This can be attributed to a lack of access to resources or funding (whilst the articles retrieved didn't not state specifically if they lacked funding) within the field of HAP monitoring (for example, inconsistent power to run HAP monitors repeatedly and for long periods of time or no access to laboratories for calibrations). Ensuring that funding and infrastructure is available should improve the accuracy and quality of HAP studies and their comparability.

While there are primarily two methods of monitoring household $PM_{2.5}$, (real time light scattering and gravimetric), there are a large variety of sampling methodologies and strategies, this leads to a lack of standardisation, making the comparisons of results difficult. While different studies will have their different aims, objectives and scopes (which may dictate the location where the sampler is placed in the dwelling, or the sampling duration or the logging intervals, for example), there are certain elements which would benefit from standardisation in order to better interrogate the quality of the data. This can include, but is not limited to collecting repeat measurements, sampling HAP for a minimum period of time and periodic calibration.

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CRediT authorship contribution statement

Rikesh Panchal: Writing – original draft, Visualization, Validation, Methodology, Formal analysis, Data curation, Conceptualization. **Matthew Benyon:** Writing – review & editing, Validation, Formal analysis. **Tracey Laban:** Writing – review & editing, Validation, Formal analysis. **Ngwako Kwatala:** Writing – review & editing, Methodology, Formal analysis, Conceptualization. **Bianca Wernecke:** Writing – review & editing, Validation, Methodology, Formal analysis, Conceptualization. **Caradee Y. Wright:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization. **Joshua Vande Hey:** Writing – review & editing, Validation, Supervision, Resources, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests:

Dr Joshua Vande Hey reports financial support was provided by Royal Academy of Engineering. If there are other authors, they declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data sharing not applicable – no new data generated as this is a review article.

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Appendix A. Supplementary data

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