Use of Low-Cost Technology in Monitoring Indoor Air Pollution

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EED Advisory Limited

90 James Gichuru Road, Nairobi – Kenya

P.O. Box 66053-00800, Nairobi | T: +254 (20) 2574927

E: contact@eedadvisory.com | W: www.eedadvisory.com

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List of Acronyms

ACR	Air Change Rate
AQG	Air Quality Guideline
BLE	Bluetooth Low Energy
CAPI	Computer-Assisted Personal Interview
CCAK	Clean Cooking Association of Kenya
CO	Carbon Monoxide
COPD	Chronic Obstructive Pulmonary Disease
HAP	Household Air Pollution
IoT	Internet of Things
KEMRI	Kenya Medical Research Institute
LPG	Liquid Petroleum Gas
NOx	Nitrogen Oxides
ODK	Open Data Kit
OpenHAP	Open Household Air Pollution
PM	Particulate Matter
SEI	Stockholm Environment Institute
SNV	The Netherlands Development Organisation
SOx	Sulphur Oxides
UPAS	Ultrasonic Personal Aerosol Sampler
VOCs	Volatile Organic Compounds
WHO	World Health Organisation

EXECUTIVE SUMMARY

The World Health Organization (WHO) estimates that 4 million people die prematurely from illnesses attributable to household air pollution (HAP) each year[1]. Of these, 23,000 deaths occur in Kenya, according to estimates from the Ministry of Health[2]. These are more deaths than those attributed to traffic accidents and malaria combined in Kenya. Household air pollution (HAP) primarily comprises of particulate matter (PM) as well as other chemical gaseous emissions such as carbon monoxide (CO), volatile organic compounds (VOCs), oxides of sulphur and nitrogen (SOx and NOx), which are all deemed injurious to the health of household occupants. Particulate matter, especially that which is smaller than 10 microns in diameters (thoracic, fine, and ultrafine particles), has a significant negative effect on health because of how deeply it can penetrate the respiratory system. In Sub-Saharan Africa household air pollution is mostly caused by cooking and, to a lesser degree, lighting, incense burning, and smoking. Cooking pollution is linked to the use of traditional stoves and fuel.

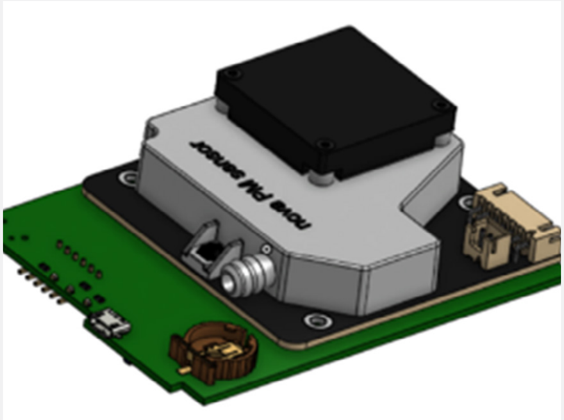
Building on the previous pre-study phase of this project, which tested the use of low-cost PM sensors in the measurement of HAP, the two overall objectives of this study were to:

i) Design and evaluate the performance of a low-cost integrated HAP, proximity, and stove use sensor, and

ii) Demonstrate the utility of the instrumentation by measuring HAP in Kenyan homes.

Both objectives were met over the course of the project. The OpenHAP device was redesigned, tested, and manufactured as the first set of actions to meet the first objective. Design changes were made in response to the supply chain limitations due to the COVID-19 pandemic and consideration of the results of the previous OpenHAP pre-study. The changes made to the design include replacing the particulate matter sensor ZH03B with SDS011, based on the results of the pre-study test of PM sensors. The general circuit design was also optimized to ensure simpler functionality by removing components such as the cellular modem, ambient temperature, and humidity sensor. Additionally, a wireless processor that supports real-time data logging and pneumatic tubing to improve airflow to the PM sensor were incorporated. These changes were validated and the manufacture of the 25 OpenHAP devices was concluded as indicated in Figure 1. Further, to ensure the uniformity of the sensing devices and minimize the deviation in the readings across the devices, a chamber co-location test was conducted on the manufactured devices.

FIGURE 1:
Updated OpenHAP electrical design and final electrical assembly



1 WHO. (2021). Household air pollution and health. Who.int; World Health Organization: WHO. https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health.

2 Government of Kenya. (2019). Empowering communities to reduce household air pollution – Ministry of Health. Health.go.ke. https://www.health.go.ke/empowering-communities-to-reduce-household-air-pollution/

This was done according to the Berkeley Air group chamber test protocol, though with minor modifications under the direction of Dr. Michael Johnson.

The research team also hosted a series of stakeholder meetings, which ultimately culminated in the inception workshop on July 28, 2021. Discussions regarding the purpose, design, and desired outcomes of the project were held with participants from the Ministry of Energy, Ministry of Health, Clean Cooking Association of Kenya (CCAK), the Stockholm Environment Institute (SEI), the Netherlands Development Organisation (SNV), World Agroforestry (ICRAF), and the Environmental Protection Agency (EPA).

Fieldwork was undertaken in Kawangware and Kibra, which are low-income areas in Nairobi. Fifty respondents from each area were selected. These respondents were selected from the list of participants who took part in the 2019 Kenya Household Cooking Sector Study. However, many were unreachable using the contact details previously provided, and some of those who were contacted declined to take part. To supplement this list, enumerators were asked to randomly select 10 households from their contacts that fit the prescribed profile. The enumerators were also trained on the structure and content of the survey questionnaire and the process of setting up the OpenHAP device.

The researcher tested 20 OpenHAP devices using linear least squares to ensure consistency in measurement performance before deployment. All the devices returned a strong positive inter-device correlation above 0.999. Human error, misconfiguration of the OpenHAP device, and tampering with devices invalidated 24 out of 100 data samples collected.

The team set up the instruments using the web portal hosted on the device. This portal, The OpenHAP Sensor Viewer, checks sensor response such as thermal camera, BLE beacons across the household respondents, starting/ending recording sessions, and downloads the collected data via the SD Card in CSV format. The infrared temperature camera did not have the stove within its field of view in some instances. The researcher used temperature fluctuations on the infrared data as a proxy indicator for stove use to fill this data gap. An emphasis on device placement should be made during future training sessions with enumerators to minimize or completely avoid this oversight. The software on the infrared driver should also be improved by enhancing the infrared framerate on the configuration portal, beyond the 1 frame per second setting used.

In total, 2.5 million data points were collected. We generated a bespoke programming script using the python data science and numeric computing utilities such as Pandas (Python Data Analysis Library) and Numpy (Numeric Python library) to analyse the complex datasets.

As indicated in Table 1, the majority of sampled respondents, use the Kerosene wick cookstove, followed by the LPG single burner stove (Meko), the three-stone open wood fire, LPG multiple burner stove and the Kenya Ceramic Jiko (charcoal). The improved charcoal stove and the Kuni Mbili stove are used by less than 4% of the respondents.

Table 1: Type of main stove used by respondents

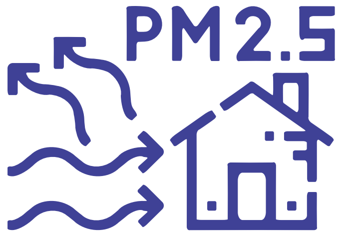
#	Sampled Cookstoves	Percentage of respondents (%)
1	Kerosene wick cookstove	31.5
2	LPG single burner stove (Meko)	27.6
3	three-stone open wood fire	17.1
4	LPG multiple burner stove	10.5
5	Kenya Ceramic Jiko (charcoal)	9.2
6	Charcoal Stoves	4

It was found that respondents who use the firewood stove primarily cook outside the house, mainly due to the amount of smoke the fuel produces, especially for respondents who live in a single-room house.

As indicated in Figure 2, the three-stone open wood fire cookstove is found to produce the greatest mean indoor air pollution when in use, producing an average PM2.5 concentration of 207 µg/m3. It is followed by the Kuni Mbili stove and Kenya Ceramic Jiko charcoal stoves, which produce 69 µg/m3 and 55 µg/m3 respectively. The LPG single burner stove (Meko), Kerosene wick stove and LPG multiple burner stove have a mean PM2.5 pollution of 44 µg/m3, 41 µg/m3 and 36 µg/m3 respectively .

Though Kerosene stoves were found to emit relatively low PM2.5 pollution, they may still emit a high amount of carbon monoxide, NOx, and SOx, which were not measured. As expected, this study confirms that the level of HAP concentration associated with cooking done in a multi-roomed house or with windows opened is significantly less than cooking done in single rooms or closed spaces. We found that double-room houses have an average air change rate (ACR) of 11.3 air changes per hour compared to single-room houses with 5.5 air changes per hour.

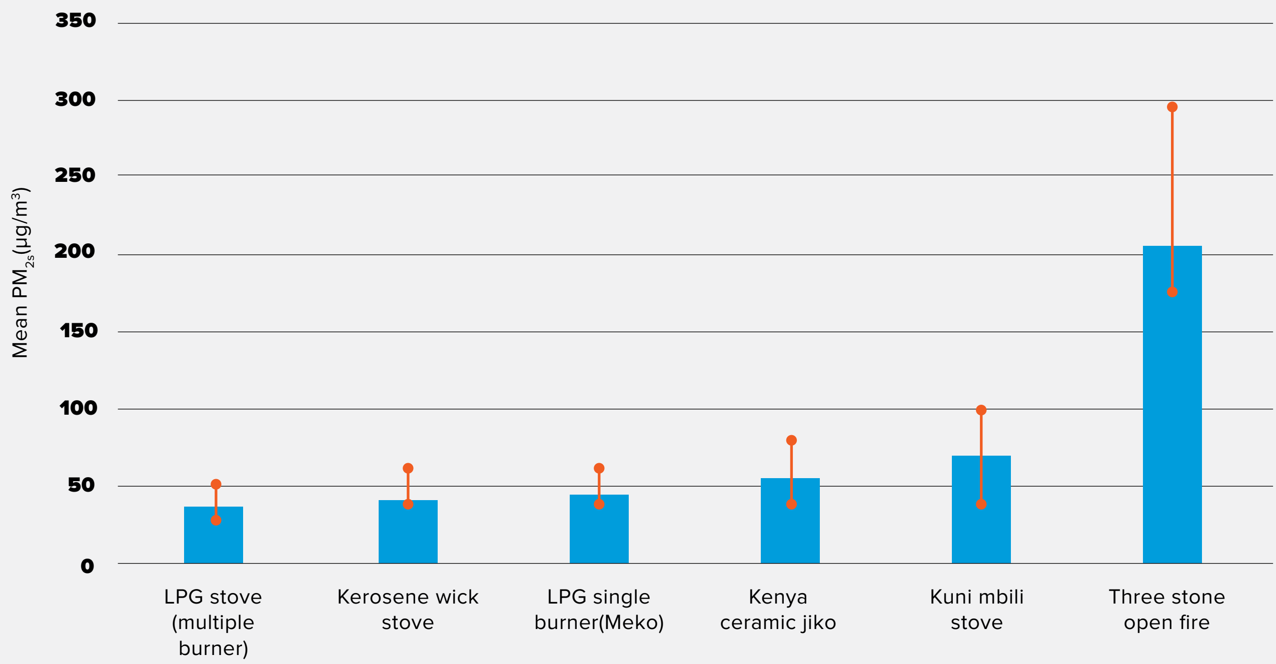
This study demonstrates the capability of the OpenHAP device as a low-cost option for measuring and tracking HAP and advises for the expansion of this body of work in future.



We found that double-room houses have an average air change rate (ACR) of 11.3 air changes per hour compared to single-room houses with 5.5 air changes per hour.

FIGURE 2:

Mean indoor air pollution per cookstove type while the stove is in use and the standard deviation (error bar)



01
Introduction

1.1 Background

The World Health Organization (WHO) estimates that approximately 4 million people die prematurely from illnesses attributable to household air pollution (HAP) each year[3]. Of these, 23,000 deaths occur in Kenya, according to estimates from the Ministry of Health[4]. These are more deaths than those attributed to traffic accidents and malaria in Kenya. The use of traditional forms of cooking fuels, including unprocessed solid fuels such as wood, crop residue, and charcoal, is a leading contributor to HAP. The wide range of health-damaging pollutants in HAP includes particulate matter (dust, dirt, soot, smoke, and liquid droplets), which is designated as PM10, PM2.5, and PM1, according to the size of the particles. Particles of less than 2.5 micrometres in diameter (PM2.5) are of great health concern due to their fine size, as they easily accumulate in the respiratory system and may result in a variety of diseases, including pneumonia, stroke, ischaemic heart disease, chronic obstructive pulmonary disease (COPD) and lung cancer.

HAP measurement instrumentation is relatively expensive, with prices running from above US$ 3,000 for gravimetric, active sampling equipment and US$ 300 for light scattering, passive sampling equipment. The range of devices are available in various specifications and are designed for diverse operations. The relatively less expensive Ultrasonic Personal Aerosol Sampler (UPAS) (~$1500) allows for gravimetric measurement, which though more accurate than light-scattering measurement devices, requires certain high precision lab equipment for sample analysis. Such lab equipment is generally unavailable in many parts of Sub-Saharan Africa, including Kenya. Less expensive light scattering, passive sampling measurement devices such as the HAPEx Nano are considered less accurate than more established air pollution measurement devices, especially for long-term monitoring[5]. Many of these monitors, while designed for personal exposure measurements, must be worn to obtain an exposure estimate, which can be burdensome and intrusive. Additionally, all of these devices are manufactured and supported by foreign companies, and thus there is no local technical support in case of a malfunction.

EED Advisory (the researcher) sought to address the limitations of current HAP monitoring solutions by demonstrating the use of a low-cost, locally developed, IoT-enabled HAP monitoring device known as OpenHAP. The device is an integrated HAP, proximity, and stove use sensor that allows for correlation between emitted PM2.5 concentration, respondent exposure, and stove use.

OpenHAP has been piloted in several households in Kenya during this study. As an output of the pre-study pilot, the researcher found that the air monitoring module has a saturation limit of 999 µg/m3 for $PM_{2.5}$. Though this is much higher than the World Health Organization (WHO) PM2.5 guidelines which are 5 µg/m3 and 15 µg/m3 for annual mean and 24-hour mean concentration respectively[6], we find this air monitoring module suitable for providing valuable relative measurements to track indoor PM2.5 concentrations in a low-cost and effective manner.

The two overarching objectives of this project are to:

1. **Design and evaluate the performance of a low-cost integrated HAP, proximity, and stove use sensor**

For this objective, the researcher optimised the OpenHAP device's $PM_{2.5}$ sensor readings in relation to the stove use and proximity sensors to derive a correlation across the sensed parameters in relation to $PM_{2.5}$ concentrations and exposure levels of respondents linked to stove use. In turn, this approach increased confidence that the OpenHAP device offers standard and repeatable service for future similar studies in other jurisdictions.

2. **Demonstrate the utility of the instrumentation by measuring HAP in Kenyan homes**

The researcher measured HAP in various urban Kenyan homes stratified across cooking fuel types and cooking area classification (i.e., one-room versus multi-roomed houses). The homes were sampled from among those in Nairobi that participated in the recently completed Kenya cooking sector study. This activity helped characterize HAP levels for key fuel user groups and illustrated how differences in behaviour and stove use patterns can impact exposure profiles.

3 WHO. (2021). Household air pollution and health. Who.int; World Health Organization: WHO. https://www.who.int/news-room/fact-sheets/detail/household-air-pollution-and-health.

4 Government of Kenya. (2019). Empowering communities to reduce household air pollution – Ministry of Health. Health.go.ke. https://www.health.go.ke/empowering-communities-to-reduce-household-air-pollution/

5 Curto, A., Donaire-Gonzalez, D., Barrera-Gómez, J., Marshall, J. D., Nieuwenhuijsen, M. J., Wellenius, G. A., & Tonne, C. (2018). Performance of low-cost monitors to assess household air pollution. Environmental Research, 163, 53–63. https://doi.org/10.1016/j.envres.2018.01.024

6 WHO. (2021). WHO global air quality guidelines: Particulate matter (PM 2.5 and PM 10), ozone, nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva https://apps.who.int/iris/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1&isAllowed=y

The use of traditional forms of cooking fuels, including unprocessed solid fuels such as wood, crop residue, and charcoal, is a leading contributor to HAP.

The output of this study includes empirical data on parameters that contribute to high levels of HAP such as cooking habits, cooking technologies, fuel sources used, and the design of the cooking area, among other factors. The information gathered through this study may help inform policies and initiatives in the cooking sector

1.2 Approach and methodology

Figure 3 provides a summary of the approach applied for the study component of this project. The steps in the approach are further elaborated in the section that follows.

FIGURE 3:
Summary of survey design

Arrange → **Deploy** → **Analyze** → **Publicize**

Arrange
- Testing and setup of air quality monitors
- Manufacture 25 Open HAP devices
- Chamber co-location test of OpenHAP devices
- Literature review
- Draft respondent questionnaire
- Inception workshop

Deploy
- Pe-test questionnaire
- Deploy units across sampling classes
- Conduct entry interviews
- Monitor data collection

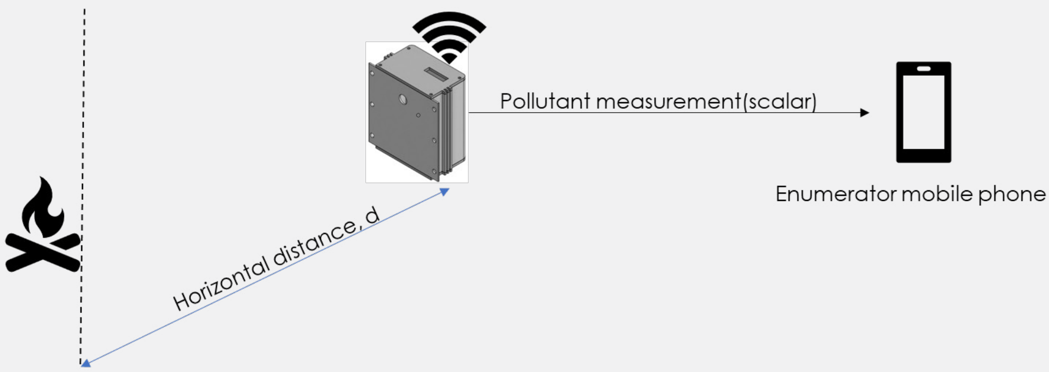
Analyze
- Descriptive analysis
- Modelling HAP incidence per user group
- Extrapolation of impacts

Publicize
- Drafting of report(full and abridged)
- Final workshop/s
- Webinar/s

1.2.1 Sensor deployment protocol

The measurement procedure used during the installation of the OpenHAP devices was standardised across the respondent's households to ensure uniformity of test conditions. Each instrument was set up on a tripod stand for stability and to achieve a fixed vertical, horizontal distance from the cookstove throughout the monitoring period. This distance was 1.5 – 2.0 m horizontally from the edge of the stove, and 1.0 – 1.5 m vertically and away from windows and doors, which mimics the breathing level of a respondent and an optimal distance in mitigating $PM_{2.5}$ saturation. Both the OpenHAP and the external battery pack were strapped onto the tripod stand.

FIGURE 4:
OpenHAP setup



After setup, the device was powered on and the sensor response was checked using the OpenHAP Sensor Viewer. This was done using a Wi-Fi network that was broadcast from the OpenHAP device, accessed by mobile phone, as indicated in Figure 4. The OpenHAP Sensor Viewer enabled the researcher to check the thermal image from the infrared sensor to ensure the OpenHAP device was pointing correctly at the cookstove. It also enabled them to set up the BLE beacons across the household respondents, to start and end recording sessions, and to download the collected data via the SD Card in CSV format.

1.2.2 Overview of data analysis process

Data cleaning corrected for input and data transmission errors, which ensured a more accurate depiction of the conditions under investigation. Interpolation improved the state of the data by filling data gaps that had been identified after visual inspection. The researcher used a moving average window of 10 minutes on the data to remove noise and smooth out irregularities introduced by the Bluetooth beacon. The researcher found that the Bluetooth signal is subject to wave effects such as reflection, dispersion, and absorption which would erroneously represent respondent presence, yet the signal did not reach the OpenHAP device. Therefore, the data was resampled using a 10-minute moving average to avoid this undesired effect. The same sliding window was also applied to other device metrics. Data with large discontinuities beyond the window length of 10 minutes were discarded.

Further, each device collected data at a rate of one sample per minute across the following variables:

1.Stove temperature in degrees Celsius (°C) as observed by a non-contact thermal camera. The stove temperature is the maximum pixel observed across 192 sensor pixels. This was used as a proxy to determine instances and length of cooking events.

2.Particulate measurement in µg/m3 at the measurement location in the room, using the onboard SDS011 particulate sensor.

3.The respondent's presence, sensed by the number of Bluetooth broadcast beacons/messages received from the Bluetooth wrist strap worn by the respondent. The Bluetooth strap produced 2 variables:

a) The number of beacons/messages.

b)The average signal strength received within the 1-minute sampling interval was used as a proxy to determine the distance of the respondent.

The definition of successful beacon reception was considered as a signal whose carrier power can be distinguished from the noise power for a given bandwidth, and whose bit error rate was permissible for successful recovery of the original information sent. To calibrate the region of detection, the wrists trap is moved to the desired limit of detection such as a door for indoor microenvironments, or a given distance from the cookstove. The wrists trap transmit power is tuned using its Android application such that any beacon outside the region of detection leads to unsuccessful beacon reception

4. Device operation data on whether the device is on, off, or has been rebooted.

5.The Coordinated Universal Time (UTC) of the sampling location.

This generated 6 streams of approximately 5,000 unique, interrelated data points per measurement period at each household. In total, over 2.5 million data points were collected. The researcher generated a bespoke programming script using python data science and numeric computing utilities such as Pandas (Python Data Analysis Library) and Numpy (Numeric Python library) to analyse the complex datasets. The team used the same utilities for both normalization of the devices and analysis of the data.

Though there are several ways of analysing the data, this report analyses:

i) the PM2.5 pollution concentration across the cooking space, which is impacted by stove technology, room aeration, and external non-cookstove pollutants, and

ii) the exposure level per household member. This was done by evaluating the quantitative data collected from the OpenHAP together with the qualitative data collected using the survey questionnaire.

02
Study Activities

2.1 Sensor equipment

2.1.1 OpenHAP redesign and manufacture

At the onset of this project, the researcher made design changes to the OpenHAP devices in response to the supply chain limitations of various components which arose from the manufacturing disruptions caused by the COVID-19 pandemic. Design changes were also made to accommodate the recommendations of the previous OpenHAP work. The changes, which were made before the manufacture of the 25 devices, include:

1. Replacement of the ZH03B particulate matter sensor, with the SDS011 sensor based on the results of the previous OpenHAP comparative pre-test of both particulate matter (PM) sensors. Further, the researcher factored in the ease of use, ease of sourcing, and availability of supporting literature on its measurement characteristics in choosing this sensor.

2. Replacement of the MLX90640 Infrared array temperature sensor with its lower pixel variant, the MLX90641, due to the unavailability of the former from the manufacturer.

3. Improved mechanical design by the use of a pneumatic tube at the air inlet of the SDS011 sensor to prevent variability of airflow across devices.

4. The general circuit design was optimized to ensure simpler functionality by removing unnecessary components such as the cellular modem, ambient temperature, and humidity sensor.

5. Improved software on the previous ESP32 processor to support wireless transmission and viewing of the data during normalization, and to repurpose its internal memory for data storage, hence reducing reliance on the SD card.

2.1.2 OpenHAP particulate measurement normalization

After the manufacture of the 25 OpenHAP devices, the researcher conducted normalization on a subset of 20 randomly chosen units. The normalization was performed to ensure the uniformity of measurement across the measurement range of the SDS011 particulate matter sensor. This normalization was conducted based on the following steps, as per the Berkeley Air chamber test protocol:

1. The devices were programmed to support synchronized measurement and wireless data transmission. This synchronization allowed them to measure and respond at the same time when instructed to do so by a computer, which would also display their measurement results in real-time.

2. The researcher chose to have 3 measurement phases and targets for normalization, targeting a concentration of 100, 400-500, and 600-800 µg/m3 respectively. This ensured adequate coverage across the 0-999.9 µg/m3 measurement range of the SDS011 particulate sensor.

3. The devices were placed within a 200-liter barrel which had been repurposed to allow for equidistant mounting. A small mixing fan was placed at the bottom of the barrel, blowing upwards. The researcher used incense sticks as a smoke pollutant source because they provide a reliable source of biomass combustion-generated PM2.5. The lit sticks were introduced into the barrel temporarily to cause the desired peak in measurement, after which it was removed so that the measurement would approach the desired steady-state concentration, defined in step 2 for the given normalization round.

4. Post analysis of the recorded measurement data was performed by generating a linear adjustment factor for each device and selecting the device with the mean measurement across all measurement rounds as the reference device to which all other devices were normalized.

FIGURE 5:
OpenHAP electrical and mechanical assembly

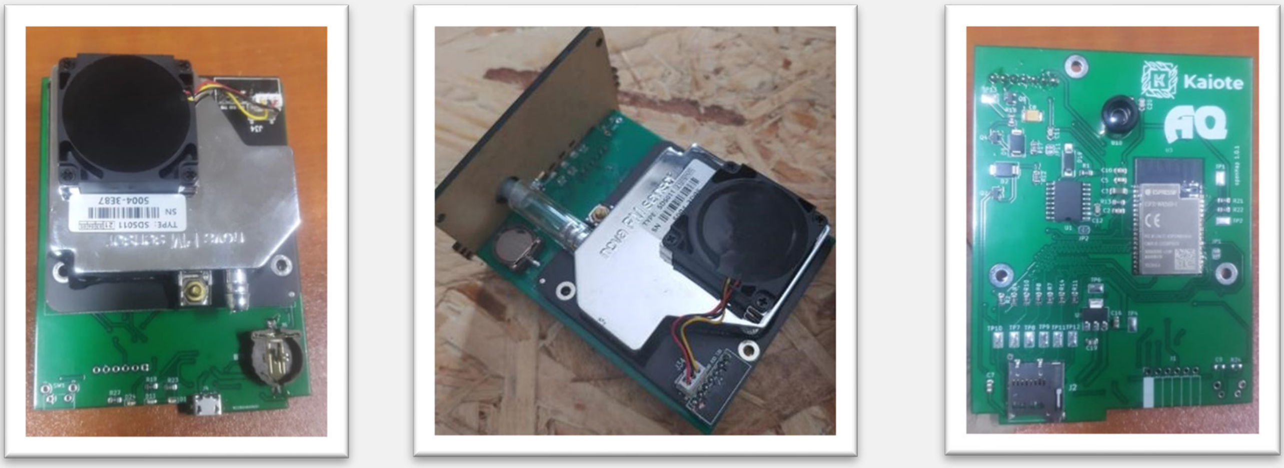


FIGURE 6:
OpenHAP mechanical assembly, programming, and mounting

FIGURE 7:
The normalization chamber, mounted devices, and associated tools

FIGURE 8:
100 µg/m3 normalization round data

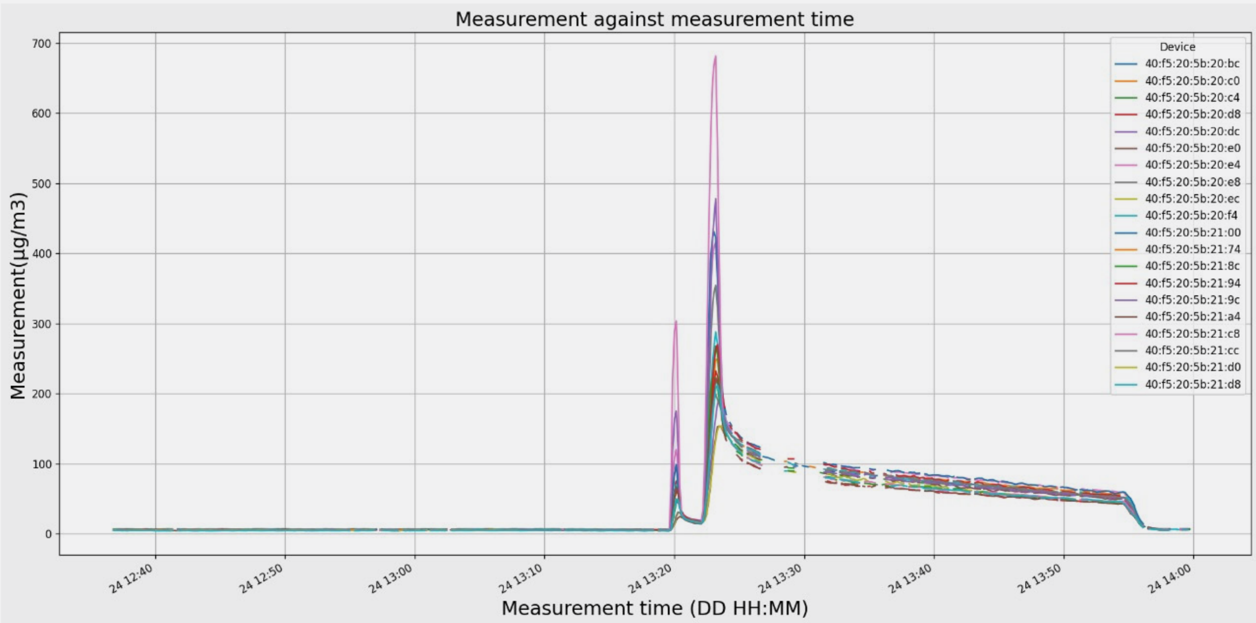


FIGURE 9:
400-500 µg/m3 normalization round data

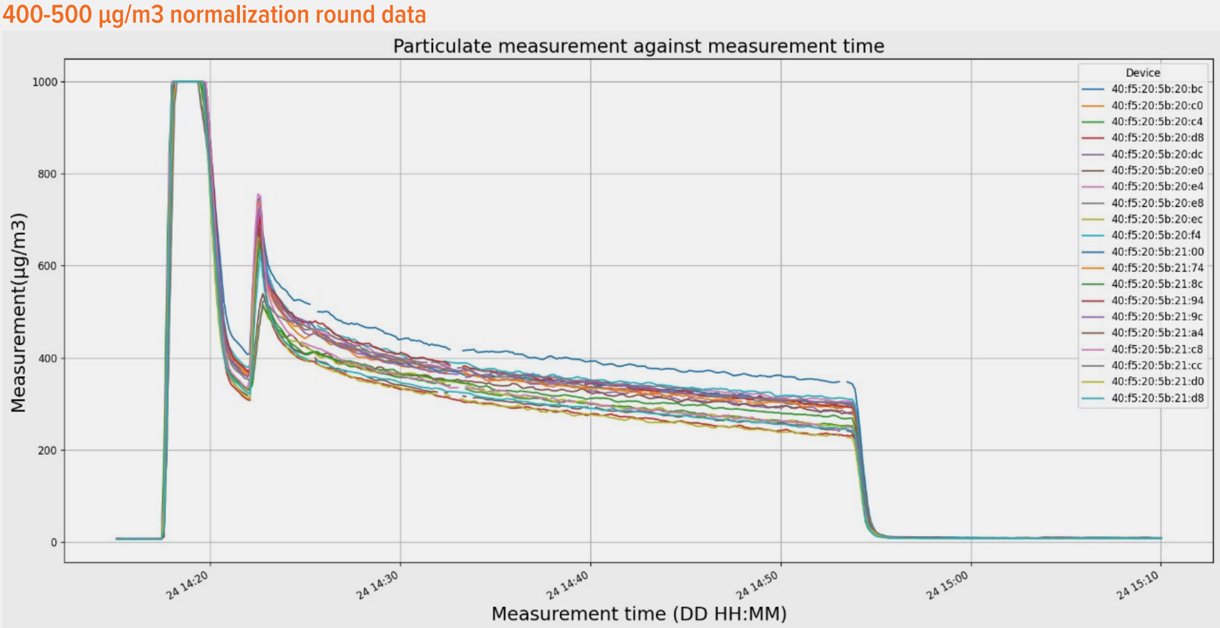
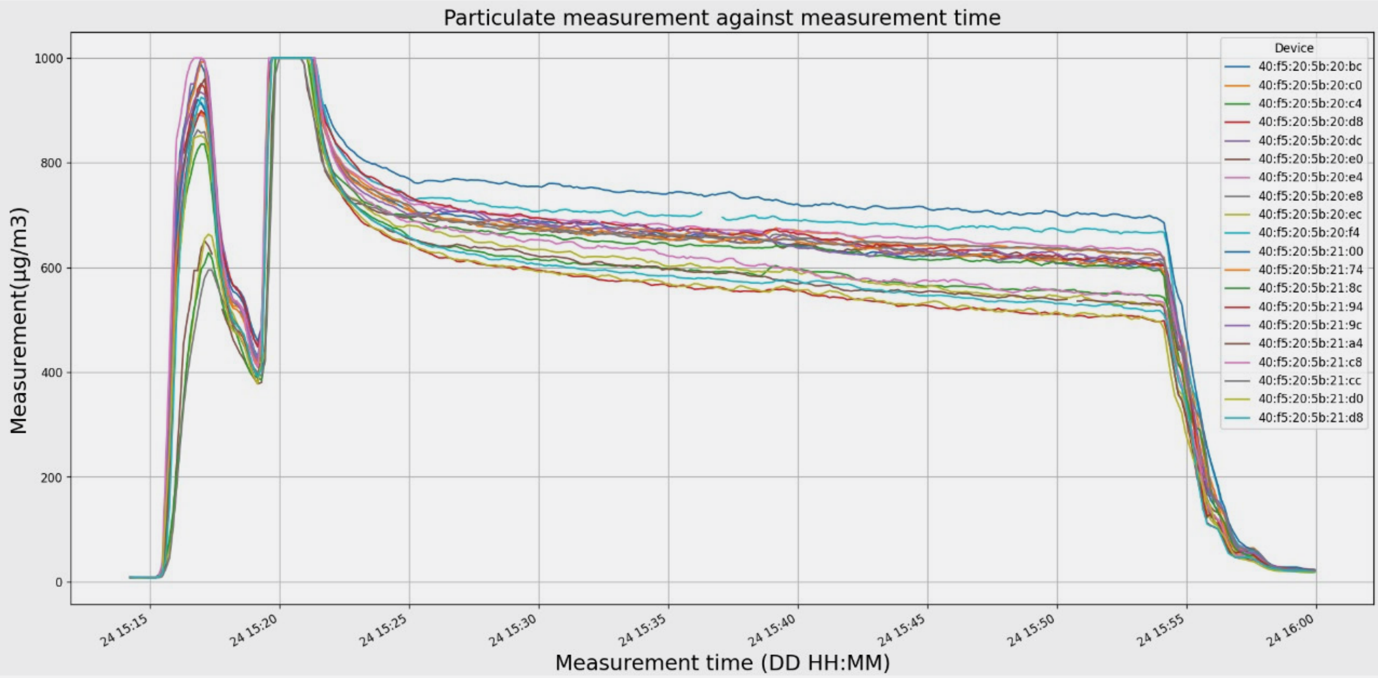


FIGURE 10:
600-800 µg/m3 normalization round data



2.2 Stakeholder workshop

In preparation for fieldwork, the researcher prepared an inception workshop and reached out to key stakeholders such as the main governmental stakeholders—the Ministry of Energy, and the Ministry of Health—and other clean cooking-focused organizations, to inform them of the nature of the study. This enabled the researcher to obtain objective opinions on the proposed approach outcomes and desired outcomes. Table 1 below indicates the list of participants who attended the inception workshop.

Table 2: List of participants at the inception stakeholder workshop

#	Name	Organization
1	Daniel Wanjohi	EED Advisory
2	Martin Kitetu	EED Advisory
3	Alois Mbutura	EED Advisory
4	Ziana Chelimo	EED Advisory
5	James Muchiri	EED Advisory
6	Morris Maina	EED Advisory
7	David Njugi	Clean Cooking Association of Kenya
8	Hannah Wanjiru	Stockholm Environment Institute
9	John Ngigi	Netherlands Development Organisation (SNV)
10	Mariam Karanja	Clean Cooking Association of Kenya
11	Moses Kirimi	World Agroforestry (ICRAF)
12	Paul Ayalo	Clean Cooking Association of Kenya
13	James Kinyua	World Agroforestry (ICRAF)
14	Michael Johnson	Berkeley Air
15	John Njogu	Netherlands Development Organisation (SNV)
16	Jetter James	Environmental Protection Agency (EPA)
17	John Mitchell	Environmental Protection Agency (EPA)

2.3 Data collection activities

2.3.1 Literature review

To understand the constantly evolving cooking sector in the country, we conducted a targeted deep-dive literature review which included sector reports, research papers, and grey literature. Although the cooking sector in Kenya is considered to be one of the most advanced in Sub-Saharan Africa—in terms of types of improved solutions available and the number of people having access to these technologies—use of solid biomass as the primary cooking solution is still common in most households. According to the Kenya Household Sector Study by the Ministry of Energy[7], 75 % of households in Kenya rely on solid biomass as their primary fuel (93% rural and 38% urban). However, there is an upward trend in the uptake of clean cooking fuels such as Liquid Petroleum Gas (LPG) at the household level, which the sector study indicates is the most preferred cooking solution, at 43% nationally. Cookstove and fuel stacking is widely practiced nationally, though more so in urban areas, with households having more than one cooking solution. For example, often one stove is used primarily, while the second and third stoves may be used as backup solutions, for specific cooking preferences, or when the cost of fuel of the primary solution is high[8]. These complex cooking patterns informed our decision to stratify the target respondents across groups that cook with ‘gas only’, ‘charcoal and gas’, ‘kerosene and charcoal’, ‘kerosene only’, and ‘firewood’.

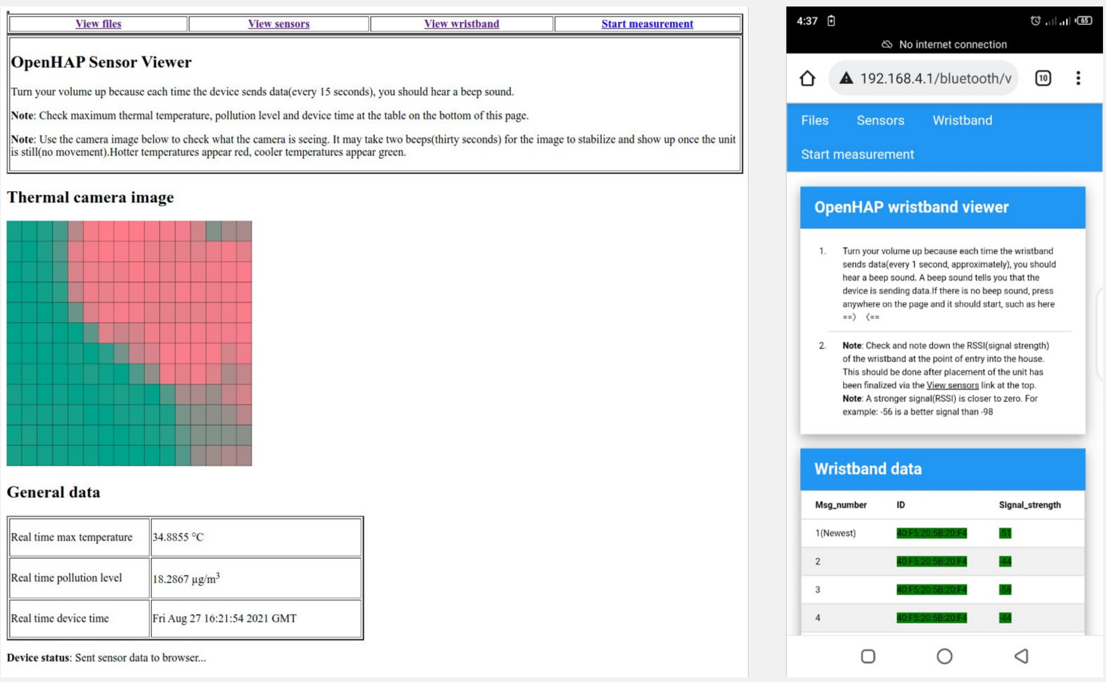
2.3.2 Pre-field work activities

i. Reviewing data collection tools

We developed a questionnaire to collect information from households within the low-income Kawangware and Kibra areas in Nairobi. The household questionnaire aimed to gather information on household characteristics, cooking technology owned, house characteristics, and cooking behaviors. The questionnaire was coded on Open Data Kit (ODK) Collect—a tool that enables data collection using Android mobile devices. ODK Collect provides for data verification, validation checks, GPS recording, audio recording, start and finish time recording, photo-taking, signature taking, uploading various file formats, and provides for a central server where all the data is downloaded in CSV or XLSX formats.

Further, the OpenHAP devices were designed to have an interface that the enumerators could use to set up the device. Enumerators accessed the OpenHAP Sensor Viewer via a Wi-Fi network that was broadcast from the OpenHAP device through their mobile devices. The setup interface allowed the enumerators to check the thermal camera positioning, the placement of the device to ensure there was no saturation of PM readings, and to check that the BLE beacon system captures room dimensions to define the boundaries of the cooking area. Figure 11 shows screenshots of the device setup interface.

FIGURE 11:
OpenHAP device setup interface



7 Ministry of Energy. (2019). Kenya Household Cooking Sector Study: Assessment of the Supply and Demand of Cooking Solutions at the Household Level. https://eedadvisory.com/wp-content/uploads/2020/09/MoE-2019-Kenya-Cooking-Sector-Study-compressed.pdf

8 Ibid.

ii. Recruitment of enumerators

The researcher selected ten enumerators from its database who understand the socio-cultural norms of Kibra and Kawangware areas and speak the local dialects, English and Kiswahili. These enumerators have previously worked with the researcher and are familiar with administering surveys using CAPI (ODK). Several members of the researcher's team were supervisors, tasked with planning the data collection exercise and addressing any challenges and questions that the enumerators had while in the field.

iii. Selection of households

Initially, households were to be selected from among those that participated in the recently completed Kenya Cooking Study. However, this recruiting approach was not possible as most of those contacted either refused to participate, had moved from Nairobi, or were unavailable during that survey period. As a result, the selection of households was done randomly within Kibra and Kawangware areas. Enumerators assisted with the selection of households by reaching out to warm contacts they know who could voluntarily participate in a form of snowball sampling. This flexibility increased the chances of getting participants, since some of those approached perceived the OpenHAP device to be intrusive. The strategy also ensured the devices were secure, as the participants were firsthand contacts of the enumerators.

The researcher enrolled a total of 100 households, based on the type of cooking technology used. Therefore, each of the five types of cooking technology—'gas only', 'charcoal and gas', 'kerosene and charcoal', 'kerosene only' and 'firewood'—had a sample of twenty respondents.

2.3.3 Training and pretest

i. Pretest

The initial training for the pretest involved two enumerators. The surveys were first done at the training venue to test their ability to use the ODK data collection platform. After a satisfactory demonstration of their understanding, the pretest was done in four households in Kibra. Each enumerator was required to administer two questionnaires and install the OpenHAP monitoring device in two households. EED supervisors reviewed the data and commented on mistakes made during the pretest before the rest of the enumerators were trained and the data collection exercise commenced.

ii. Training

During the training, supervisors provided an overview of the project's background, objectives, and relevance to the enumerators. The importance of their role in this research was communicated to allow enumerators to take ownership of the project and ensure they remain committed throughout the data collection exercise. This was particularly important because the survey would last several weeks. Even though the enumerators had previous experience in data collection using CAPI, they had not been involved in the initial development of the OpenHAP data collection tools. Therefore, part of the training involved taking the enumerators through all the survey questions to ensure common understanding and interpretation. While electronic approaches provide a safe and easy way to collect and upload data quickly and accurately, incorrect use of the tablet can lead to data loss. To avoid that, all enumerators were taken through all protocols to follow, such as saving, reviewing, and uploading data. The supervisors also explained data collection ethics, and tips on how to conduct a good interview.

To ensure the OpenHAP device would work optimally and collect the required data, the enumerators were taken through the device's functions, and the logistical considerations for placing the device in a house. Some of the logistical considerations explained include: placement of the sensor at least 2 meters from the cooking devices and away from obstructions that would interfere with the measurement; taking a photo of the device installation; ensuring reliable communications, i.e. device Wi-Fi before installation; ensuring the power bank is fully charged; determining requirements (permission) to install the device in the house; ensuring the device is secure and protected from vandalism and does not interfere with activities of occupants.

Generally, the key topics covered during the training were:

- Assignment description, roles, and responsibilities.
- Data collection tools (ODK).
- Ethical guidelines and standards for field data collection.
- COVID-19 safety protocols.
- Survey questions with elaborations on problematic and sensitive questions.

- Placement of the device in houses, extraction, and renaming of data from the device.
- How to extract and send the data from the OpenHAP device to the supervisors.

In addition, the following points were emphasized, and enumerators were directed to:

- Prioritize personal safety when carrying out the survey and check with the supervisors in case of any safety concerns.
- Counter-check that all questions are answered before submitting a questionnaire.
- Report any failures with the OpenHAP device.
- Quality control measures, which in severe cases, could involve redoing the wrongly implemented surveys.

2.3.4 Data collection

Data collection commenced on Monday, September 13th after the verification of the pretest data. During data collection, there was continuous support to enumerators and monitoring of submitted data to ensure the data quality remained the same throughout the study. The survey coordinator from EED formed a WhatsApp group, which the EED supervisors and enumerators used for communication. Crucial points of communication included mistakes in submitted data and challenges in the field. Examples of critical errors flagged included wrong inputs such as household ID and OpenHAP device ID, and incorrectly labeling the data from the device.

The supervisors guided the enumerators in correcting these mistakes and, where necessary, the supervisors made a follow-up phone call. The map below shows some of the households the enumerators surveyed. The dotted circles represent the surveyed households.

FIGURE 12:
Distribution of sampled households across sub counties in Nairobi

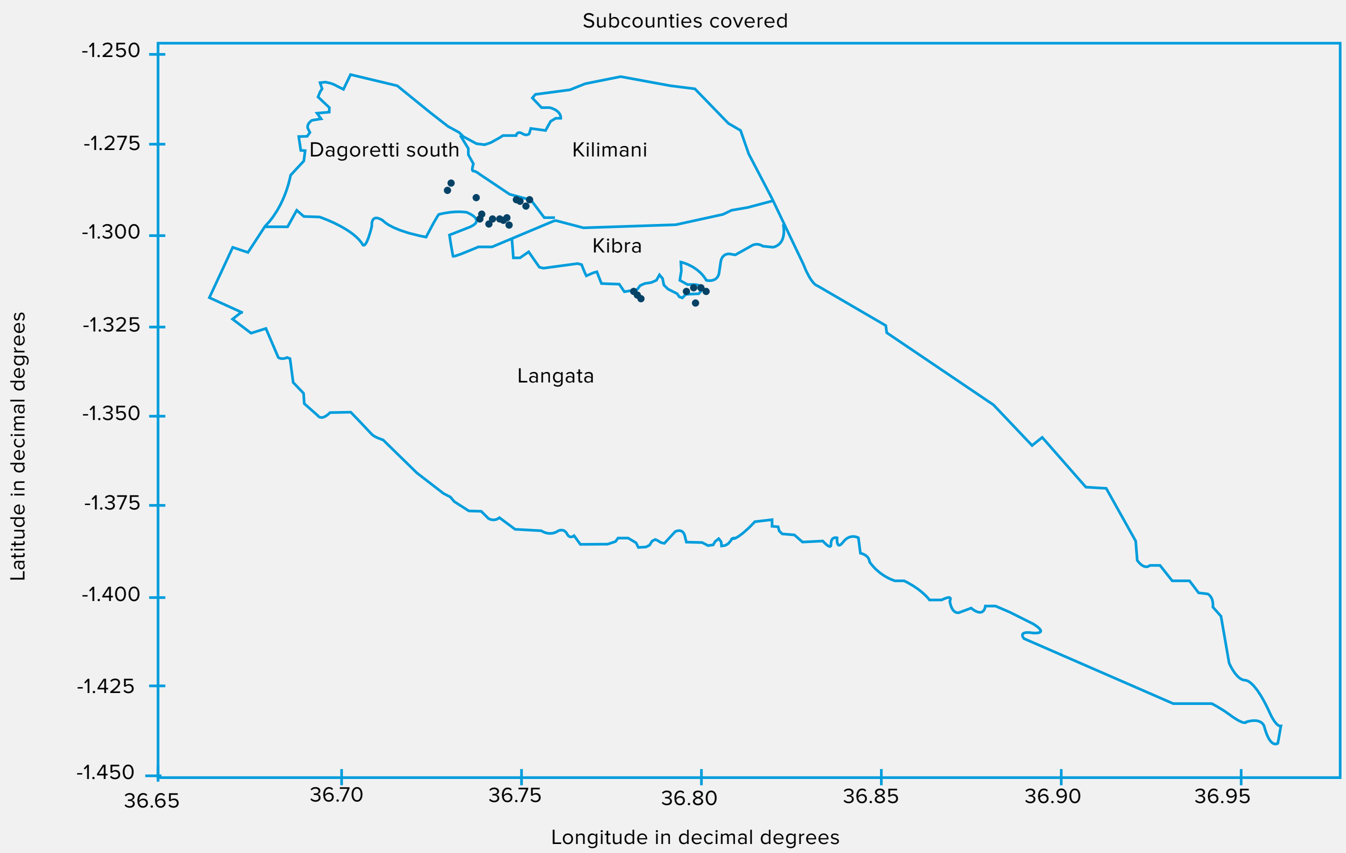


FIGURE 13:
Sampled households within Kawangware area, Nairobi Kenya

FIGURE 14:
Sampled households within Kibra informal settlement area, Nairobi Kenya

2.3.5 Data collection challenges and solutions

The key challenges encountered during training and pretesting include the following:

- There is a general aversion to wearing masks in Kibra and Kawangware areas. EED supervisors advised adherence to COVID-19 safety protocols, including wearing a mask, social distancing, and hand sanitization.

- There were cases of hostility in some households threatening the safety of enumerators. In one case, a household member who was not present during the installation of the devices insisted on removing the device from the house. However, after explaining the purpose of the research and how the device works, the household member agreed to have the device installed.

- Interference with the device by household members, especially children, was a significant challenge. To counter this, enumerators called the household head to follow up on the device's safety and ensure it was still working.

- The enumerators also experienced a few challenges finding participants who used firewood as their household's primary cooking fuel. Those who could not find participants who use firewood were advised to find participants using alternative cooking technologies.

- Some participants did not wear the wristband for the survey's duration for safety reasons such as avoiding wetting the wristwatch. This affected the final data collected.

2.3.6 Data analysis

PM2.5 measurement data captured during the three instrument normalization rounds was stored in separate CSV files and analyzed using Ipython v7.12.0. Each round data was pivoted and summarised by device and steady state datapoints extracted and merged across all rounds. From this resultant data, the device with the median area under the curve was selected and normalization of all device data to the device with the median measurement performed using ordinary least squares, generating measurement correction factors by device.

Quantitative survey and device measurement data were analyzed using the same Ipython v7.12.0 software as the device normalization. The survey data was independently analyzed to determine stove use information such as main stove, stove stacking et cetera. The two datasets were linked by the captured device identifier. The linked dataset was then analysed to inspect data from different device placements and check for measurement saturation. Stove state data (In use / not in use) was generated from the stove temperature data using timeseries decomposition to check for residual changes in temperature and encode this to the necessary on / off signals using mean normalization. For the Bluetooth data specifically a calibration procedure was performed in order to determine the region of detection where beacons within the cooking area will be properly received by the OpenHAP device and those outside will not be received.

03
Results

3.1 Instrument performance

3.1.1 Instrument normalization

The researcher performed a PM2.5 measurement normalization procedure using burning incense across all target concentrations. The results from this exercise show strong positive correlation between all OpenHap devices and the reference device, with a minimum correlation of 0.998. Given the evidence of a strong positive correlation, linear regression was used to produce the correction factors listed in Table 2.

Table 3: Device correction factors

#	Device identifier	Slope	Intercept
1	40:f5:20:5b:20:bc (Reference)	1.000	0.000
2	40:f5:20:5b:20:c0	0.982	3.879
3	40:f5:20:5b:20:c4	1.105	3.037
4	40:f5:20:5b:20:d8	1.178	4.203
5	40:f5:20:5b:20:dc	0.999	3.445
6	40:f5:20:5b:20:e0	1.004	5.836
7	40:f5:20:5b:20:e4	0.968	1.767
8	40:f5:20:5b:20:e8	1.000	0.159
9	40:f5:20:5b:20:ec	1.102	2.701
10	40:f5:20:5b:20:f4	0.938	3.370
11	40:f5:20:5b:21:00	0.890	-1.968
12	40:f5:20:5b:21:74	1.003	2.661
13	40:f5:20:5b:21:8c	1.022	6.859
14	40:f5:20:5b:21:94	0.983	0.779
15	40:f5:20:5b:21:9c	0.993	1.153
16	40:f5:20:5b:21:a4	1.122	5.707
17	40:f5:20:5b:21:c8	1.078	5.983
18	40:f5:20:5b:21:cc	0.990	-0.361
19	40:f5:20:5b:21:d0	1.170	5.646
20	40:f5:20:5b:21:d8	1.137	3.606

Performing a post normalization analysis comparing each device's data to the reference device should ideally yield a slope and intercept of 1 and 0 to show the goodness of fit. This is shown in Table 3 below.

Table 4: Goodness of fit of data in comparison to the reference device

#	Device identifier	Slope	Intercept
1	40:f5:20:5b:20:bc (Reference)	1.000	0.000
2	40:f5:20:5b:20:c0	1.000	0.071
3	40:f5:20:5b:20:c4	1.000	-0.319
4	40:f5:20:5b:20:d8	1.000	-0.747
5	40:f5:20:5b:20:dc	1.000	0.004
6	40:f5:20:5b:20:e0	1.000	-0.023
7	40:f5:20:5b:20:e4	1.000	0.056
8	40:f5:20:5b:20:e8	1.000	0.000
9	40:f5:20:5b:20:ec	1.000	-0.275
10	40:f5:20:5b:20:f4	1.000	0.210
11	40:f5:20:5b:21:00	1.000	-0.218
12	40:f5:20:5b:21:74	1.000	-0.008
13	40:f5:20:5b:21:8c	1.000	-0.154
14	40:f5:20:5b:21:94	1.000	0.013
15	40:f5:20:5b:21:9c	1.000	0.008
16	40:f5:20:5b:21:a4	1.000	-0.697
17	40:f5:20:5b:21:c8	1.000	-0.466
18	40:f5:20:5b:21:cc	1.000	-0.003
19	40:f5:20:5b:21:d0	1.000	-0.960
20	40:f5:20:5b:21:d8	1.000	-0.494

3.1.2 Data quality

From 100 measurement samples, 76 had usable data, with the majority of unusable data being largely due to human error. A summary of the results of failure analysis conducted on the unusable measurements is shown in Table 5. Of the 76 successful samples above, none showed PM2.5 measurement saturation.

Table 5: Summary of causes of unusable device data

Failure type	Quantity	Percentage
Unusable measurements due to human error (Unsubmitted data)	16	16%
Unusable measurements due to improper configuration	4	4%
Unusable measurements due to tampering	4	4%
Unusable measurements due to system failures	0	0%

$PM_{2.5}$ data

As indicated in the section above the researcher found that the PM2.5 measurement indicated linearity across all the devices because of co-location normalization. We note however that the PM2.5 sensor uses the light scattering PM2.5 sensing method which is not as accurate as the gravimetric PM2.5 sensing method and further the co-location exercise did not incorporate a reference gravimetric sensor for possible error correction. In this regard the OpenHAP is considered to measure relative and not absolute concentrations of PM2.5 across the sampled stoves.

The researcher found that data from 7 out of the 76 respondents had incidence of PM2.5 sensor saturation with peak readings capped at 1100 µg/m3 which is the upper limit of the sensor (after device normalization). All these respondents were found to use the three-stone open fire stove which is the most polluting stove. The remaining samples did not record saturation primarily because of correct placement of the OpenHAP device 1.5 metres from the cookstove.

We calculated the average pollution per stove type by computing the mean of the average pollution across all respondents with the same stove type. We define the average pollution per respondent as the average value of PM2.5 measured for a given stove type, while the stove is in use.

Temperature data

In 4% of the respondent data, the device was found to be incorrectly placed, with the infrared sensor facing away from the stove. Our method to analyse stove use data from incorrect placement of the device is based on the fact that though incorrect placement may cause a lack of defined peaks in the temperature signal, as indicated in Figure 15, the signal detected will experience greater variance in measurement while a stove is on. This can be used to determine if a stove is on or off. For use, the temperature data needs to be decomposed into its constituent parts, namely trend and variance of the trend (residuals).

FIGURE 15:
Incorrect placement of OpenHAP device

3.1.3 Instrument usability

Through training, the enumeration team became proficient in the device setup, configuration, and data downloading. Setup using the device's OpenHAP Sensor Viewer was performed well by the enumerators, with only 4% instance of improper configuration as mentioned above. The low incidence of improper configuration suggests that OpenHAP can be readily programmed by research teams.

Regarding installation, the team was able to set up most of the devices correctly, with the PM2.5 sensor in the correct location and the stove use temperature sensor properly facing the stove of interest (see Figure 19). However, as mentioned above, 4% of the device data indicates incorrectly placed devices with the infrared sensor facing away from the stove, which caused a relatively low dynamic range on the sensed temperature. This can be improved in future through thorough training and software improvements on the infrared driver to improve the infrared frame rate on the configuration portal beyond the 1 frame per second setting used.

FIGURE 16:
Lack of defined peaks in temperature data from incorrect device placement

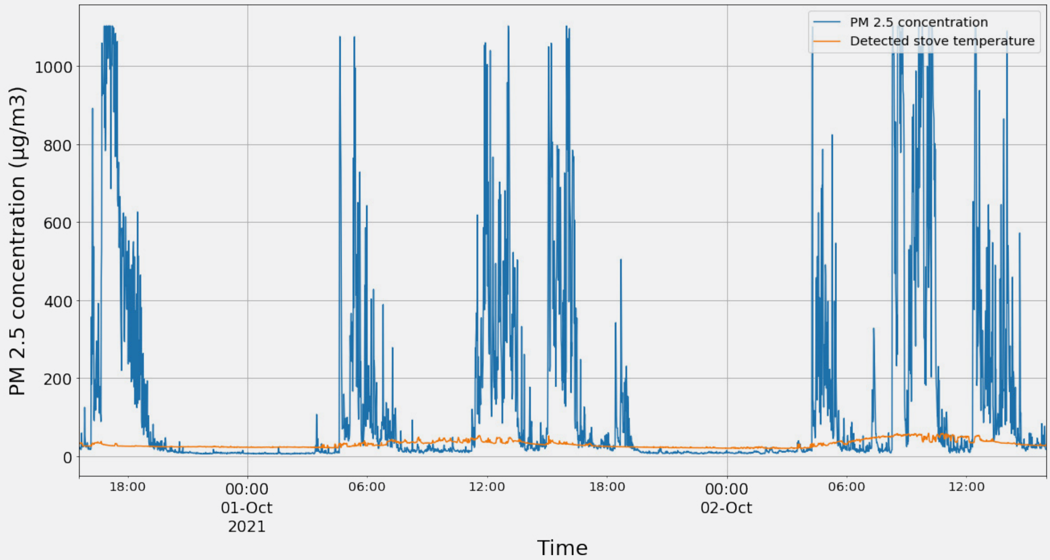


FIGURE 17:
Decomposition of the temperature data showing general trend and residuals

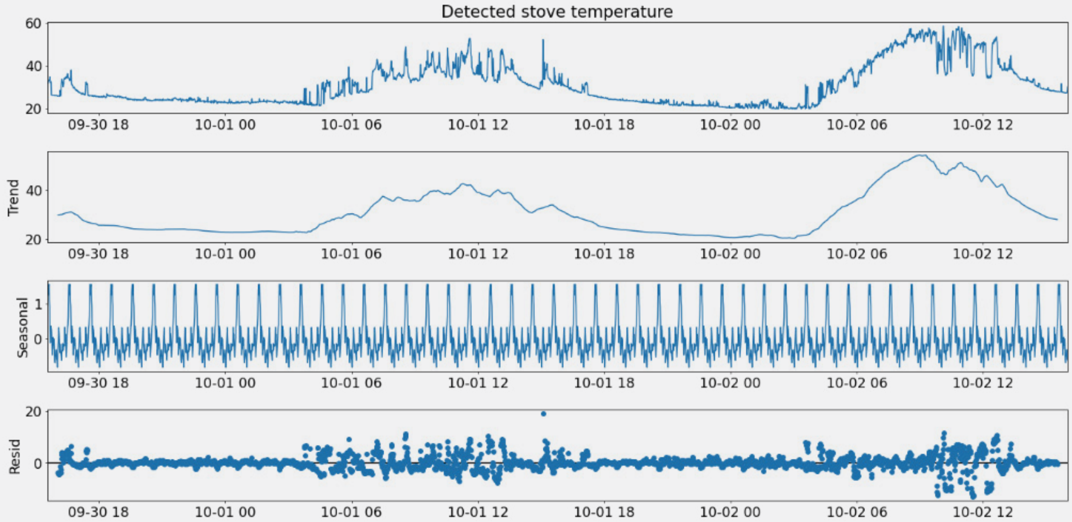


FIGURE 18:
Resultant stove use data generated from using the original temperature data residual

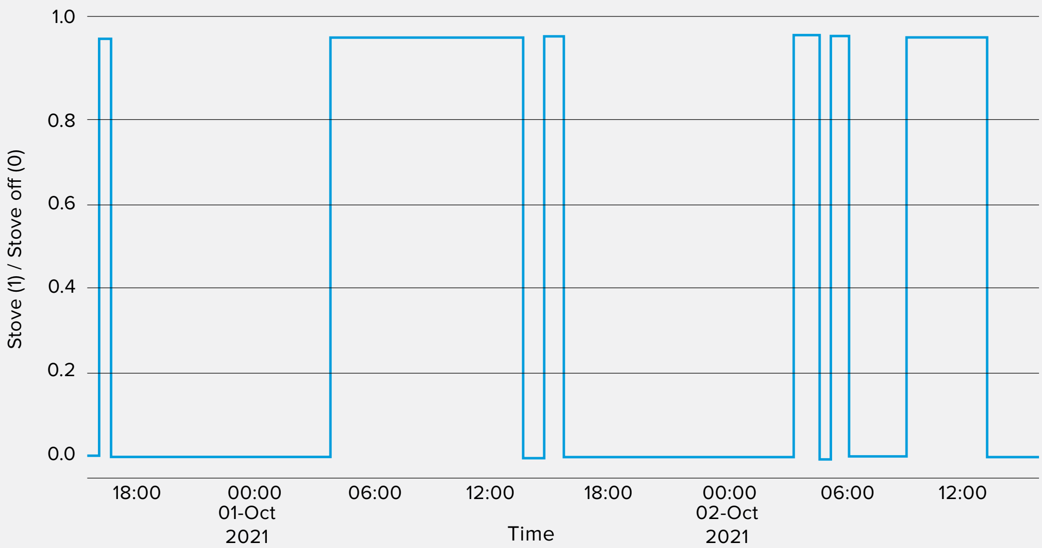


FIGURE 19:

A correctly set up device with its infrared sensor field of view facing the stove

3.2 Household air pollution results

3.2.1 PM2.5 pollution concentration

Stove prevalence

As indicated in Table 5, the majority of the sampled respondents, 31.5%, use the Kerosene wick cookstove. This is followed by LPG single burner (Meko) (27.6%), three-stone open wood fire (17.1%), LPG multiple burner stove (10.5%) and Kenya Ceramic Jiko (charcoal) (9.2%). The improved charcoal stove and the Kuni Mbili stove are used by less than 4% of the respondents. As this study was aimed at sampling different cooking fuels the researcher did not conduct a representative sample and the usage of the various cookstoves is not representative of the cooking stove distribution in Nairobi or the low-income regions of Nairobi.

It was also found that approximately half, 38 out of the 76, households used multiple stoves. Common stove us patterns for respondents with multiple stoves included having the main stove as Kerosene wick stove (34.2 %), LPG single burner (28.9%), LPG multiple burner (15.8%), Kenya Ceramic Jiko (charcoal) (15.8%) and the three-stone open fire (5.3%). Stove stacking respondents using the Kerosene wick stove as a main stove mostly used the Kenya Ceramic Jiko (charcoal) as their secondary stove (84.6%) with the rest using a LPG stove or charcoal stove. It was found that respondents who use firewood primarily cook outside the house, mostly due to the amount of smoke the fuel produces, especially for respondents' who live in a single-room house. In such instances, the researcher did not monitor the outdoor cooking pollution profile. 82% of respondents indicated that they do not use their cookstoves for space heating. The 18% who do heat their homes, use mainly charcoal stoves (43%), with the rest using the Kerosene wick stove (29%) or the LPG single burner (Meko) stove (28%). Furthermore, charcoal or kerosene is most likely used as a substitute for cleaner fuels such as the liquified petroleum gas in the event of an outage.

HAP concentration across stoves

We determined the average pollution per stove type by computing the mean of the average pollution across all respondents. We define average pollution per respondent as the average value of PM2.5 measured of a given stove type, while the stove is in use. The Three-stone open wood fire stove is found to produce the highest mean pollution when in use, with an average PM2.5 concentration of 207 µg/m3 (see Figure 20). The use of the Kuni Mbili stove (wood/charcoal) and Kenya

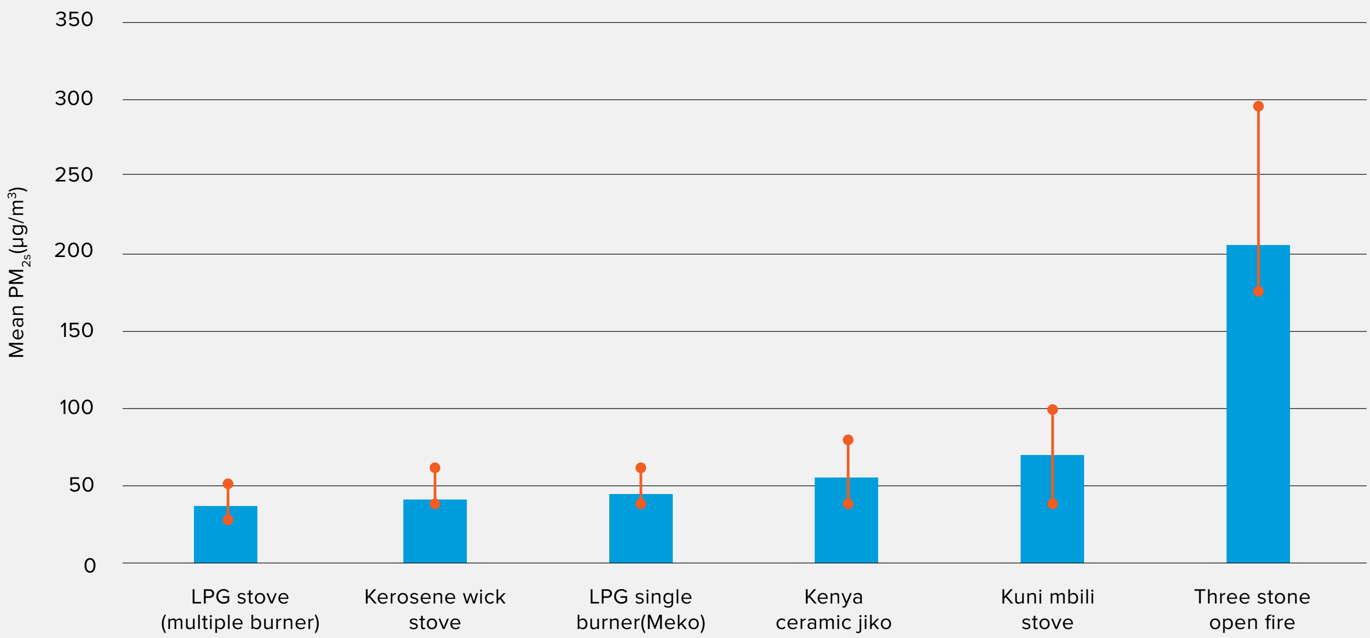
Table 6: Type of main stove used by respondents

Main stove type	Number of respondents	Percentage of respondents
Kerosene wick stove	24	31.5 %
LPG single burner (Meko) stove	21	27.6 %
Three-stone open fire (wood)	13	17.1 %
LPG multiple burner stove	8	10.5 %
Kenya Ceramic Jiko (KCJ) (charcoal)	7	9.2 %
Improved charcoal stove	2	2.6 %
Kuni Mbili stove (Jua kali) (wood/charcoal)	1	1.3 %

Ceramic Jiko (charcoal) was associated with a PM2.5 concentration of 69 µg/m3 and 55 µg/m3, respectively, during cooking events. The LPG single burner (Meko), the Kerosene wick stove and the LPG multiple burner stove had a mean PM2.5 pollution of 44 µg/m3, 41 µg/m3 and 36 µg/m3 respectively.

FIGURE 20:

Mean indoor air pollution per cookstove type while the stove is in use and the standard deviation (error bar)



3.2.2 Room aeration and external pollutants

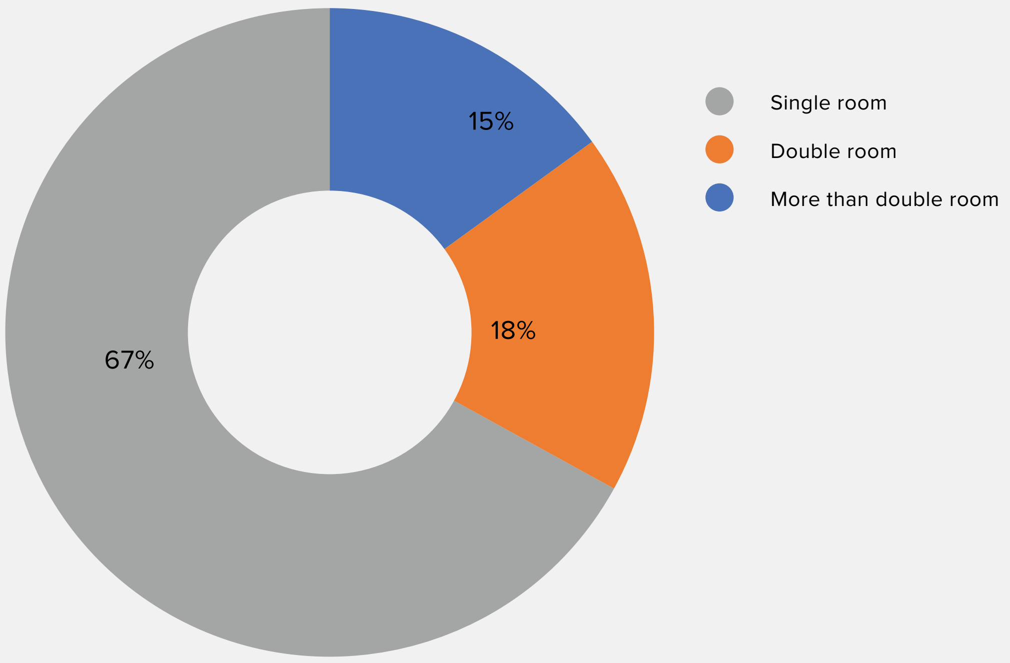
Room Aeration

We found that a large proportion of respondents within the research area live in single-room dwellings, as indicated in Figure 21. These respondents' homes have only one window and one door. Further, it was found that 66% of respondents have an unpartitioned indoor kitchen, and half of the respondents do not open the windows for ventilation when cooking.

We further calculated the air change rate (ACR) to be a representation of the level of aeration in the respondent's cooking areas. ACR is the frequency at which outdoor air replaces air within a building or room. ACR was calculated by ascertaining the decay rate after the peak pollution during cookstove use, by taking the natural log of the decay curve using least squares regression analysis.

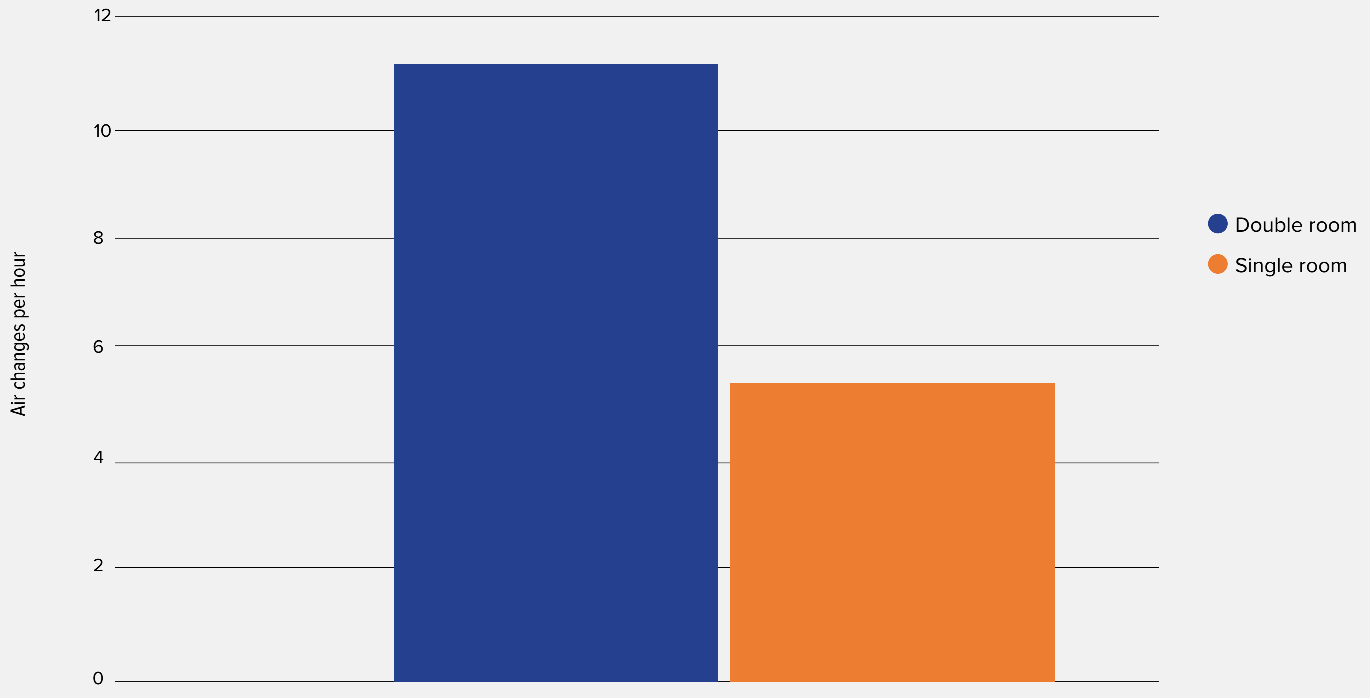
We chose the Kenya Ceramic Jiko (charcoal) data set for this analysis due to the high PM2.5 emissions it produces, which would produce a good decay curve. We further compared the ACR between double-room and single-room households. To standardise variables that can affect this analysis, we only analysed data from respondents who indicated that they open the window when cooking. As seen in Figure 22, double-room houses have an average ACR of 11.3 air changes per hour compared to single-room houses with 5.5 air changes per hour.

FIGURE 21:
Household type



Although these estimates are not representative given the selection of only charcoal users with open windows, these ACR estimates illustrate how OpenHAP can be used to calculate ventilation.

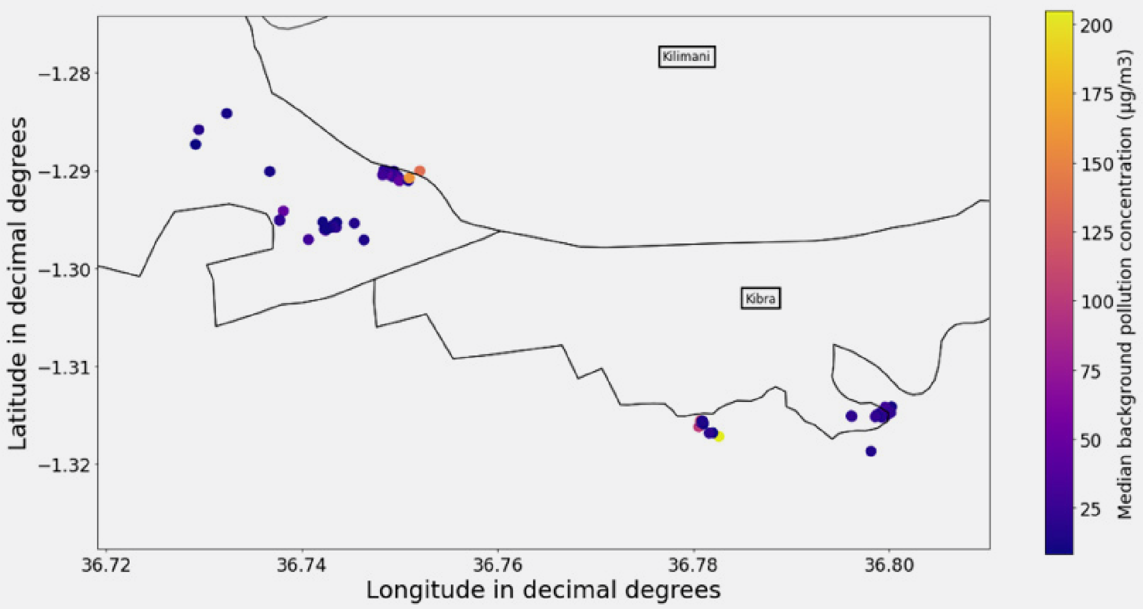
FIGURE 22:
Air change rate in a double and single room house



Non-cooking pollutants

Measurement of the PM2.5 concentration when the stove is off was found to be useful for performing pollutant comparisons between stove use and stove non-use cases. The stove temperature data was collected using the infra-red camera that faced the stove and was used to determine whether the stove was on or off. A spike in temperature from ambient indicated the stove was on and a cooking activity was happening. Across all respondents, the mean indoor PM2.5 concentration when the stove is off was found to be 28 μg/m3, with 82% of the respondents having mean concentrations of less than 40 μg/m3 when the stove was off. Only five locations had a higher mean concentration (> 100 μg/m3), which could have been due to some local pollution source other than the participant's stove (see discussion below). The background pollution is independent of geographical location as seen in Figure 23.

FIGURE 23:
Respondent background pollution by geographical location



The researcher found several instances of non-cooking-related PM2.5 pollution hikes throughout the study. Figure 24 indicates an example of these instances. The respondent whose data is shown uses an LPG single burner (Meko) cookstove. The orange line highlights when the stove was used, and the blue line is the PM2.5 concentration measured. In most instances that the cookstove is used, there is a reciprocal but slight increase in PM2.5. At point A, the cookstove is not measured to be used, yet the PM2.5 measurement spiked to nearly 250 μg/m3. The researcher presumes that though the respondent indicated that they keep the window closed during cooking, the spike in PM2.5 may be as a result of various uncharacterised pollution sources and observes that external or non-cooking-related pollutants have a significant effect on HAP, especially in low-income neighbourhoods that have high-density housing and unpaved roads.

Further, the researcher found that a comparison of this respondent, who indicated closing their window during cooking, and another respondent who also uses the LPG single burner stove (Meko) but indicated having the window open during cooking yielded interesting results. As shown in Figure 25, a significant PM2.5 spike is recorded at point B which incidentally is at the end of a recorded cooking session in the room of the respondent with the open window. In addition, the PM2.5 peaks concurrent with cooking sessions are on average higher in the room of the respondent with open window than in the room of the respondent with closed window during cooking events. This indicates a source of pollution other than the cookstove (e.g., ambient dust entering through the window, smoking, house cleaning).

FIGURE 24:
LPG single burner (Meko) using respondent external pollution

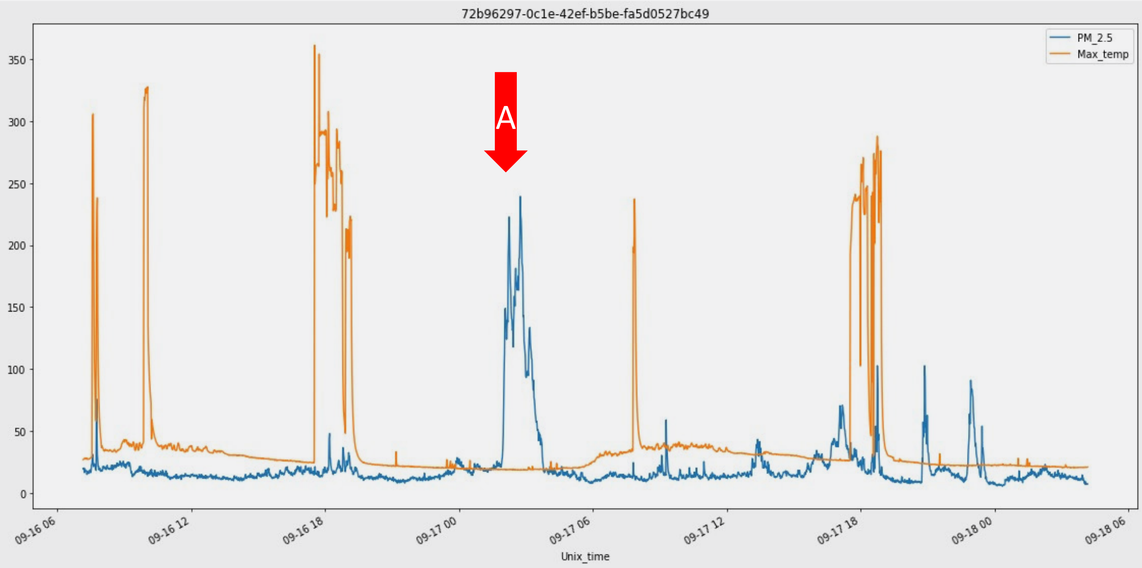
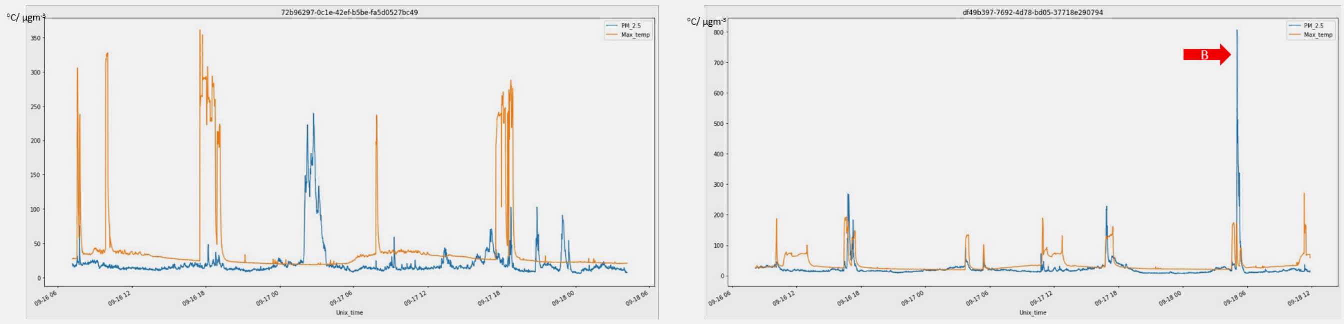


FIGURE 25:
LPG single burner (Meko) closed/open window comparison

LPG Meko single room, closed window

LPG Meko single room, open window



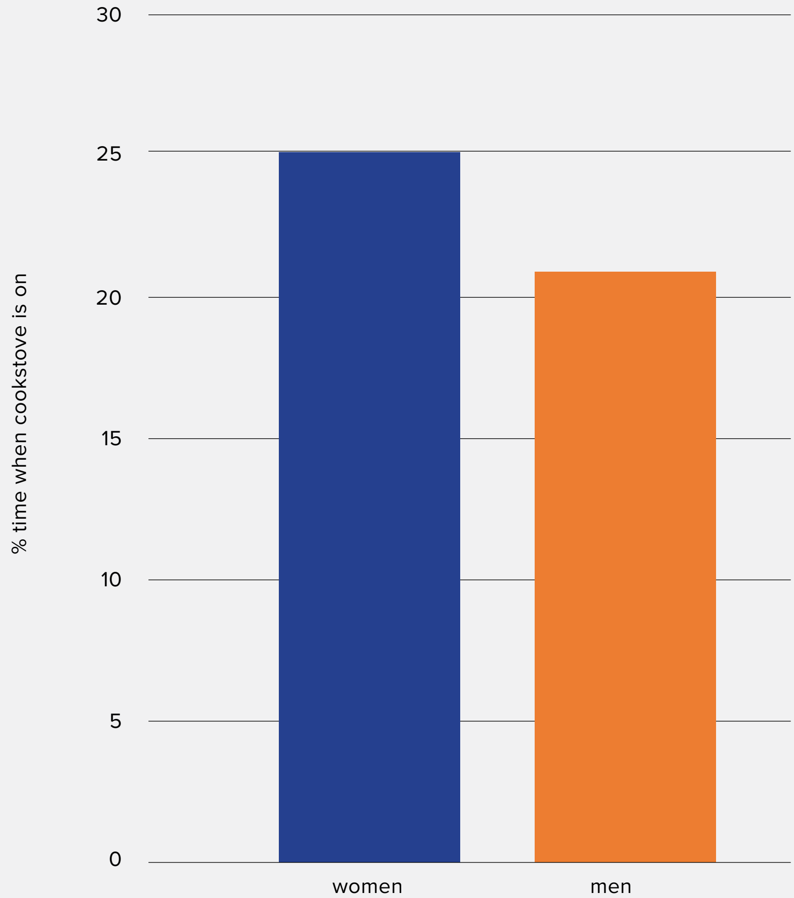
3.2.3 Exposure

Gender

The researcher found that 68% of the respondents were female and 32% male. To determine each one's exposure level, respondent cookstove proximity data was used as a proxy. Cookstove proximity data was collected from the Bluetooth straps worn by the respondents. The Bluetooth detection perimeter was adjusted by enumerators during the setup of the OpenHAP device to be specific to the size of the cooking area of each house using the OpenHAP viewer and the Bluetooth strap's Android app and processed through the following steps:

Determine a presence index Bv to classify respondent presence. This is calculated by obtaining the Bluetooth sample points received, compared to the total sample points in the file. This will yield a value 0 <= Bv <= 1, where 1 indicates that the respondent is next to the cookstove 100 percent of the time of the study and 0 indicates the respondent is not present.

FIGURE 26:
Respondent's presence in the cooking area as percentage of time the cookstove is on



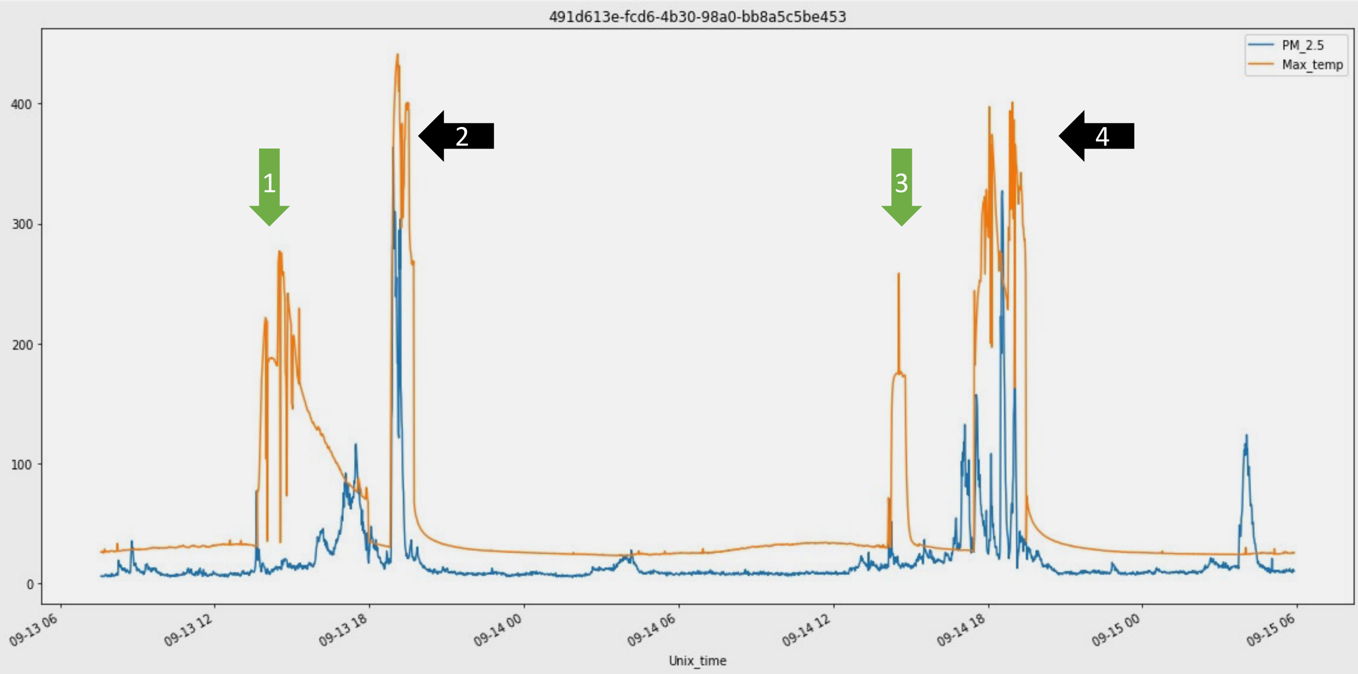
The researcher found that on average male respondents spend almost 10% less time within 5 m radius of the cookstove compared to female respondents. Further, when the cookstove is on, male respondents are present 4% less time than female respondents, as indicated in Figure 26. This suggests that the female respondents may be more prone to higher levels of exposure to PM emissions from the various cookstoves, though the differences in time close to the stove were minimal and our samples sizes were too small to make definitive conclusions.

Stove Stacking

Due to the unique conditions of setup at each household, the researcher found that stove stacking, such as the joint use of a Kerosene wick stove and Kenya Ceramic Jiko charcoal stove, or LPG single burner (Meko) and Kenya Ceramic Jiko charcoal stove, leads to a pollution profile and exposure potential similar to that of the more polluting of the two stoves. For example, in cases where a higher polluting stove is used at the same time as a less polluting stove, the benefit of the less polluting stove is not apparent. In Figure 27 we see the usage profile of a respondent who has both the Kerosene wick stove and the Kenya Ceramic Jiko charcoal stove. At points 1 and 3, we see an instance of the use of the Kerosene wick stove only leading to a relatively low emission profile. At points 2 and 4 the charcoal stove is either used alone or in combination with the Kerosene wick stove, resulting in PM2.5 emissions that are higher by a factor 3 compared to the single use of the Keresone wick stove. The respondent has set up both cookstoves side by side at the cooking area. When used at the same time, the respondent does not benefit from the lower PM2.5 emission profile of the Kerosene wick stove and therefore is exposed to the much higher emissions from the Kenya Ceramic Jiko (charcoal) stove. This scenario is replicated in various households surveyed that stack with multiple stoves; regardless of how clean or modern one of the cookstoves is, the respondents do not benefit, if it is used sparingly or if it is used alongside a more traditional stove.

FIGURE 27:

PM2.5 concentrations of a Kerosene and KCJ charcoal stove used side by side. At points 1 and 3 only the Kerosene stove is used, at points 2 and 4 the charcoal stove is used alone or in combination with the Kerosene stove



04
Conclusion

$PM_{2.5}$ measurements

The OpenHAP measurements do not provide absolute emission values, as the OpenHAP measurement devices were not referenced with a gravimetric reference device. Nevertheless, they do provide valuable information about the relative differences in emissions of the individual cookstove types and their risk profile.

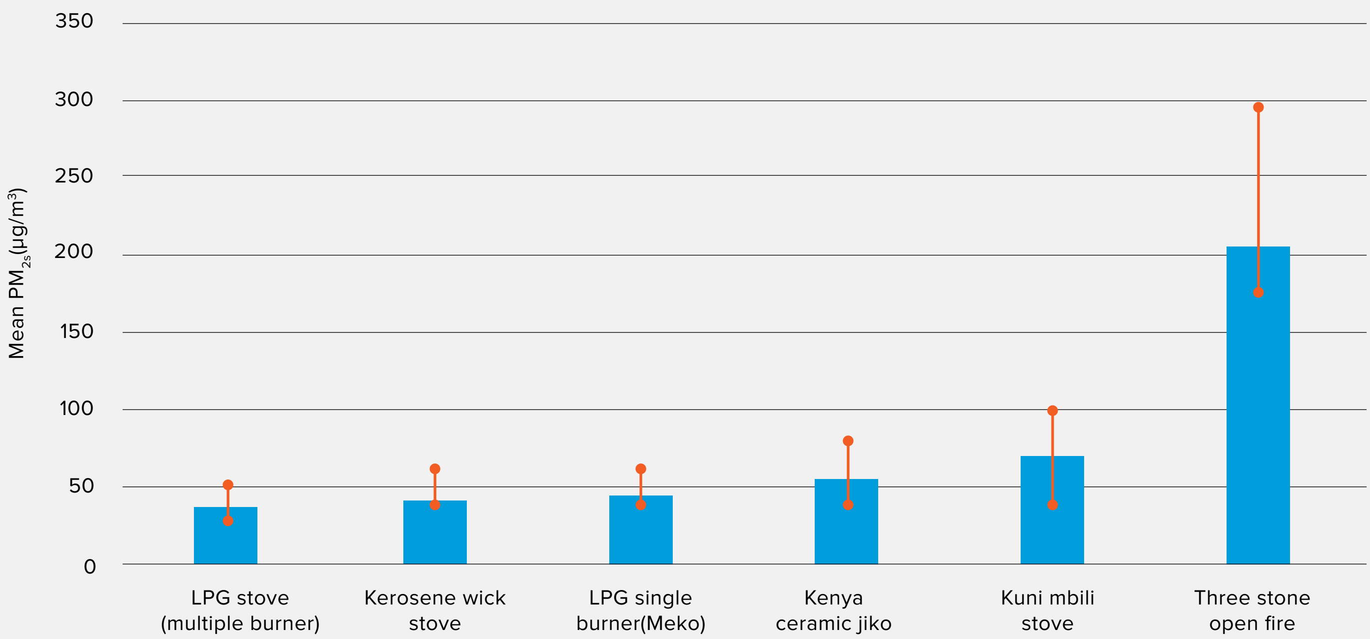
The researcher validated previous assumptions that the three-stone firewood cookstove produces the highest levels of indoor air pollution, with a mean PM2.5 concentration of 207 µg/m3 while the stove is in use (see Figure 20). The Kuni mbili and Kenya Ceramic Jiko (charcoal) cookstoves, which use charcoal as main fuel, produce mean PM2.5 concentration of 69 and 55 µg/m3 respectively.

The LPG single burner (Meko), the Kerosene wick stove and the LPG multiple burner stove had a mean PM2.5 concentration of 44 µg/m3, 41 µg/m3 and 36 µg/m3 respectively. These cookstoves using LPG or kerosene as fuels were found to produce lower PM concentrations in comparison to the cookstoves using biomass fuels (firewood or charcoal).

The WHO PM2.5 air quality guideline (AQG) level for the 24-hour mean concentration is 15 µg/m^3 ([9]. Although the measured PM2.5 emissions are not equivalent to a 24-hour mean concentration and the OpenHAP device was not calibrated using a gravimetric reference device, this gives an indication of the risks posed by using the high polluting cookstoves. Previous research by Jie Chen and Gerard Hoek[10], indicates that there is a clear increased risk for mortality even at exposure levels below 10 µg/m3 PM2.5 (below WHO AQG level). Further, research by Burnett et al[11] indicates that there is an increase in the hazard ratio of stroke, Chronic obstructive pulmonary disease and Lung cancer with the increased exposure to outdoor PM2.5.

Furthermore, although the kerosene and LGP stoves have lower PM2.5 emissions compared to the cookstoves using biomass fuels, they may still emit a high amount of carbon monoxide, NOx, and SOx, which were not measured in this project but are equally harmful to the environment and personal health.

FIGURE 20:
Mean indoor air pollution per cookstove type while the stove is in use and the standard deviation (error bar)



Room ventilation and exposure levels

The variability in the HAP results reflects the diversity of the respondents and their individual kitchen/cooking area setups, and whether they ventilate the room when cooking by opening a door or a window.

The level of ventilation, as measured using the ACR, illustrates that cooking in a multi-room house and with open windows allows for quicker ventilation of pollutants than in a single roomed house, even when using high polluting cookstoves. Unfortunately, this indicates that respondents living in single roomed house, usually people in the ultra-low-income demographic, are more prone to HAP than those with multi-roomed houses even in the same low-income region. It is advisable that people living in single roomed houses ensure ventilation within the house by opening doors and windows while cooking.

The analysis of the PM2.5 concentration time series showed that also non-cooking related events can lead to high peaks of indoor air pollution. These peaks can for example be caused by ambient dust entering the house through open doors/windows, indoor smoking or dust being stirred up through cleaning.

Although limited in its scope as non-representative, this study finds that during cooking the PM2.5 exposure of men is comparable to that of women in a low-income urban area context where gender roles in cooking are similar. Male respondents were found to be present near the cookstove only 4% less time than female respondents when the cookstove is on, which suggests comparable levels of exposure during cooking.

Lessons learned

This study evaluated the use of OpenHAP as a low-cost method of performing indoor air pollution measurement. The OpenHAP hardware and software was developed, manufactured and calibrated by EED in Nairobi. Through this study, a method to evaluate and normalize the field performance of particulate sensors was developed, tested and automated. It is recognized however that due to drift, such sensors may shift parameters and require additional normalization over time. The following are some of the limitations analysed in the data collection:

1. Participants using other stoves than the main stove indicated in the data collection exercise. In such cases, multiple OpenHAP installations per home would be required to capture the stove use of all cooking technologies in the home.

2. Limited space in the households, requiring the enumerators to judge where to best place the device to avoid obstruction to the cook. This led to depressed stove temperature readings in some households resulting in variations in stove temperatures, which occurred minimally above baseline measurement.

3. Presence of other participants using the same stove. This is the case where other members of the household start the cooking process when the main participant of the study is away.

4. Though the devices were normalized by co-location, they were not calibrated for error correction using a gravimetric PM2.5 sensing device. Therefore, the PM2.5 measurements are considered relative rather than absolute.

5. Sampling was conducted to provide a range of typical cooking technologies but was not a random/representative sample.

The level of ventilation, as measured using the ACR, illustrates that cooking in a multi-room house and with open windows allows for quicker ventilation of pollutants than in a single roomed house,

9. WHO. (2021). WHO global air quality guidelines: Particulate matter (PM 2.5 and PM 10), ozone,nitrogen dioxide, sulfur dioxide and carbon monoxide. Geneva https://apps.who.int/iris/bitstream/handle/10665/345329/9789240034228-eng.pdf?sequence=1&isAllowed=y

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11. Burnett, R., Chen, H., Szyszkowicz, M., Fann, N., Hubbell, B., Pope, C. A., Apte, J. S., Brauer, M., Cohen, A., Weichenthal, S., Coggins, J., Di, Q., Brunekreef, B., Frostad, J., Lim, S. S., Kan, H., Walker, K. D., Thurston, G. D., Hayes, R. B., & Lim, C. C. (2018). *Global estimates of mortality associated with long-term exposure to outdoor fine particulate matter.* Proceedings of the National Academy of Sciences, 115(38), 9592–9597. https://doi.org/10.1073/pnas.1803222115

This study builds upon the expected relationship between household income and the type of cooking solution. OpenHAP demonstrated that low cost, locally manufactured HAP measurement devices can generate valuable data on cooking practices, particulate emissions from different types of cookstoves and the related indoor air pollution exposure of inhabitants captured and analysed using the researcher's (EED) bespoke software tools. Although the measurements don't reach the accuracy and reliability of much more expensive measurement devices commonly used, they allow valuable insights in the complex interaction between cooking technologies and indoor air pollution in real life settings in low-income households.

Low-cost measurement devices can contribute to the development, implementation and the monitoring of policies and measures to mitigate indoor air pollution and its impact on resident's health. It sets the stage for advancing this exploratory study to a larger more inclusive study that can define high-level universal indicators of risk to HAP. Also, the role of ambient and non-cooking emissions needs to be further investigated, as it could contribute to similar or even higher health impacts. The researcher therefore proposes to scale up this research to build upon the outcomes of this study. Forthcoming research must consider the following issues to ensure a more robust study:

1. Improved placement of monitor for consistency, taking note of small cooking spaces and households that have young children who tend to play with the OpenHAP device.

2. Improved respondent sampling and training to ensure correct setup of the OpenHAP device.

3. Clear description of ambient conditions to understand the environment's impact on sensed data parameters.

A possible next step study would be to conduct a controlled kitchen test among the different cookstoves to explore the PM2.5 emission profiles of the cookstoves, devoid of ambient and respondent factors such as environmental dust, smoking and house cleaning that causes ambient dust, etc.

This OpenHAP study is important not only to determine exposure to cooking emissions at household level but also to provide policymakers, public health officials and the general public with adequate information on indoor air quality using low-cost methods. Discussions and results from this study are important for advocacy to improve indoor air quality. The data and knowledge is important in supporting programs that aim at reducing the use of traditional forms of cooking as well as dirty fuels. As a result of this study, the researcher has opened up discussions with the Kenya Medical Research Institute (KEMRI) on possible use of the device in monitoring county level indoor air pollution regulations.