ANALYSIS OF CLEAN ENERGY TECHNOLOGIES' EFFECTS ON ENERGY POVERTY: HOUSEHOLD AIR POLLUTION AND HUMAN HEALTH IN VIHIGA COUNTY, KENYA

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DECLARATION

This is an original work, and it has not been submitted to this or any other university for the purpose of earning a degree.

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DEDICATION

This thesis is dedicated to my parents, Mr and Mrs. Inaweti, and Minslet, who have been a continual source of encouragement and support as I have navigated the challenges of post graduate studies and life in general. I am incredibly grateful to have you in my life. I would also like to dedicate this work to the members of my Church family and to the several friends who have been encouraging me throughout this entire process. I will always value everything that each of them has done in their respective roles to make an impact on this work. I am also grateful to the Church family for setting good examples and encouraging me always to put faith and trust in God and work hard to attain my goals.

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ABSTRACT

Limited access to modern energy is a significant challenge in developing countries, substantially impacting the environment, economy, and human health. Although significant advantages are expected from the ongoing efforts to ensure universal access to clean energy, research on household energy characteristics and associated risks is very limited. This study analysed the effects of clean energy technologies on energy poverty: household air pollution (HAP) and human health in Vihiga County. Maslow's hierarchy of needs theory was applied. Specifically, the study sought to (i) evaluate factors affecting household decisions towards clean energy technologies, (ii) quantify household air pollution from cooking fuels and technologies and model its impacts on human health, and (iii) determine the effects of energy poverty on human health. To achieve the stated objectives, the study adopted a quantitative experimental design. A household survey of 487 households was conducted. The methods used include the probit model, multidimensional energy poverty framework, inverse propensity score weighting (IPSW), and marginal structural models. Particulate matter (PM_1, $PM_{2.5}$, and PM_{10}), Carbon monoxide (CO), and total volatile organic compounds (TVOCs) were used as HAP indicators. Particulate matter, CO, and TVOCs in 42 randomly selected households were monitored using the Multifunctional Air Quality Detector EGVOC-180 and Carbon Monoxide Meter. The AirQ+ v 2.1 model was used to simulate the health impact.

The probability that a household will use clean cooking fuels and technologies increased with increase in income, access to credit, male as household head, higher education attainment, and increase in age. Marital status (married) and number of rooms also enhanced the probability of using clean fuels for lighting, while unemployment suppressed the probability of using clean fuels and technologies for cooking and lighting. Kitchen PM_1, $PM_{2.5}$, $PM_{10,}$ and CO concentrations were observed to be higher for biomass cookstoves (three stone cookstove, improved cookstove (*chepkube*), ceramic *jiko*, and sawdust *jiko*) than for non-biomass cookstoves (kerosene stove, liquefied petroleum gas (LPG), and electric cooker). The maximum average $PM_{2.5}$ concentrations for the cookstoves were three stone (481.2 $\mu g/m^3$ ±119.9 $\mu g/m^3$), improved cookstove (*chepkube*) (304.3 $\mu g/m^3$ ±82.7 $\mu g/m^3$), ceramic *jiko* (162.4 $\mu g/m^3$ ±40.3 $\mu g/m^3$), sawdust *jiko* (273.1 $\mu g/m^3$ ±84.9 $\mu g/m^3$), kerosene stove (80.2 $\mu g/m^3$ ±14.3 $\mu g/m^3$), LPG (36.3 $\mu g/m^3$ ±6.5 $\mu g/m^3$), and electric cooker (29.5 $\mu g/m^3$ ±5.6 $\mu g/m^3$). The AirQ+ model results showed that approximately 484 (85.4%) annual mortality cases due to acute lower respiratory infection, Chronic obstructive pulmonary disease, ischemic heart disease, and lung cancer could be averted if households switch from biomass cookstoves (three stone) to clean cooking technologies (LPG and electricity). The multidimensional energy poverty index ranged between 0.580 and 0.726. Most (90.9%) households were classified in the multidimensional energy poverty bracket. A strong, statistically significant impact of energy poverty on health was confirmed. Causal relative risk and causal risk differences of 1.883 and 1.403, respectively, were obtained between energy poverty and health, implying that energy poverty is also a precursor to poor health. This study concludes that socio-economic and demographic factors affect household decisions on cooking and lighting fuels and technologies. Exposure to HAP among rural households in Vihiga county is a significant cause of cardiovascular, pulmonary, and respiratory diseases. Energy poverty also negatively impacts human health, especially poor respiratory health, e.g., cough, wheezing, and nasal irritation. The adverse effects of the energy-HAP-health nexus can be eased by (a) encouraging the use of solid fuels in a way that is more sustainable, efficient, and less polluting, and (b) facilitating the transition to modern, clean, and environmentally friendly cooking fuels and technologies.

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ABBREVIATIONS AND ACRONYMS

ALRI - Acute Lower Respiratory Infection

AQGs – Air Quality Guidelines

CIDP – County Integrated Development Plan

COPD - Chronic Obstructive Pulmonary Disease

COV – Coefficient of Variation

GACC – Global Alliance for Clean Cookstoves

GHGs – Greenhouse Gases

HAP – Household Air Pollution

IAP – Indoor Air Pollution

ICS – Improved Cookstove

ICT – Information, Communication and Technology

IEA – International Energy Agency

IPSW – Inverse Propensity Score Weighting

IPTW – Inverse Probability of Treatment Weighting

IHD - Ischemic Heart Disease

KNBS – Kenya National Bureau of Statistics

LIHC - Low Income High Costs

LMIC – Low and Middle Income Countries

LPG – Liquefied Petroleum Gas

MEPI – Multidimensional Energy Poverty Index

MIS - Minimum Income Standard

PM_1 - Particulate matter that has a diameter less than one microns (1µm)

$PM_{2.5}$ - Particulate matter that has a diameter less than two and a half microns (2.5µm)

PM_{10} – Particulate matter that has a diameter less than ten microns (10 µm)

SD – Standard Deviation

SDGs – Sustainable Development Goals

PS – Propensity Score

SRH – Self-Rated Health

TB – Tuberculosis

VOCs – Volatile Organic Compounds

TVOC – Total Volatile Organic Compounds

WHO – World Health Organization

DEFINITION OF KEY TERMS AND CONCEPTS

Acute lower respiratory infections - Acute lung diseases such as acute bronchitis and bronchiolitis, influenza, and pneumonia (WHO, 2014).

Air Pollution - Solid particles, liquid droplets, and gases make up most of the air pollution we see. Many factors can cause air pollution, including open waste burning, industrial emissions, transportation exhausts, home and commercial fuel burning, power generation, and agricultural operations (WHO, 2021b).

Biomass fuel refers to all biological material, living or dead, but excludes that which has become fossilised or mineralised that are purposefully burned for household energy. Biomass energy is a renewable energy resource that includes all plant matter (trees, crops, crop residues, animal dung etc.) (Hemstock et al., 2019).

Chronic obstructive pulmonary disease - A group of chronic lung disorders defined principally by persistent airflow obstruction from the lungs (WHO, 2014).

Emissions - The rate at which a pollutant is released per unit of time or per unit of fuel. Often measured directly from the combustion source, it can be done in the lab or the field (Anenberg et al., 2017).

Energy poverty – The concept of energy poverty refers to a household's inability to provide essential energy services such as lighting and heating in their homes at affordable costs. It is the absence of sufficient options for obtaining and utilising adequate, affordable, reliable, high-quality, safe and environmentally benign energy services to support economic and human development (Kumar, 2020b).

Energy security - the constant (uninterrupted) and reasonable (affordable) availability of energy sources (International Energy Agency) - IEA).

Fuel or technology adoption – is the initial purchase/acquisition of a fuel or technology and subsequent utilisation in the immediate future (less than one year) (Guta et al., 2022)

Household - one or more people residing under the same roof and using the same kitchen facilities (Beaman & Dillon, 2012).

Household air pollution - Air pollution that results from the combustion of domestic fuels, which leads to indoor air pollution and adds to the overall level of air pollution in the environment (WHO, 2014).

Household energy use refers to domestic energy services provided by direct combustion of fuels such as biomass, fossil fuels, etc., to meet household energy needs for cooking, lighting and space heating. This study also categorises electricity among household energy sources (Leal Filho et al., 2020).

Improved cookstove - a cooking stove that is more efficient and emits less indoor air pollution or is safer than the traditional cookstoves or three-stone stoves. Improved cookstoves burn firewood, charcoal, agriculture residues or dung (Leal Filho et al., 2020).

Indoor air - air contained within a building that has been occupied for at least one hour by individuals in varied states of health (WHO, 2005).

Indoor air pollution refers to a condition within a building in which specific substrates (e.g., gases, aerosols, particulates, etc.) are present in a form and concentration that can produce undesirable effects to people and their environment. Biomass which is burned for cooking, heating and lighting homes, is recognised as the primary source of indoor air pollution (United States Environmental Protection Agency - EPA).

Ischemic heart disease - Disease characterized by reduced blood supply to the heart (WHO, 2014).

Modern energy - In the context of cooking and heating at household level, this term has been used to refer to the use of electricity, solar, biogas and sources other than solid biomass.

Pollutant concentration - Pollutant mass as a percentage of volume of air. The level of emissions and room characteristics like ambient concentrations and ventilation rates, as well as processes like pollutant deposition on surfaces, all contribute to indoor concentrations. In houses, concentrations are typically monitored by mounting a monitor on the wall for 24 hours in a specific room, such as the kitchen or living room. Individuals' presence is not considered when calculating concentrations (Anenberg et al., 2017).

Sustainable use - signifies using a fuel/technology for a medium to lengthy period (more than a year) (Guta et al., 2022).

CHAPTER ONE

INTRODUCTION

This chapter presents the background, objectives, justification, scope, and limitations of this study on clean energy technologies' effects on energy poverty; household air pollution, and human health.

1.1 Background

Energy security, energy consumption, and emissions reduction are widely acknowledged as the most significant environmental challenges of our time while also essential for advancing social and economic conditions and enhancing human well-being. The current global energy agenda is mainly concerned with eliminating energy inequalities in terms of access and quality. Following the Sustainable Development Goals and the 2015 Paris Agreement, all countries are striving to offer affordable and clean energy to all by 2030 (Wang et al., 2021).

There have been significant gains in the overall quality of life and well-being in other areas, as indicated by measures such as education, social integration, and life expectancy, among others, over the past several decades. Nonetheless, a significant proportion of the world population have not reaped the benefits of the advancements and continue to live in deplorable conditions, particularly regarding modern energy access. Generally speaking, energy is not viewed as a fundamental human requirement. However, it is a prerequisite for addressing the vast majority of essential human needs. While energy is the driving force behind social and economic growth, it is also the epicentre of some of the most pressing social, economic, and environmental concerns of our time (Kumar, 2020a). Recent studies portray a troubling emerging trend in the provision of essential household energy services such as cooking and heating, with about two billion people still reliant on solid biomass for these services (IEA et al., 2019; Ouedraogo, 2017).

Clean energy access and energy equity have received more attention worldwide. The United Nations General Assembly proclaimed 2012 the international year of sustainable energy for all. However, despite these efforts, the world population without electricity access stood at 636 million people in 2021, while more than 2.5 billion people had no access to clean cooking energy the same year (IEA, 2021b). Asia and Sub-Saharan Africa are home to the vast majority (about 95%) of the world's population without access to modern energy. In Sub-Saharan Africa, modern energy access is very low, prompting more households to rely on solid biomass for essential energy services. Solid biomass use for cooking and heating is of great concern because of its role in Household Air Pollution (HAP), which adversely affects human health and is also a source of carbon-based greenhouse gases (Chakraborty et al., 2014). Based on a study by Mbaka et al., (2019), Kenyans use solid biomass as a primary energy source to the tune of 68% of the total energy consumed, implying that approximately three-quarters of the country's population is entirely reliant on biomass for their lighting, heating, and cooking needs.

Since the 1970s, several programs have been launched throughout Africa, Asia, and South America with the goal of increasing access to clean energy. Most developing countries have implemented initiatives to encourage the uptake and use of clean energy technologies such as solar, biogas, liquefied petroleum gas (LPG), and improved cookstoves at the household level. For example, access to clean energy is one of the most fundamental goals pursued by national plans in Kenya, such as the Least Cost Power Development Plan 2017–2037, Vision 2030, grid extension renewable off-grid solutions, the last mile connectivity, among others. The objectives of these programs and plans have been to relieve households of indoor air pollution (IAP) (Deng et al., 2020), reduce deforestation (Bensch & Peters, 2013; Brooks et al., 2016) and environmental emissions, and also save users' resources (Urmee & Gyamfi, 2014).

Although some initiatives like the last mile connectivity have achieved their objectives, addressing users' needs remains a challenging issue, resulting in the failure of several programmes, e.g. Least Cost Power Development Plan 2017–2037 and Vision 2030 (Gebreegziabher et al., 2018). This failure is partially caused by the fact that, in developing countries, diverse energy sources may suit varied energy demands, which presents a significant issue. For example, electricity is mainly utilised for lighting and powering electrical equipment, but it is rarely used for cooking due to high tariffs (Ang'u et al., 2020). The same is valid with solar energy. As a result, despite achieving high rural electrification rates in recent years, Kenya's rural areas continue to suffer from high levels of energy poverty (Kioli & Ngare, 2019). Although LPG is a feasible choice, the high cost of refuelling makes it less accessible to rural households. This has resulted in initiatives such as improved cook-stove programs, which disseminate improved cook-stoves in rural communities with high concentrations of firewood users. Improved cook-stoves use biomass and are designed to maximise fuel efficiency, shorten cooking time and minimise emissions (Shankar et al., 2014).

Currently, greater emphasis is being placed on cleaner energy solutions, including improved cookstoves (ICS), smallholder solar-powered energy devices (such as solar lamps), biogas, LPG, and rural electrification programmes, among others. Improved cookstoves and solar-powered devices provide 'triple benefits' in terms of health improvement and time-saving while maintaining forests and their ecosystem services and reducing emissions, thereby mitigating the adverse effects of climate change (Bensch et al., 2021). Despite the benefits of clean and renewable energy technologies, there has been plodding progress in their adoption and utilization (Chanchangi et al., 2022). Explanations for low adoption and sustained use have focused on behavioural and cultural aspects and financial barriers. However, these explanations are inconsistent with the diffusion of other technologies, which has been easier despite behavioural, cultural, and economic implications.

1.2 Problem Statement

It is well acknowledged that energy impacts several sectors of the economy and influences sustainable development and environmental management initiatives (Liko, 2019). Energy has also been at the centre of environmental governance measures worldwide and features prominently in various multilateral environmental agreements. These global-scale initiatives have focused mainly on the climate impacts of energy use. However, household energy use is responsible for the most pertinent repercussion of energy due to its impact on human health (González-Eguino, 2015). The World Health Organization (WHO) recognises that energy is a prerequisite for good health and estimates that unclean energy accounts for over 3.8 million deaths annually, more than malaria or tuberculosis (WHO, 2021a). Combustion of coal, agricultural residues, and solid biomass in different forms using inefficient and traditional cooking technologies is a major source and contributor to HAP (Wang et al., 2016). Moreover, incomplete solid fuels combustion produces harmful gaseous and particulate pollutants, hydrocarbons, carbon monoxide, nitrogen and sulphur oxides, and inhalable particulates. These pollutants, particularly fine particulate matter, are harmful to human health (Giani et al., 2020; Ni et al., 2021). Exposure to indoor air pollution is associated with acute and chronic diseases, including acute lower respiratory infections and cardiovascular diseases (Zhang et al., 2018). The ultimate impact of these diseases is higher premature mortality and morbidity rates. The underprivileged who fall within the energy poverty bracket spend a significant part of their time and energy on essential household activities like wood fuel collection. Consequently, this limits the ability of these populations to improve their living conditions by engaging in other gainful activities.

1.3 Objectives

1.3.1 Main objective

This study's main objective was to analyse the effects of clean energy technologies on energy poverty: household air pollution and human health in vihiga county, Kenya.

1.3.2 Specific objectives

The specific objectives were to:

i) Evaluate factors affecting household decisions towards clean energy technologies in Vihiga county

ii) Quantify household air pollution from cooking fuels and technologies and model its impact on human health

iii) Determine the effects of energy poverty on human health

1.4 Hypothesis

The following hypotheses were tested in order to attain the aforementioned objectives.

H_o: Socio-economic, demographic, and household governance factors do not affect a household's decisions towards clean fuels and technologies.
H_1: Socio-economic, demographic, and household governance factors affect a household's decisions towards clean fuels and technologies.

H_o: Solid biomass cooking fuels and technologies do not account for more household air pollution than non-biomass fuels and technologies
H_1: Solid biomass cooking fuels and technologies account for more household air pollution than non-biomass fuels and technologies.

H_o: Energy Poverty has no effect on human health"
H_1: Energy poverty negatively affects human health

1.5 Justification

Three significant phenomena are expected to plague the energy sector in the coming decades: energy security, climate change, and energy poverty (González-Eguino, 2015; Kyriakopoulos et al., 2022). Energy security and climate change have been extensively studied, however, energy poverty has received less scrutiny. Access to modern, affordable, and sustainable energy is one of the United Nation's 2030 Agenda goals for Sustainable development. The global energy demand was predicted to rise by approximately 4.6% in 2021, with developing countries accounting for 70% of the projected increase (IEA, 2021a). Unless there is a dramatic shift in energy use patterns across developing countries, especially in sub-Saharan Africa, the rise in energy demand will likely have its share of repercussions. Most sub-Saharan African populations rely heavily on traditional biomass fuels as their primary energy source. More than 59% of total primary energy in these countries is sourced from biomass (UNCTAD, 2017), which is combusted inefficiently (Khatiwada et al., 2019).

Traditional biomass fuels, including wood fuel, charcoal, and other agricultural residues, poses challenges, derailing sustainable development. Wood fuel impact public health (Gordon et al., 2014; Jagger & Shively, 2014; Lim et al., 2012), contribute to deforestation (Rudel, 2013) and climate change. Climate impacts of wood fuel are attributed to CO_2 emissions resulting from the portion of wood fuel that is harvested unsustainably (Bailis et al., 2015). Incomplete wood fuel combustion also produces methane (CH_4), black carbon, and other short-lived climate pollutants (Bond et al., 2013). Thus, lowering emissions from conventional biomass and fossil fuels is critical since it is anticipated to significantly reduce public health concerns, deforestation, and greenhouse gas emissions.

Although there has been increased public awareness of the link between energy use and health, this has not been reflected in actual practice. Moreover, most rural populations in Sub-Saharan Africa will continue to rely on biomass for the foreseeable future (World Bank Group, 2019).

Health effects resulting from biomass combustion occur at different levels – household, community, regional and global. A study on HAP is necessary because humans spend about 80-90% of their time indoors (Saini et al., 2020), and 90% of households in developing countries depend on solid biomass fuel, which is burnt in open fires and simple stoves without proper ventilation (Majdan et al., 2015).

Household air pollution is a significant environmental risk factor for human health, particularly in low and middle-income countries. In 2019, it was estimated that about 60% of the World's population in rural areas rely primarily on unclean fuels and technologies (WHO, 2021c). It has been established that incomplete biomass combustion produces harmful by-products such as carbon monoxide (CO) and particulate matter (PM). These by-products have been linked to deleterious impacts on human health and the environment. However, a disproportionate amount of research on household energy usage and emissions in Africa has placed a premium on the efficiency of cooking devices, with very few examining the health consequences. Therefore, most evidence of energy use-HAP-health nexus is from the high income countries and countries outside Africa (Huang et al., 2017; Li et al., 2021; Mu et al., 2013), even though Africa accounts for the majority of global biomass users for household energy needs (WHO, 2021c).

In addition, a few studies in sub-Saharan Africa have investigated HAP from the perspective of clean and unclean household fuels and technologies, with most studies examining a single technology (Majdan et al., 2015). Although HAP is a global problem, regional and local disparities exist due to environmental and social factors, climatic conditions, housing characteristics, and fuel types. This and the heterogeneity in household cooking practices have affected emissions monitoring outcomes, thus making most HAP assessments inadequate. There is also limited evidence that HAP interventions yield health benefits.

The western region of Kenya has one of the country's worst energy poverty rates. The energy poverty index in this region of Kenya was reported to be 0.8 (Nussbaumer et al., 2012, 2013) in 2012, which was second only to the North-Eastern part of Kenya, where the energy poverty index was found to be 0.91. The western region of Kenya is characterised by high population density, with most of the population residing in rural areas. For instance, Vihiga County is Kenya's third most densely populated county, with 1,047 people per square kilometre (KNBS, 2019). Though Vihiga county is rural, its population density is higher than most city/town counties in Kenya.

This work will catalyse the design of policies, regulations, and financial plans to address HAP and health-related problems and accelerate the uptake of clean fuels and technologies in rural areas. Identifying significant causal links will be critical in developing effective interventions to improve the health of those living in energy poverty settings.

1.6 Scope and Limitations

The focus of this study was household fuels, technologies, and practices and their effects on HAP and human health. HAP is measured indoors and results from domestic activities, including cooking, lighting, and heating. Products of incomplete biomass combustion include CO, PM, VOCs, and NO_2. Therefore, the pollutants of interest in this study were CO, PM, VOCs, and NO_2. In contrast, outdoor air is the ambient air in the neighbourhood instead of that inside building. Industrial effluents, traffic, agricultural activities, and solid waste management contribute to outdoor pollution. Selected outdoor air pollutants (CO and NO_2) attributed to energy use were also investigated. The nature of this research may omit other aspects that are likely to influence individuals' HAP exposure and health. However, most factors associated with household energy use, HAP, and associated health consequences were considered. Only air pollution-related health consequences were investigated.

A limitation of this study is that the outdoor pollutants were not recorded. However, the sampling frame was carefully selected to ensure that outdoor pollution could not interfere with the measurements. This was achieved by sampling households that were not within the vicinity of any polluting sources. Robust checks were also implemented, including monitoring pollutant concentrations before the tests were conducted to ascertain that the air quality was within the acceptable range. In addition, no extreme events such as gusts, outdoor fires or rainfall were observed throughout all the monitoring sessions. Other sources of uncertainties in the survey conducted include fuel stacking. Even though fuel stacking was identified in some cases, the study focused on the primary fuel used by households. The primary fuel was also the basis for estimating pollutants concentration. The cross-sectional point estimate as opposed to the longitudinal design is also a limitation of this study.

This thesis is broken into five major sections. Chapter one comprises the background information, objectives, problem statement and the study’s justification. Chapter two is on literature review, including the conceptual and theoretical frameworks. The literature in chapter two is presented systematically in line with the study’s objectives. Chapter three describes the study’s materials and methods. The approaches this study undertook to achieve the three objectives are discussed in detail in chapter three. Chapter four presents the study’s findings and discussions in line with the objectives. Conclusion and recommendations are covered in the last section.

CHAPTER TWO

LITERATURE REVIEW

2.1 Introduction

This section reviews past work on the effects of household energy technologies on energy poverty, HAP, and human health. The purpose of this review was to critically examine the existing literature to identify areas where further research is needed. This review begins by examining the corpus of research surrounding the factors affecting household energy choices. This is crucial because, subject to certain limits, household energy decisions will determine the extent of energy poverty. Reviewing household energy decisions was aimed at determining which factors support clean or unclean fuels and technologies. Consequences of decisions favouring unclean fuels and technologies include HAP and the associated health impacts. Consequently, the second section focuses on HAP from household fuels and technologies and its health impacts. However, HAP alone is insufficient to explain the health impacts of household energy use. The third section introduces the concept of energy poverty, a holistic approach encompassing HAP, clean energy, and modern energy services. The research gaps and conceptual and theoretical frameworks are presented in the subsequent sections.

A wide number of sources were used in this study, including peer-reviewed journals, reports, and research archiving databases such as Science Direct, PubMed, Web of Science, Google Scholar, and university research repositories.

2.2 Factors Affecting Household Energy Choices

2.2.1 Overview of Household Energy Options

Most end-use energy services in developing countries are for household cooking. However, this is not the case in developed countries, where other end-use functions such as space heating or cooling, entertainment, food processing, and washing or cleaning take primacy (Daioglou et al., 2012). The type of energy services provided determines the application of energy technologies. For instance, in developing countries, solid fuels, kerosene, LPG, and biogas are the most prevalent fuels and technologies. However, LPG constitutes a minor portion of residential energy consumption, whereas electricity is typically utilised for lighting and powering basic electronics rather than cooking and heating (Malla & Timilsina, 2014). Most of the energy used for cooking in developing countries comes from solid fuels (Arku et al., 2018).

Solid fuels can be utilised in a variety of ways using different stoves. Some examples include wood, coal, animal manure, and crop waste. These fuels are used in a wide range of stoves, necessitating research into the development of fuel-efficient and environmentally friendly stoves, commonly referred to as improved cookstoves (ICS). Common ICSs in Kenya include *jikokoa*, ceramic *jiko*, and *chepkube*. Although some of these ICSs offer improved performance, their higher upfront costs have been an obstacle to widespread adoption (Sharma & Dasappa, 2017). Alternative sustainable energy sources that can help reduce air pollution from cooking, such as biogas digesters, are also plausible fuel options for resource-scarce countries. In addition to being a source of cooking fuel, biogas digesters also produce reusable fertiliser and facilitate sustainable waste disposal (Tumwesige et al., 2017). However, when compared to ICS, initial acquisition and maintenance costs have been the major hindrances to biogas use.

Significant regional and national variances exist in the percentage of the population that use solid fuels, with Sub-Saharan Africa, South-East Asia, and the Western Pacific reporting the highest rates (Puzzolo & Pope, 2017). Solid fuels are typically considered unclean fuels with high emission levels than modern ones. Clean fuels either do not produce indoor air pollution (mainly CO and particulate matter) or, if they do, the concentration is very low (Kapsalyamova et al., 2021). Consequently, LPG, biogas, solar, and electricity are frequently classified as clean fuels, whereas all forms of solid biomass and coal are considered unclean fuels. Recently, kerosene was added to the list of fuels that are responsible for HAP (WHO, 2016). Kerosene is therefore also classified as an unclean fuel, as recent research has demonstrated that its effect on HAP is significant.

Household fuel choices are influenced by a complex network of social-economic factors, varying considerably from country to country. These factors can be categorised into household preferences, socio-demographic factors, economic factors (incomes or expenditure and prices or costs), technological characteristics, energy supply factors, and other external factors (Guta et al., 2022; Muller & Yan, 2018).

2.2.2 Economic Factors Affecting Household Energy Decisions

Income features prominently in econometric studies on factors affecting household fuel choices. This is because income is the simplest economic indicator of affordability. A household's income has been demonstrated to positively affect the adoption of renewable energy technology in industrialised countries such as the United States of America (Masrahi et al., 2021). In developing countries, Mperejekumana et al., (2021) demonstrated that access to credit increases the probability of using LPG in South Sudan. However, the study only included LPG, charcoal, and firewood as fuel options, and thus, it does not provide information on how other energy sources, such as electricity and biogas, would fair in this situation. Similarly, Karimu et al., (2016) reported that income was a major factor in households' selection of LPG as the primary cooking fuel in Ghana. In developing countries, income is a significant enabler of the sustained use of modern fuels such as LPG. In situations with a high uptake of LPG, such as in the peri-urban household in Ecuador, the fuel is heavily subsidised (Gould et al., 2020).

To shift from traditional fuels such as biomass to modern fuels such as LPG and electricity, income and credit are crucial. This, however, is not true for all conventional and modern fuels. According to Mbaka et al., (2019), the likelihood of utilising charcoal increases as household income rises. However, such households were less likely to consume fuel wood than lower-income households. These findings illustrate a classic incidence of fuel stacking, in which modern fuels have failed to displace traditional fuelwood, and even affluent households continue to use fuelwood alongside modern fuels (Baiyegunhi & Hassan, 2014). Households use various fuels for various reasons, including price fluctuations, unstable service or supply, and more familiarity with traditional cooking methods. In South Africa, Adeeyo et al., (2022) reported that wood fuel use was significantly influenced by income.

Other studies have also examined energy pricing and how it affects household energy decisions. Evidence from existing literature demonstrates that fuel price negatively affects the probability that a household will embrace that fuel. Rural homes typically prefer less expensive fuels that can fit locally designed stoves. For instance, fuelwood is preferred over charcoal since traditional three-stone cook stoves are more readily available. The high cost of solar home systems continues to be a significant obstacle to the widespread use of solar power for residential lighting in developing countries. Apart from concerns about the upfront costs, several modern energy technologies like solar home systems also raise questions about expected financial returns and operation and maintenance costs (Lo et al., 2018; Rai et al., 2016). In addition, Puzzolo et al., (2016) note that for many households that currently use traditional fuels, LPG is an aspirational fuel. However, the initial investment cost is a major deterrent, especially for low-income households.

When the cost of a particular fuel goes up, consumers are more likely to switch to an alternative fuel that is less expensive. For example, a hike in kerosene prices reduces kerosene consumption. However, this does not necessarily cause a shift towards modern fuels. Rather, households turn to more affordable fuels such as fuelwood. Lee, (2013) reported that fuelwood pricing affects kerosene consumption in Uganda. This suggests that kerosene may replace fuelwood as a cooking fuel when fuelwood becomes costly. As modern fuel prices rise, households in developing countries like Ghana are turning to more affordable traditional fuels like charcoal and firewood (Bofah et al., 2022). However, Muller & Yan, (2018) note that most of the evidence on the substitutability of fuels based on prices is deduced from direct price effects and lacks the robustness of consumer models. In addition, although an increase in fuel price is expected to reduce fuel use, it is also feasible for fuel consumption to increase if household income increases (Yalcintas & Kaya, 2017).

Subsidies are a remedy for price barriers to acquiring modern energy technologies. This has been successful in Peru, where the Peruvian government implemented the “Fondo de Inclusión Social Energético” FISE programme to encourage the use of LPG by providing subsidies (Wolf et al., 2017).

In Kenya, Baek et al., (2020) reported that when a household’s income improves, the likelihood of choosing grid electricity as its primary lighting fuel likewise increases. The study utilised multinomial probability models with macro-level survey data, omitting micro-level effects. Using stepwise multiple regression, Kariuki, (2021) came to the same conclusion in Kenya on the socioeconomic determinants of fuelwood and charcoal use. The narrow focus on only one energy source (biomass) is a significant limitation of the study by Kariuki, (2021). In addition, the study excludes micro-level effects due to its reliance on macro-level data. More evidence in Kenya shows that income is a key determinant of adopting solar home systems (Lay et al., 2013).

Affordability has also been a major impediment to the widespread adoption and sustainable use of clean energy solutions. Even the simplest clean energy technology, such as improved cookstoves, are underutilised due to their perceived high costs. Households in the counties of Machakos and Laikipia in Kenya have mentioned high costs as a major barrier to their adoption of ICS (Nzengya et al., 2021). Low-income households may not prioritise ICS when cheaper options, such as the conventional three-stone stove, are available. Their spending focuses on essentials such as food, clothing, and school expenses. In addition, rural households may lack basic knowledge and understanding of the environmental and health benefits of clean energy technologies over the long run.

In metropolitan areas, where energy consumption patterns differ greatly from those in rural areas, the effect of income on fuel choices is also obvious. In Kenya's urban areas, an increase in a household's income is associated with a reduced likelihood that the household will select kerosene rather than charcoal as their fuel source (Waweru & Mose, 2022). This is especially true for low-income urban residents transitioning from traditional biomass to cleaner fuels. However, higher household income has been associated with a higher likelihood of using cleaner fuels in both urban and rural settings.

2.2.3 Socio-demographic and Cultural Factors Affecting Household Energy Decisions

When assessing the factors impacting household fuel choices, researchers have also investigated factors such as household energy preferences and socio-demographic patterns. Household energy preferences and demographic patterns comprise a wide range of factors, including household size, age, gender, occupation, education, food taste preferences and lifestyle.

Varied schools of thought have surfaced among scholars regarding the role of age. Researchers have documented a shift to modern fuels among the elderly. Chattopadhyay et al., (2017) found that older people are more inclined to adopt cleaner fuels than younger people in India. Older individuals may have more savings than younger individuals and be able to afford cleaner fuels. Danlami et al., (2019) also found a positive relationship between the age of a household head and the probability that the household will adopt electricity as the main lighting source. A study in Turkey by Özcan et al., (2013) found similar results when examining factors affecting home energy use. In India, Brooks et al., (2016) reported that older female household heads are associated with improved cookstoves usage rates compared to younger female household heads. It is realistic to anticipate that as time passes, the household head's salary will increase, allowing a household to afford expensive energy sources. This premise holds if all other factors remain constant as one ages.

In Nigeria, Onyeneke et al., (2019) reported that the use of more efficient improved cookstoves was negatively affected by advancing age. Similar findings are reported by Li et al., (2021) for solar PV in China, Gebreegziabher et al., (2012) for electricity transition in Ethiopia and Rahut et al., (2014) for clean cooking and lighting technologies in Bhutan. These studies show a tendency towards traditional fuels with increasing age. The reasons for this trend are varied. For instance, Rahut et al., (2014) ascribe the preference for fuelwood among elderly heads of households to traditional practices, while Li et al., (2021) attributed it to adoption unwillingness. Moreover, it is more challenging to alter long-established cooking patterns and behaviour. The literature presents diverse views on the role of age on household energy choices, thus require further investigation.

Also commonly addressed as affecting household energy decisions and technology adoption generally, is gender. On how this variable affects a household's energy decisions, there is disagreement, nevertheless. For instance, Rahut et al., (2014) and Bhojvaid et al., (2014) reported that households headed by females tend to prefer modern fuels, which is inconsistent with Link et al., (2012a), who reported a tendency towards traditional fuels in female-headed households in rural Nepal. In numerous distinct social and demographic contexts, gender roles can be shown to play considerably varied functions. In some societies, women are often the principal users and beneficiaries of modern cooking technologies. As a result, women may profit more from adopting these technologies than men. According to Jagger et al., (2019), households that have female chefs did well in early adoption of improved household energy systems in Rwanda.

Attainment of higher levels of education has been associated with a decrease in the use of traditional fuels (Baland et al., 2015). The household's head education level has been found to positively affect the propensity to use cleaner fuels (Nlom & Karimov, 2015). Higher education increases the likelihood of utilising clean fuels and decreases the likelihood of using firewood and charcoal (Alem et al., 2016). Those with a university degree and the literate are more likely to use clean fuel (Dendup & Arimura, 2019). This is so because household members with higher levels of education are more aware of the advantages of switching to cleaner fuels and the dangers of cooking with biomass. On the other hand, education may be influenced by other factors such as income, with higher levels of education often implying more income. However, in rural Tanzania, Kulindwa et al., (2018) found no evidence of a link between better education and increased use of improved cookstoves.

Household size also impacts energy choices; in general, an increase in household size has been linked to the usage of unclean fuels. Soltani et al., (2019) found a negative relationship between LPG adoption and household size in Iran, whereby small-sized households were more likely to use LPG than larger households. In Afghanistan, Paudel et al., (2018) also concluded that larger households are less likely to embrace clean cooking fuels. This trend is likely attributable partly to economies of scale and the fact that larger households are frequently associated with high poverty rates. Mohapatra & Simon, (2017) opined the characteristics of a modern stove might make it more difficult to prepare meals for larger groups. In addition, cleaner fuels, such as LPG, tend to be prohibitively expensive for larger households, who typically choose cheaper options. However, Baiyegunhi & Hassan, (2014) and Thomas et al., (2016) reported a paradoxical trend in which larger households tend towards cleaner fuels. Cooking in large families requires substantial time and fuelwood, hence large households would prefer more efficient cooking methods than smaller ones. Other studies have reported absence of a relationship between household size and the sustained use of cleaner fuels (Mamuye et al., 2018; Mohapatra & Simon, 2017).

Social and cultural factors play a significant role in households' choices regarding energy systems. In fact, the failure of most clean energy programs has been linked to a disregard for local culture and social context. Common issues include low cultural acceptance of improved cookstoves to suit daily cooking needs (Rehfuess et al., 2014). Other studies have reported that a household's choice of cooking fuel is typically impacted by the type of fuel used by its peers (Jagger & Jumbe, 2016; Martin et al., 2013). In Ethiopia, Asgele & Teklencheal, (2020) found that 71.9% of households who adopted improved cookstoves had early adopter neighbours. Peer influence may operate as both an enabler and a barrier to adopting and sustaining new household energy technologies. For instance, positive peer influence emphasising modern cooking technologies' cleanliness, affordability, and effectiveness encourages their acceptance and use. In contrast, unfavourable peer remarks such as excessive smoke or broken cooking pots hindered uptake (Seguin et al., 2018).

Solid fuel use for cooking is linked to other structural components, including ingrained customs and a sense of community. The use of new cooking technology increases when the technology has a good reputation for being compatible with local cooking customs (Adane et al., 2020; Tigabu, 2017). When determining whether to implement new cooking technologies, other factors tied to the local culture include cooking techniques, taste, and dietary preferences.

Researchers have observed that a possible hurdle to the widespread use of LPG stoves is the desire to retain the distinct flavour of food cooked on conventional stoves (Goswami et al., 2017; Hollada et al., 2017). For instance, the study by Goswami et al., (2017) reports that *Chapatti*, a traditionally prepared delicacy in India, is prejudiced against the use of improved cookstoves. Traditional cookstoves are designed to accommodate specific cooking techniques and fuels. The stoves make it easy for users to cook and are also simple to maintain. Nguyen, (2017) opined that stove users in Timor-Leste might struggle with patience, self-training, and learning how to adapt to new energy technologies because of cultural issues. In addition, Akintan et al., (2018) concluded that traditional norms and taboos peculiar to a particular ethnic group significantly impact fuel selection and cooking behaviours in Nigeria.

However, some studies have reported that adopting modern household energy technologies is not always associated with local culture. A lack of interest in improved cookstoves in Burkina Faso is not attributable to a desire for traditional cooking, as reported by Bensch et al., (2015). In addition to cultural factors, other technology-related preferences have been found to influence household energy decisions. Women in Western Kenya favoured the improved cook stove over the conventional three-stone stove due to its simplicity of use, fuel efficiency, reduction in smoke, and health benefits (Loo et al., 2016).

2.2.4 Environmental Factors Affecting Household Energy Decisions

Environmental factors influencing household energy choices have also been investigated by researchers. This is partially a result of the challenges in accounting for these variables in quantitative investigations. However, effects of environmental factors such as climate change are evident in some studies. For instance, Vurro et al., (2022) investigated climate change influences on energy choices and efficiency measures in households of Bari, Italy. The study by Vurro et al., (2022) reports that heating requirements during winter and cooling requirements in summer are the main determinants of household energy requirements with regards to the climate. The extent to which climatic factors affect household energy choices depends on other factors such as income and location. Higher temperatures in summer increase electricity demand for cooling while low temperatures in winter increase electricity demand for heating. However, climate change has been reported to decrease household heating requirements and increase household cooling requirements (European Commission. Joint Research Centre., 2018). With increasing effects of climate change, household energy efficiency measures will serve as a suitable remedy for cooling and heating requirements.

2.2.5 Other External Factors

External factors are those factors outside a household that might affect energy use decisions. Recent literature has emerged on external factors affecting household energy decisions. Access to markets and geographical location are some factors that fall into this category (Bharadwaj et al., 2022). In addition, there is a dearth of robust political and communal networks (Neto-Bradley et al., 2021). The availability of more established consumer markets for various types of fuels is a significant impetus for the proliferation of cooking stoves (van der Kroon et al., 2014). While some of these factors are contextually relevant, their evaluation alongside specific household characteristics is contingent on the climatic and geographical variability of the study area. This approach is consequently appropriate for geographically expansive investigations and may not offer value to micro studies that focus on homogenous zones.

Access to and utilisation of modern, clean energy alternatives, such as solar, LPG and grid electricity, is still limited in developing countries, particularly for cooking. Therefore, biomass remains the most viable fuel for the foreseeable future. In light of this fact, there have been efforts to design cook stoves that are more efficient and suitable for biomass use, particularly in rural areas. Improved cookstoves and fuel programmes have been implemented in developing countries for decades, but they have only had limited success. This demonstrates the difficulties associated with modernising energy. Previous research has also attributed this trend to cultural, political, institutional, and environmental factors (Vigolo et al., 2018).

2.2.6 Energy Poverty

Under household energy decisions, energy poverty can be used to refer to the propensity towards unclean household fuels and technology. Energy poverty conditions may worsen because of the socioeconomic factors discussed above. For instance, since household income can affect other characteristics like education level and energy expenses, which might affect energy poverty, it can be thought of as a significant driver of energy poverty (Halkos & Gkampoura, 2021). Energy poverty is typically correlated with higher poverty levels, particularly in rural regions (Thomson & Snell, 2013). Section three offers a more thorough explanation of energy poverty and its measures.

The evaluated literature reveals contradictory findings regarding the effects of different variables on household energy decisions. The effects of the vast majority of socioeconomic, demographic, cultural, and environmental factors on household energy choices are still controversial and inconsistent. Furthermore, earlier research has primarily concentrated on improved cookstoves in developing nations, ignoring other clean energy technologies and fuels utilised at the household level. This necessitates more research into the factors contributing to the sustained use of clean fuels and technologies, particularly from a holistic perspective that considers all the energy options accessible to households. In addition, effective policymaking and implementation of energy transition require the understanding of choices and determinants of household energy.

2.3 Household Air Pollution and Human Health

The term "Household Air Pollution" (HAP) refers to the air pollution that results from the combustion of domestic fuels, which leads to indoor air pollution and adds to the overall level of air pollution in the environment (WHO, 2014). Several causes contribute to household air pollution, and these vary by region. They include household activities such as cooking, lighting, heating, burning incense, and use of mosquito repellents (Apte & Salvi, 2016). Household fuel combustion is a significant source of HAP, which has become the world's most serious environmental health concern (Ahmed et al., 2019). The decisions and preferences that households make regarding their energy use can impact HAP. Therefore, this section aimed to describe the primary HAP sources and types, their effects on human health, and the existing strategies for reducing HAP.

2.3.1 Characteristics of Household Air Pollution

Sources, types, and HAP concentrations vary considerably amongst microenvironments. The primary energy consumption in developing countries is largely fuelled by traditional solid fuels like wood, charcoal, and other agricultural residues. Due to the substances produced during its combustion, such as carbon monoxide, particulate matter, and nitrous oxides, biomass is the primary source of HAP in rural households of developing countries (Crentsil et al., 2019; Liao et al., 2016). In addition to biomass, HAP is also significantly influenced by coal, kerosene, candles, and tobacco products (Alessandra Cincinelli & Tania Martellini, 2017).

In developing countries, various cooking techniques and appliances are used, from conventional stoves to advanced (improved) cooking methods. Among these techniques and appliances is the three-stone stove, which is widespread throughout Africa. The *Jiko* stove is widely used in Kenya, the *Justa* stove is popular in India, and the *Tsotso* stove in Zimbabwe

(Adeeyo et al., 2022). Due to their low efficiency, these stoves produce a considerable amount of incomplete combustion products per unit of energy (Zhao et al., 2021).

Plate 1: The ceramic *jiko* (left) and the *Tsotso jiko* (middle) and *Justa stove* (right)
Source: Global Alliance for clean cookstoves, new dawn engineering & stoves online

The link between indoor and outdoor pollutants has not been explicitly studied. In the absence of cooking activities, outdoor $PM_{2.5}$ concentration levels are higher than indoor $PM_{2.5}$ levels (Yulinawati et al., 2021). However, indoor $PM_{2.5}$ concentrations during cooking periods tend to exacerbate outdoor $PM_{2.5}$ concentrations (Kouao et al., 2019). Although some researchers have shown the existence of a direct relationship between indoor and outdoor pollutants, findings by (Scheepers et al., 2017) negate this assertion. This is after investigating VOCs, NO_2 and $PM_{2.5}$, in indoor and outdoor environments. The results showed that known indoor sources accounted for most indoor air pollutants, with little discernible contribution from known outdoor sources.

High emissions from traditional three stone biomass cookstoves compared to modern stoves with ventilation mechanisms have been reported. Although traditional stoves have undergone various alterations to improve their performance, evidence suggests that improvements such as the existence of a chimney do not appreciably lower pollutants exposure. As a result, rural households that rely exclusively on biomass fuels for cooking have six times higher daily indoor HAP concentrations than urban households (Pollard et al., 2014).

Typically, emissions from these biomass cookstoves are exacerbated during the lighting and refuelling phases (Deng et al., 2018). For instance, average daily $PM_{2.5}$ concentrations from traditional biomass cookstoves in Southern Nepal were one hundred times greater than the WHO's guidelines (Chen et al., 2016). Compared to electric cookstoves, $PM_{2.5}$ and CO personal exposures from biomass cookstoves were twice as high and twenty times higher, respectively, in Ethiopia (Downward et al., 2018).

Most pollutants from biomass and solid fuels are gaseous in their natural state. These gaseous pollutants can be divided into primary and secondary categories (Ahmed et al., 2019). Volatile organic compounds (VOCs) are examples of primary gaseous pollutants, whereas fine particulate matter, free radicals, alcohols, aldehydes, and ketones, are examples of secondary gaseous pollutants. Bari et al. (2015) note that combustion processes, household products, and cigarette smoke are the principal sources of HAP. Household characteristics and activities also play a significant role in the concentration of indoor pollutants. Cigarette smoking, gas appliances, and household items are the primary sources of $PM_{2.5}$, NO_2 and VOCs, respectively (Vardoulakis et al., 2020). However, combustion processes within households, primarily from cooking, have been reported by many researchers as the leading contributor to HAP (Chakraborty et al., 2014; Leal Filho, 2020).

Particulate Matter (PM), Carbon Monoxide (CO), and Polycyclic Aromatic Hydrocarbons (PAH) have been identified as the primary HAP pollutants. However, Park et al., (2018) contend that $PM_{2.5}$ is the most accurate indicator of HAP exposure and the most accurate in predicting health outcomes. Some researchers have also proposed that CO measurements can serve as surrogates for PM because their sources and distributions are comparable. Significant correlations have been reported between PM and CO in contexts where both originate from biomass. This has been reported in studies in Peru (Pollard et al., 2014), and Guatemala (McCracken et al., 2013). Other researchers, however, have noted substantial variances in CO and PM correlations across various contexts. For example, Klasen et al., (2015), found no evidence that indoor CO concentration might substitute for indoor $PM_{2.5}$ after tests in rural areas of Kenya, Nepal, and Peru. Nevertheless, CO and PM are significant HAP pollutants with distinct environmental effects and should be assessed separately.

PM and CO are the most significant and widely studied pollutants in HAP monitoring compared to other household energy use-related pollutants due to their impact on human health. Other common HAP pollutants include volatile organic compounds (VOCs), Nitrogen dioxide (NO_2), Sulphur dioxide (SO_2), Carbon dioxide (CO_2), and aerosols.

2.3.1.1 Particulate Matter

Particulate matter is characterised as carbonaceous particles combined with reactive metals and organic compounds that have been adsorbed. Sulphates, nitrates, endotoxin, polycyclic aromatic hydrocarbons, and other heavy metals like iron, nickel, copper, zinc, and vanadium are the primary constituents of PM (Hamanaka & Mutlu, 2018). PM is generally categorised according to the sizes of the individual particles that characterise it as follows: (a) course particles (PM_{10}) have an aerodynamic diameter less than 10 µm; (b) fine particles ($PM_{2.5}$) have an aerodynamic diameter less than 2.5 µm, and (c) ultra-fine particles ($PM_{0.1}$) with an aerodynamic diameter less than 0.1 µm (Tran et al., 2020).

PM is unique in that, depending on the size, it can be inhaled into the respiratory tract, making it a significant HAP pollutant (Amnuaylojaroen et al., 2022). In general, PM_{10} particles are too large to pass through the upper bronchus, whereas $PM_{2.5}$ and $PM_{0.1}$ can enter the smaller airways and alveoli (Chin, 2015). Both outside environments and indoor activities are the primary sources of PM in households. Household PM mainly originates from natural and anthropogenic processes such as cooking activities and smoking cigarettes. However, cooking has the most significant impact on the concentration of PM in households (Kim et al., 2018). Smoking has been reported to be a major source of $PM_{2.5}$, while cooking activities involving oil and wood are mainly responsible for $PM_{0.1}$ and $PM_{2.5}$ and PM_{10} (Yu et al., 2015).

Fine particulate matter has received more attention in the literature than other PM types. This is because of its greater significance in epidemiology and the availability of monitoring technologies. The type of cooking fuel used has been observed to have an impact on HAP estimations for $PM_{2.5}$. In Ethiopia, Admasie et al., (2019) reported that $PM_{2.5}$ concentration was much higher in households that primarily used biomass (926.34 g/m^3) for cooking than in those that utilised mixed fuels (279.42 g/m^3). Helen et al., (2015) also reported comparable findings in Peru while investigating $PM_{2.5}$ emissions from cooking with biomass and gas. Other studies that have confirmed this trend include Caubel et al., (2018) and Rapp et al., (2016).

The type and form of biomass used have an impact on $PM_{2.5}$ emissions as well. Even though the instantaneous peak emissions for wood fuel are higher than that of cow dung, the $PM_{2.5}$ levels recorded by cow dung stoves are higher than those recorded by wood fuel stoves. This is owing to the varying energy intensities of the two fuels, which result in distinct combustion characteristics that influence emission factors. Time also influences the emission factors of each fuel type. This pattern has been observed in rural Bangladesh, where higher $PM_{2.5}$ levels from biomass cookstoves were recorded (Medgyesi et al., 2017).

A more extensive study on the contribution of different cooking technologies on PM was carried out by Shupler et al., (2018). In the study, $PM_{2.5}$ and PM_{10} concentrations were studied in twelve developing countries, four of which were in Africa (Ethiopia, Rwanda, Gambia, Ghana). The study relied on archival secondary data instead of kitchen experiments.

Nevertheless, the study's findings were in line with experiment-based micro-studies, which reported lower average $PM_{2.5}$ and PM_{10} levels in households that used gas or electricity cooking. Compared to traditional cookstoves, ICSs significantly reduced $PM_{2.5}$ emissions (290 $\mu g/m^3$ for traditional cookstoves and 150 $\mu g/m^3$ for ICSs), while animal dung stoves recorded much higher $PM_{2.5}$ concentration levels. Kumar et al., (2021) and Mitchell et al., (2020) also reported a significant reduction in $PM_{2.5}$ when ICSs were used compared to traditional biomass cook stoves.

However, other studies have concluded that ICSs' effect on reducing PM is negligible. This is because ICSs can take on various forms depending on the region. Therefore, their effectiveness in reducing HAP depends on their design quality, implementation, and monitoring (Thomas et al., 2015). In Nigeria, Onyeneke et al., (2019) found no evidence of emissions reduction by ICSs, although the study was primarily qualitative. Experiments conducted by Soneja et al., (2017) in Nepal demonstrate that a chimney can increase the efficiency of ICS in reducing $PM_{2.5}$ emissions.

Rural areas have been the focus of most studies on household $PM_{2.5}$ monitoring because of the high number of biomass users in these locations. Nonetheless, this condition is equally frequent in informal urban settlements where biomass and unclean cooking fuels are utilised. Consequently, few research have examined $PM_{2.5}$ concentration levels in urban information communities. An example of such studies was conducted by Muindi et al., (2017) in two slums in Kenya's capital city, Nairobi. Most of the inhabitants of these slums use charcoal and kerosene as their primary cooking fuels. Households utilising charcoal had average $PM_{2.5}$ concentrations higher than those using kerosene. Similar findings have been reported by Shezi et al., (2020) in Durban, South Africa and Nishu & Rampal, (2019) in Jammu, India. Therefore, interventions promoting clean cooking are also recommended in informal urban communities.

Even though the findings of these studies follow a similar pattern, the sample sizes and durations of the investigations differ. For instance, Admasie et al., (2019) sampled 109 households for 24 hours each, while Helen et al., (2015) sampled 100 households for 48 hours each. However, other research with significantly smaller sample sizes have reached similar conclusions. For instance, Prasasti et al., (2021) investigated household $PM_{2.5}$ concentrations across 25 locations in Surabaya for 30 mins each. As such, there are diverse views regarding the sample size and sampling duration for HAP monitoring in the current literature.

2.3.1.2 Carbon Monoxide

Similar to particle matter, combustion processes like cooking and heating are the principal sources of CO in households. Carbon monoxide can, however, occasionally infiltrate the inside environment through leakage from outdoor sources. Wood stoves, gas stoves, unvented kerosene, generators, and tobacco smoke are among the leading sources of CO in households. In a building that does not contain any gas stoves, the CO concentration is typically between 0.5 and 5 parts per million (ppm), although the concentration can reach as high as 30 ppm in the presence of gas stoves (Tran et al., 2020). Most households that use biomass produce CO, primarily due to incomplete biomass combustion.

Comparative research by Paudel & Sharma, (2017) on CO emissions from various cookstoves in Nepal found that emissions from traditional cookstoves were five times more than those from ICS and six times higher than those from LPG. Nonetheless, the study investigated a significantly smaller sample size (21) in a stratified randomised experiment without a control study. In addition, the types of food, kitchen conditions, and temporal variation were not considered. Considering the type of food, Legonda et al., (2013) found a comparable trend in CO emissions across traditional and modern stoves in Tanzania.

Geographical and climatic factors impact the concentrations of $PM_{2.5}$ and CO in households. For instance, a study by Huboyo et al., (2014) in Indonesia reported that rural highland households had higher levels of $PM_{2.5}$ and CO than rural coastal households. This was primarily due to household and kitchen characteristics, where coastal households had larger kitchens and cooked for less time than those in mountainous areas. However, there was more flaring of wood burning in coastal areas than in mountainous ones. In addition, there was a stronger positive correlation between the observed concentrations of CO and $PM_{2.5}$ in highland regions than in coastal regions.

2.3.1.3 Volatile organic compounds (VOCs)

Volatile organic compounds are gases released from liquids or solids that include a wide range of chemicals (USEPA, 2022). Indoor VOCs concentrations have been found to be at least 10 times greater than outdoor concentrations, regardless of the geographic location. Cooking and smoking are some of the activities that produce VOCs in households. Other indoor VOC sources include building materials, chemical reactions, cleaning products, and infiltration from outdoor sources (Amann et al., 2014). Due to their low boiling point owing to their chemical composition, VOCs are easily volatilised and at room temperature. The WHO has categorised VOCs into the following four categories: very volatile organic compounds (VVOCs) (boiling point of 50-100 ^{o}C), VOCs (boiling point 100-240 ^{o}C), semi-volatile organic compounds (SVOCs) (boiling point of 240-380 ^{o}C), and particulate organic matter (POM) (boiling point greater than 380^{o}C) (Bandehali et al., 2021; Lucattini et al., 2018).

Liu et al., (2016) investigated the contribution of human sources to indoor VOCs at the University of Colorado. The study's outcomes indicate a strong human influence on VOCs via human breath and human skin lipids ozonolysis. It was also established that the concentration of VOCs in a building increased with the number of people present but decreased when ventilation rates were increased. In Korea, Lee et al., (2018) characterised indoor and outdoor

VOCs levels in thirty centres with the aim of identifying environmental factors contributing to increased indoor air pollution levels. According to the study's findings, the levels of VOCs in the indoor environment were significantly greater than in the outdoor environment. The presence of common household items like carpets, wooden furniture, or paint was attributed to the differences in the VOCs levels estimated in the various research sites.

The recent literature has also identified household cooking as a significant source of VOCs. In Shanghai, China, Wang et al., (2018) investigated VOCs emissions from household kitchens, canteens and restaurants. The study found that alkane and oxygenated VOCs account for the majority of cooking-related VOCs emissions. In addition, VOCs emissions from catering businesses (canteens and restaurants) were the highest. However, the study's main concern was the role of cuisine types, while fuel types received no special consideration. Medium and large-scale restaurants were significant contributors to VOCs.

The above limitation was addressed in a more recent study by Sun et al., (2019), in Guanzhong, China. The study investigated VOCs from traditional and modern cooking and heating methods. There were noticeable differences between coal and biomass's total VOC emission profiles. Total VOC emissions can be significantly reduced using clean stoves and coal briquetting for cooking and home heating. Comparatively, they produced less total VOCs than the traditional cooking and heating methods. However, in a similar study by Sun et al., (2018), semi-gasifier stoves did not significantly impact total VOCs reduction.

There is growing evidence that biomass fuels exacerbate VOCs. The highest TVOCs concentration levels have been recorded for biomass fuels such as charcoal in Ethiopia (Embiale et al., 2019). However, the amount of VOCs produced by burning biomass fuel is dependent not only on the amount of fuel burned but also on the species and moisture content of the biomass. On the other hand, electricity proved to be a more effective means of lowering

TVOC levels. The study by Embiale et al., (2019) controlled for the effects of the cuisine type by using the same type of local cuisine in Ethiopia (*Wot*).

Volatile organic compounds exhibit seasonal variation. Several researchers have accounted for this aspect in their investigations, in which the studies are structured to span multiple seasons. For instance, Norris et al., (2022) compared indoor VOCs concentrations in urban India during the winter and summer seasons. Indoor VOCs concentrations measured during winter were higher than those recorded in summer. Additionally, the study demonstrated that indoor VOCs concentrations were higher than outdoor VOCs values.

Researchers have also investigated how VOCs emissions are affected by various types of cooking methods and stoves. Fleming et al., (2018) measured VOCs emissions factors from different cookstoves in one village in India. A local type of stove known as *angithi* in combination with dung fuels, produced significantly higher VOC emissions. VOCs emissions were cut by half when the same fuel was used in a different stove (the *chulha*).

Plate 2: *Angithi* (left) and *chulha* (right). Source: D'source

This highlights the significant role of stove type in VOCs emissions, primarily attributed to differences in the burning efficiency of various stoves. In Nepal, Stockwell et al., (2016) conducted source characterization of emissions and reported significantly higher emissions from dung fuels than wood fuels. The type and concentration of cooking emissions depend on the stove type, fuel source, and the food being cooked (Gokhale & Salimifard, 2019).

2.3.2 Link between HAP and Human Health

Household air pollution is regarded as a significant global environmental risk factor for human diseases and among the top risk factors examined by Global Burden of Diseases (GBD) estimates. Health effects of HAP commonly recognised globally include pulmonary diseases, respiratory infections, reduced lung function and impairment of the immune system (Ahmed et al., 2019). Possible acute health effects associated with HAP include acute lower respiratory infections (ALRI), nasal irritation, eye irritation, cough, and pneumonia in children. Long-term HAP exposure has been linked to adverse birth outcomes, including low birth weight and stillbirths. Prevalence of chronic illnesses such as lung cancer, diabetes, stroke, hypertension, cardiovascular disease, and chronic obstructive pulmonary disease (COPD) are also attributed to chronic HAP exposure (Gibbs-Flournoy et al., 2018). Globally, close to 4 million premature deaths are attributed to HAP exposure (Cohen et al., 2017; WHO, 2021c).

2.3.2.1 Acute Respiratory Infections (ARIs)

Airborne pollutants frequently make their way into the human body through inhalation. The respiratory system is thus the critical target for HAP impacts. Acute respiratory infections can be categorised into acute lower respiratory infections (ALRI) and upper respiratory infections (URI) based on the affected area of the respiratory tract (Simkovich et al., 2019). URIs are caused by biological contaminants and are generally mild upper respiratory tract infections (throat, nose, trachea, mouth), such as cough, pharyngitis, laryngotracheitis, sinusitis and laryngitis (Grief, 2013). On the other hand, ALRI is an acute lung infection caused by viruses or bacteria, which results in the inflammation of the lungs. HAP is responsible for about 78% of the increased risk of ALRI in children, which results in one million fatalities among children under the age of five every year. However, there is no unanimity about the relationship between ALRIs and HAP exposure in adults (Jary et al., 2016).

Most studies evaluating the link between HAP and ALRI have focused on children younger than five years old. Because children have substantially larger lung surface areas than adults, they may be more susceptible to the effects of ALRI (Kim et al., 2018). Enyew et al., (2021), in a systematic review, concluded that compared to other fuels, children exposed to biomass fuels had a roughly threefold increased risk of contracting ARIs. Non-experiment-based studies have also come to similar conclusions. For instance, Nie et al., (2016) reported that women who cook with cleaner fuels like LPG had a considerably lower risk of chronic or acute diseases and were more likely to rate their health higher than those who cook with wood or straw. In sub-Saharan Africa, Bede-Ojimadu & Orisakwe, (2020) did a systematic review on the health impacts of wood smoke. The review found a high link between exposure to wood smoke and respiratory illnesses, such as acute respiratory illnesses and reduced lung function.

Kurti et al., (2016) reported that HAP was associated with respiratory and non-respiratory symptoms, including reduced lung function among children and adults in Belize, with more significant symptoms experienced in adults than children. A study in Pakistan into the effects of wood fuel demonstrated that children exposed to this type of fuel were 1.5 times more likely to exhibit acute respiratory infection symptoms than those in households that use clean fuels (Khan & Lohano, 2018). In Ethiopia, Sanbata et al., (2014) found that households using biomass fuel had an odds ratio of 2.97 for children developing an acute respiratory illness, compared to 1.96 for households using kerosene. Compared to cleaner fuels, unclean fuels were 2.5–3% more likely to cause respiratory infections in Bhutan (Rahut et al., 2017). However, some studies, such as Misra et al., (2018) in South Africa, have shown scant support for the hypothesis that respiratory ailments are related to fuel use. This was linked to the use of cooking methods that ensured cleaner burning of wood fuel, which reduced exposure to HAP.

2.3.2.2 Pulmonary Diseases

Allergic and pulmonary disorders such as asthma and allergic rhinitis are linked to air pollution inhalation. HAP is considered one of the most significant causes of chronic inflammatory pulmonary disorders, such as COPD, lung cancer and asthma (Raaschou-Nielsen et al., 2016). COPD is characterised by an exacerbated chronic inflammatory response to PM in the airways and lungs. Inflammation of the lungs and a significant decrease in pulmonary function has been attributed to PM produced from fossil fuels combustion in households. Research by Medgyesi et al., (2017) showed evidence of decreased pulmonary function among women in Bangladesh due $PM_{2.5}$ exposure from biomass cookstoves. Household fuel smoke can also lead to COPD disorders with clinical symptoms and fatalities comparable to those of tobacco users (Yang et al., 2020). However, Yang et al., (2017) found that a significant number of patients with lung cancer and COPD had never smoked.

Chronic obstructive pulmonary disease has been defined as a widespread, preventable, and treatable condition characterised by recurrent respiratory symptoms and airflow restriction brought about by anomalies in the airways or alveoli, typically a result of prolonged exposure to irritant particles or gases (Prasad, 2019). COPD is mainly an adult illness associated with an irreversible airflow reduction resulting from a combination of small airways illness and parenchymal damage (Angelis et al., 2014). COPD comprises chronic bronchitis, characterised by at least two years of daily phlegm for three months yearly (Amaral et al., 2018). Smoking, environmental pollution, genetics, low socioeconomic position, and a history of TB are all recognised risk factors for COPD. Among environmental pollutants, HAP exposure stands out as a significant cause of COPD.

Many households in developing countries are certainly exposed to prolonged levels of HAP. The smoke that is produced by the combustion of biomass is not significantly different from that of tobacco. However, COPD caused by HAP has been demonstrated to be distinct from that caused by tobacco smoke (Assad et al., 2015). In South Asian countries, exposure to solid fuel smoke has been found to be significantly linked with COPD mortality and prevalence rates (Shetty et al., 2021). Even though exposure to HAP has been linked to a significant disease burden attributable to COPD, conflicting studies and expert perspectives make this claim somewhat debatable. An intervention trial involving different cookstove types, cleaner fuels, and ventilation conducted in China lends credence to the hypothesis that HAP and COPD are closely associated (Zhou et al., 2014).

However, some studies have not identified a significant relationship between HAP and COPD. A study conducted in India revealed a low frequency of COPD and found no link between COPD and exposure to biomass smoke (Mahesh et al., 2018). Although a comparable study in Tanzania reported a high COPD prevalence rate, the authors could not demonstrate a link because 99.5% of the individuals in the study had been exposed to biomass smoke (Magitta et al., 2018). Additionally, a study by Brakema et al., (2019) in rural Kyrgyzstan found no link between COPD and biomass $PM_{2.5}$ exposure. However, the study's findings were probably confounded by age, high altitude, and smoking.

Exposure to HAP also aggravates asthma symptoms. Household combustion of wood, kerosene and coal has been reported to pose a 1.6 risk of asthma exacerbation in children between the ages of five and fourteen (Jiang et al., 2016). In New York, researchers have reported a strong correlation between elevated levels of indoor NO_2 and $PM_{2.5}$ and worsening asthma symptoms, as well as increased cases of severe to very severe asthma in children who required urgent treatment (Schachter et al., 2020). Improved asthma symptoms and decreased indoor $PM_{2.5}$ levels were observed in Mexican children after asthma management and healthy home environment educational intervention (Moreno-Rangel et al., 2020). Most investigations on the effects of HAP on asthma have been undertaken in developed countries, with China leading the list of developing countries where such studies have been conducted. However, as reported by Jary et al., (2015), tobacco smoking is the primary risk factor in developed countries, while HAP is the most recognised risk factor in low and middle income countries (LMIC).

The following types of cancers have been associated with air pollution; cancer of the lungs, the stomach, the breasts, and the cervix. However, of these air pollution-related problems, lung cancer is the most common (Ahmed et al., 2019). Smoking has been highly linked to lung cancer, which is more common in high-income countries. Lung cancer cases are, however, increasing in low and middle income countries as tobacco use becomes more common, especially among men (Islami et al., 2015). In 2016, biomass-related HAP was classified as a human carcinogen by the International Agency for Research on Cancer (IARC). In particular, $PM_{2.5}$ significantly impacts the mortality rate associated with lung cancer (Zhang et al., 2022). In addition to smoking and HAP, environmental pollutants, including radon and asbestos are risk factors for lung cancer.

A strong association has been reported between exposure to HAP and the development of lung cancer in females. This is attributable to the time spent cooking, where females spent more time cooking than males (Bruce et al., 2015). According to a study conducted in Guatemala, reducing maternal and infant exposure to HAP using an intervention such as a chimney stove during pregnancy and early infancy may enhance lung function (Heinzerling et al., 2016). On the flip side, a study by Lee et al., (2019) in Ghana found that higher prenatal exposure to HAP (CO) was associated with reduced lung function in new-borns. Even though lung cancer is typically associated with tobacco smoking, it has been established that long-term cooking exposes women to a high risk of lung cancer (Tran et al., 2020).

2.3.2.3 Cardiovascular Diseases

Pollutants such as PM, PAHs, CO, and other organic pollutants generated by solid fuels have been associated with cardiovascular diseases (CVDs). The risk of developing certain cardiovascular diseases, such as ischemic heart disease (IHT), cardiac arrhythmia, stroke, and heart failure, increases when an individual is exposed to $PM_{2.5}$ (Singh et al., 2017). Exposure to both $PM_{0.1}$ and $PM_{2.5}$ have been found to cause significant effects on human cardiovascular function. A higher risk of CVDs has also been linked to the combustion of kerosene or diesel, whilst using cleaner fuels such as gas has been associated with a lower risk of CVDs (Samet et al., 2016).

After both short- and long-term exposures to PM, the absolute mortality risk is higher for cardiovascular disorders than for pulmonary disorders (Wilkins et al., 2017). However, a limited number of research has been done on the impact of HAP on CVDs, especially in sub-Saharan Africa. One such study was carried out by Al-Shammari, (2020) in Saudi Arabia. The results of this investigation showed a substantial correlation between cardiovascular illnesses and ventilation and exposure to different types of smoke. In Albania, individuals exposed to polluting fuels in their households had a 17% increased risk of developing hypertension compared to those not exposed to HAP (Abba et al., 2022). A more detailed analysis of the results shows that the likelihood of hypertension was higher among women, rural inhabitants, and individuals older than 24 years. Nonetheless, a similar study by Milojevic et al., (2014) in England and Wales found no clear evidence linking air pollution (CO, $PM_{2.5}$, NO_2) to stroke.

Case modelling of scenarios showed that premature cardiovascular mortality in southwestern China was reduced by 48,000 people annually by the exclusive use of LPG or electric stoves (Snider et al., 2018). Of these, 26,000 were due to stroke and 7,000 to ischemic heart disease.

For every 10 mg/m^3 rise in $PM_{2.5}$ concentration, the odds ratio for hypertension has increased by 1.04 (Arku et al., 2020). Nevertheless, a linear depiction of this relationship is not implied.

2.3.2.4 HAP and General Human Health

The health consequences of HAP from various cooking techniques have been examined by the available literature, including novel case studies and systematic literature reviews. Evidence on the impact of HAP on human health can be grouped into two categories; those that investigate HAP changes and accrued health benefits from interventions and cross-sectional studies focusing on the barriers and enablers for clean energy technologies to alleviate HAP (Quinn et al., 2018; Vigolo et al., 2018). The latter has been widely researched in low and middle-income countries.

Significant reductions in HAP have been reported in clean fuels and technologies interventions. However, the reductions were still above the recommended exposure limits in most cases. For instance, Pope et al., (2017) reported a reduction in $PM_{2.5}$ and CO following various interventions, including ethanol stoves, improved cookstoves, and chimneys. Quansah et al., (2017) reported that the average PM and CO concentrations in household kitchens exhibited the greatest reductions following stove interventions. Similar results have been reported by Adane et al., (2021) in Ethiopia, Thomas et al., (2015) in selected low and middle income countries, and Sharma & Jain, (2019) in India. However, all the reductions attained were insufficient to bring down HAP levels below the current air quality guidelines (WHO, 2021b).

In Kenya, Majdan et al., (2015) without reference to any particular cooking technology, reported that biomass use could alleviate indoor air pollution ($PM_{2.5}$ and CO). Yip et al., (2017) investigated HAP from traditional and selected improved cookstoves (ICS) in western Kenya. Although ICS reduced $PM_{2.5}$ and CO emissions, the study concluded that cleaner fuels were still required to reduce emissions to the set guidelines. Despite this, studies and various programs continue to advocate for improved biomass cookstoves as potential interventions for HAP reduction in developing countries (Schilmann et al., 2019). In practice, however, it is extremely challenging to burn solid biomass in household stoves in a manner that is sufficiently clean to meet the set health standards (Goldemberg et al., 2018). Medina et al., (2019) opined that since traditional fuels may not be totally replaced by clean cooking options, fuel stacking ought to be considered in the evaluation of the health and environmental effects of HAP. However, fuel stacking is most prevalent in peri-urban settings, whereas most rural communities have reported using only wood fuel (Esong et al., 2021).

The relationship between indoor environment quality and occupants’ health has been established. Previous studies have mainly focused on establishing relationships between certain indoor environmental factors and their link to occupants' health and well-being. Volatile organic compounds, PM, CO and other combustion gases have detrimental effects on health. In particular, compared to men and boys, women and girls are exposed to HAP at substantially higher rates as reported by Okello et al., (2018) from evidence gathered in Ethiopia. Modern cleaner fuels are associated with a low probability of acute or chronic diseases. This is supported by the evidence presented by Nie et al., (2016) for the case of LPG use among women in rural China. Building characteristics also play a role in HAP concentration and health outcomes. Wallner et al., (2017) investigated the effect of different ventilation types on indoor air quality and health outcomes. Occupants of energy-efficient and ventilated homes perceived better indoor air quality and improved self-rated health. This finding supports the existing literature on the role of ventilation in mitigating the effects of HAP. However, HAP reduction effectiveness relies on the type of fuel utilised, which has been demonstrated in the reviewed literature.

2.3.3 Outdoor Air Pollution

Ozone, CO, nitrogen oxides, sulphur oxides, and particulate matters (PM) of various particle sizes make up the majority of outdoor air pollutants (Leung, 2015). Because of poor dispersion characteristics and the large concentration of pollution sources, outdoor air pollution is primarily a concern in metropolitan areas. Road traffic, power plants, incinerators, petrochemical facilities, fossil fuel combustion, industrial boilers, etc. are the main contributors of outdoor air pollution. Sulphur dioxide is mostly generated in industrial settings by combusting high-sulphur coal and petroleum (Gawande & Kaware, 2015). However, the majority of outdoor air pollution is caused by road traffic, with CO, NO_2, and ozone being the most significant pollutants (Chen & Guo, 2019).

Nitrogen dioxide in the atmosphere is a precursor to photochemical smog. It has been linked to a rise in the incidence of asthma cases. Ozone in the atmosphere is a secondary air pollutant produced through a photochemical process involving NO_2, hydrocarbons, UV light and molecular oxygen. Ozone exposure is associated with airways inflammation, bronchial hyperresponsiveness and asthma exacerbation (Mumby et al., 2019). However, from a public health standpoint, indoor air pollution is more significant than outdoor air pollution in developing countries, particularly Sub-Saharan Africa (Schwela, 2014). This is as a result of the widespread use of inefficient household fuels and appliances. Therefore, indoor air pollution is the priority air pollution issue in most developing countries.

2.4 Energy Poverty and Human Health

The concept of energy poverty, its evolution, and its impact on human health are discussed in this section.

2.4.1 The Concept of Energy Poverty

This section approaches the concept of energy poverty in two ways; the qualitative view, and the quantitative view.

2.4.1.1 Qualitative View

Following the 1973 oil crisis, researchers began discussions about “fuel poverty.” Fuel or energy poverty has been defined in various ways, but there has been no consensus on what constitutes fuel or energy poverty because their realities vary globally. Energy poverty phenomena vary significantly between developed and developing countries and between climatic zones. By 2014, only the United Kingdom had taken an official stance on measuring fuel poverty (Schuessler, 2014).

The demand side of energy-related problems has been described using a variety of terminologies, including energy poverty, fuel poverty, and energy burden. While the geographical context and measuring techniques of these phrases vary, they nonetheless speak to the same set of concerns: modern energy access, affordability, and consumption. It is important to note that energy burden and fuel poverty are two synonymous phrases that are used individually in distinct geographic locations; the former is used mainly in the United States, whilst the latter is used primarily in the United Kingdom, Ireland, and New Zealand (Jessel et al., 2019). A household is termed energy burdened or fuel poor if its energy expenditure exceeds 10% of gross income (Hernández, 2016). Several researchers, including Legendre & Ricci, (2015), and Mould & Baker, (2017) embraced this definition. However, works by Hills, (2012) and Moore, (2012) describe fuel poverty as a household’s inability to afford adequate heat levels to keep homes sufficiently warm.

These definitions have restricted applicability because they do not apply to all geographical situations. Other key factors of domestic energy usage, such as lighting and cooking, are also left out of the equation. For example, the criteria may not be true in tropical regions where climatic conditions do not vary significantly, resulting in minimum space heating and cooling requirements. Furthermore, developed nations have practically universal access to modern energy, with variances among families solely resulting from differences in economic circumstances, but developing countries continue to struggle with issues of accessibility and affordability. In some ways, the term fuel poverty has become identical with energy poverty. Unfortunately, gaining a clear picture of energy poverty is not simple. Some scholars believe that energy poverty is a notion that describes energy issues in developing countries, while fuel poverty is a problem that affects Organisation for Economic Co-operation and Development (OECD) countries as well. A more recent phrase, energy vulnerability, was proposed to bridge the geographical study divide between fuel poverty and energy poverty and emphasize energy hardship as a worldwide issue (Bouzarovski & Petrova, 2015).

Energy poverty cannot be conceptualised in a single way, as is widely understood. Therefore, researchers must rely on a variety of indicators to determine the extent of energy poverty and piece together a comprehensive picture from disparate metrics, much as they do when studying poverty in general. The terms energy burden, fuel poverty, and energy vulnerability are frequently the focus of research and policy, resulting in financially driven initiatives. Such an economic-centric approach does not address the whole breadth of the problem since it overlooks behavioural aspects that contribute to energy poverty. Consequently, a more comprehensive definition of what constitutes fuel or energy poverty is necessary. Perhaps going back to the origin of the concept of energy poverty may be crucial in understanding its evolution and, eventually, the whole spectrum of energy poverty.

Lewis, 1982 used the term “fuel poverty” to refer to households that cannot afford energy services and hence cannot maintain a comfortable indoor temperature, thereby lowering their living standards. Boardman, 1991 expanded on this concept by including the percentage of income spent on energy. However, as a result of increased research in this area, the concept was broadened to include lack of access to modern energy services (IEA, 2002; Okushima, 2017; Zhang et al., 2019). Due to the binary character of accessibility (having or not having), it is the simplest and most easy metric to measure. However, single indicator measurements of affordability or accessibility are insufficient to describe the complex nature of energy poverty, which has several causes.

The absence of modern energy services and low energy usage are commonly associated with the Global South, according to the term “energy poverty” (González-Eguino, 2015). Consumption of energy and economic development are inextricably related. Generally, a country’s core macroeconomic indicators include energy and electricity use, car ownership, and, per capita CO_2 emissions (González-Eguino, 2015). Therefore, energy poverty’s outcomes and indicators should be centred on socioeconomic development, well-being, and poverty.

According to the standard definition, an energy-poor household is one that does not have access to modern energy services and sources, such as electricity and clean cooking fuels/technologies for its basic energy needs and instead relies on traditional energy sources, such as biomass (IEA, 2010; Parajuli, 2011). This definition may also be used to define “green energy poverty” if we just examine modern energy from natural sources. However, if we only consider modern energy from natural sources, this definition will be limiting as efficient technologies meant to minimise biomass emissions would be omitted. In the words of (Reddy, 2000), energy poverty can be described as the lack of sufficient choice in obtaining appropriate and affordable energy services that are dependable, high-quality, safe, and environmentally sustainable in order to enable economic and human growth. This definition was chosen for this study because it approaches the concept of energy poverty holistically by incorporating all the aspects mentioned in other definitions.

In recent years, researchers have devised indices that represent the complex character of energy poverty, taking into account variables such as access to modern and sustainable energy services as well as human development (Nussbaumer et al., 2012; Sadath & Acharya, 2017; Sher et al., 2014). Nussbaumer et al., (2012) developed the multidimensional energy poverty framework MEP and investigated energy poverty at the macro level in developing countries. Multidimensional energy poverty considers both the incidence and intensity of energy poverty and focuses on deprivation (a key measure of poverty) rather than just accessibility or affordability. The MEP framework has been applied by Ahmed and Gasparatos (2020) and Crentsil et al. (2019) in Ghana, Mendoza et al. (2019) in the Philippines and Gafa & Egbendewe (2021) in Senegal and Togo. This new body of literature mainly evaluates MEP at the macro (national and regional) level, thus omitting individual characteristics at the micro (household) level.

2.4.1.2 Quantitative Approach

Objective metrics, e.g., those based on expenditure or epidemiological data, or subjective impressions, e.g., self-developed indicators, have been used to measure energy poverty and fuel poverty. Waddams et al. (2012) examined the relationship between objective and subjective measures of fuel poverty and concluded that, while both measures are complexly connected, they should be addressed when developing social policy. Miniaci et al. (2014) on the other hand, opined that the results vary depending on the measure of fuel poverty used.

One of the most objective measurements of energy poverty is the 10% indicator, which was common in studies on fuel poverty before (Hills, 2012) and (Moore, 2012) proposed the low income high costs (LIHC) and minimum income standard (MIS) indicators, respectively. The

10% indicator offers some advantages. It is straightforward to compute, simple to express, and quite adaptable from a pragmatic standpoint. However, it has substantial shortcomings that have been well-documented in the literature. The indicator exhibits significant sensitivity to changes in energy costs, resulting in an underestimation of the magnitude of the problem when prices are low and an overestimation of the problem when prices are high (Schuessler, 2014). It has also been demonstrated that the 10% criterion estimated for different countries may contain a sizable proportion of households that are not energy poor, for example, high-income households with inefficient dwellings or excessive energy usage (Heindl, 2015; Moore, 2012).

The MIS indicator refers to a household's minimal income that enables its members to choose from various options that allow them to participate fully in society. If a household's energy expenditures exceed the household's income after additional housing costs and the above-mentioned minimum income criteria, the household is said to be in fuel poverty (Miniaci et al., 2014). In other terms, a household is considered energy poor if it lacks the income to meet its essential energy bills after paying for housing and other necessities. The MIS is one of the most reliable indicators for determining objective, income-based energy poverty since it confronts the problem at its very economic root. However, it introduces a technical complication – how to objectively determine the minimal income.

The Low Income High Cost (LIHC) indicator was designed to consider the high cost of energy. The index considers a household's low income and high energy expenses. Households are defined as energy poor if they (1) have necessary fuel expenses that are more than the median level, and (2) if they spend that amount, they would be left with a residual income that is lower than the official poverty line (Hills, 2012; Newell, 2016). In addition to determining the total number of people impacted, the LIHC includes an indicator of the fuel poverty gap, which helps determine the severity of fuel poverty at the household level. The fuel poverty gap is the disparity between the estimated energy demands of low-income households and the appropriate cost of providing that energy.

The fuel poverty indicators discussed so far (10% indicator, MIS, and LHC) strongly emphasise affordability and household income and can therefore be regarded as representing economic situations rather than the more complex concept of energy poverty. The multidimensional energy poverty index (MEPI) turns out to be the most objective measure in energy poverty research. It is calculated using several variables by considering energy deprivations likely to impact a household, such as the quality of energy services, their dependability, accessibility, and affordability of those services. This relates to multidimensional poverty measurements, which emphasise the need to evaluate poverty from the absence of possibilities and choices.

Three unique but complementary techniques for measuring energy poverty can be summarised as technological, physical, and economic thresholds (González-Eguino, 2015). The technological threshold approach is predicated on the notion that energy poverty is caused by inadequate access to modern energy services. This method measures energy poverty by determining the proportion of the population lacking access to modern energy services. The physical threshold approach determines the bare minimum regarding energy consumption related to essential requirements. Those who fall below this criterion are considered to be in energy poverty.

The economic threshold aims to identify the maximum proportion of revenue that can be allocated to energy expenditures. It is the most prevalent system for assessing energy poverty in industrialised countries, where the issue is mainly related to purchasing power, pricing, and the inability to maintain sufficient home temperatures. Certain drawbacks limit physical and economic threshold techniques in various settings. For instance, in the context of the physical approach, it is difficult to determine what exactly constitutes essential necessities. Because of the relative nature of the economic threshold approach, it is challenging to make comparisons across nations that are in significantly different stages of their respective economic cycles.

Using the aforementioned measures, researchers have examined energy or fuel poverty in European and Asian countries. Charlier & Legendre (2016) assessed fuel poverty in France using a fuel poverty index (FPI) comprised of three objective measures (disposable income, energy consumption and indoor temperature), although the study's focus was not to identify energy poor households. In their study, Legendre & Ricci (2015) analysed the differences between the effects of several measurement methodologies on the magnitude and composition of fuel poverty in France using logit, clog log and mixed effect logit models. According to the study's findings, the severity of fuel poverty varies greatly depending on which fuel poverty metric is used. People who are retired and live alone, rent their home, heat using individual boiler, cook with butane or propane, and have inadequate roof insulation have a greater chance of slipping into fuel poverty.

When objective and subjective energy poverty indicators are compared, households judged to have a bad energy profile are not always the same. As a result, it is now essential to use a wide array of indicators, all of which work in conjunction to capture various facets of the problem and offer a more comprehensive perspective on the matter. Papada & Kaliampakos (2016) reached a similar conclusion for the example of Greece using a combination of objective and subjective indicators. According to the study's findings, based on the objective expenditure technique, at least 58% of Greek homes were categorised as energy poor, with energy poverty rates exceeding 90%. The subjective indicators were employed to shed light on other facets of energy poverty (Papada & Kaliampakos, 2016). In Spain, Romero et al., (2015) used a variety of fuel poverty indicators (the MIS index, the 10% threshold, and the LIHC indicator) to examine the impact of various individual and family factors on fuel poverty. The MIS index revealed that 8-9% of Spanish households experienced fuel poverty. The rate of fuel poverty rose to 18.2% for the 10% criterion and 8.7% for the LIHC indicator. The 10% threshold seems to provide distorted and inflated estimates of the number of people living in fuel poverty, as was previously noted. The study also found a high likelihood of fuel poverty in households with poor income, unstable employment, and dependent children.

Due to their interconnectedness, energy poverty can also influence development outcomes. Although rigorous macroeconomic indicators of energy poverty have not been developed, available studies have relied on subjective measurements to establish the relationship between energy poverty and economic development. In Ghana, Adom et al. (2021) examined the impact of energy poverty on various development outcomes. The study focused on the consequences of energy poverty and the shift to renewable energy on development outcomes. The results indicate that switching to green energy can somewhat compensate for the adverse effects of energy poverty on various development outcomes such as income, education, life expectancy, and employment. However, there was a skewed focus on renewables in the study, which left out other essential components of energy poverty.

Due to socioeconomic inequalities, a more significant proportion of rural households live in energy poverty than their urban counterparts. Gafa and Egbendewe (2021) used primary data from Senegal and Togo to analyse the levels of energy poverty in rural West Africa and the factors that contribute to it. The study used a comparative approach to compare multiple indicators, including the multidimensional measure, per capita energy consumption, and expenditure-based metrics. Senegal's rural energy poverty ranged from 31.2% to 98.5%, whereas Togo’s ranged from 53.5 to 98.8 percent. However, per capita energy consumption-based measurements resulted in higher energy poverty rates in rural Senegal than Togo. This is attributed to larger household sizes in Senegal. Similarly, multidimensional and expenditure-based energy measurements generated higher levels of energy poverty in rural Togo than in rural Senegal. This is because Senegal has a higher per capita income and greater access to modern energy sources than Togo. Therefore, the number of people per household, as well as the average income per person, are factors that influence energy poverty, and the selected indicator ought to be sensitive to these factors.

Energy poverty is exacerbated by a lack of access to energy and individual energy preferences. In light of the energy poverty definition's emphasis on modern energy access, it is evident that households with lower incomes and countries with less developed energy infrastructure will be disproportionately affected by energy poverty. This is confirmed by Olang et al. (2018), who used the MEP index to elucidate the link between fuel choice and energy poverty in low-income households of Kenya’s lakeside Kisumu city. Higher levels of energy poverty were associated with concerns about access, whereas lower levels of energy poverty were associated with concerns about utilisation because they already had access to modern energy. Despite the energy poverty severity, the majority of the households expressed an interest in using modern energy sources. Therefore, the MEP index is a reliable indicator of energy poverty because it considers access, utilisation, affordability, and environmental concerns. This contrasts with past indicators, which concentrated on one aspect of energy poverty.

2.4.2 Link between Energy Poverty and Human Health

Most recent research on energy poverty identifies economic development and environmental sustainability as the fundamental motivations for evaluating energy poverty. This is not always the case, however. Despite this, there has been a growing corpus of research on the connection between energy poverty and general health in recent years. Using panel data from Australia, Churchill & Smyth, (2019) found a negative link between energy poverty and self-assessed overall health. The researchers employed both objective and subjective energy poverty criteria in their study. However, the low income, high cost (LIHC) paradigm employed in their study focuses solely on affordability and disregards other critical components of energy poverty.

A household's energy poverty is significantly correlated with the type of fuel used and its low usage of costly clean energy. Thus, energy-poor households are characterised by inexpensive, unclean energy, including the use of traditional fuels for both heating and lighting. Therefore, these households are more likely to have individuals with respiratory problems, spend more on medical care, have a more significant percentage of school dropouts, and have fewer earning options than those without energy poverty (Phoumin & Kimura, 2019). Besides direct emissions from traditional fuels such as biomass, exposure to low indoor temperatures during cold seasons also impacts health (Liddell & Morris, 2010; Zhang et al., 2019). The inability to afford contemporary energy services, such as those needed to keep a household warm in winter or cool in summer, is the primary cause of this problem. However, space cooling and heating are more domiciled in the global north. As a result, this study's main focus was on human health concerns associated with indoor air pollution brought on by using unclean energy sources for cooking and lighting.

According to findings by Llorca et al. (2020), poor living circumstances, fuel poverty, and other forms of material deprivation negatively impact an individual's overall health. The study investigated the association between several socioeconomic characteristics of individuals and their health, focusing on fuel poverty. Those who regarded themselves as fuel poor also tended to have poorer physical and mental health. The negative impact of objective fuel poverty on health was also more pronounced. The researchers utilised an ordered probit model to quantify the impact of fuel poverty on health. However, the fuel poverty index (FPI) adopted by the study considers only affordability indicators such as income, energy expenditure, MIS, and other related indicators. Similar findings have also been reported by Rodriguez-Alvarez et al., (2019) in the same country.

Beatty et al. (2014) examined the potential for a “heat or eat” trade-off in the United Kingdom. The research was conducted under the presumption that an unexpectedly cold weather shock causes households to spend more money than they had intended to maintain their comfort level. A household may be forced to choose between eating and heating their home if the weather shock significantly impacts their income. This is a classic case of fuel poverty. According to the study, low-income households could reduce their food expenditures to a statistically significant degree when winter temperatures were at least two standard deviations below what was anticipated.

According to a study by Oum (2019) in the Lao People’s Democratic Republic, energy-poor households are prominent among those with lower incomes, fewer durables, who reside in rural communities without electrical connections, and who are located distant from major roadways. The study confirmed a negative correlation between energy poverty and health status (both transient and persistent disorders). The adverse effects of energy poverty on health are primarily attributable to indoor air pollution, which is exacerbated by the living arrangements of households, such as a limited area with an in-house kitchen. However, the study’s methodology is limited by choice of traditional measurements for energy poverty, which concentrate on grid access and the 10 % criterion.

The use of subjective measurements to quantify energy poverty and health gives additional evidence of their link. Oliveras et al., 2021 investigated the prevalence of energy poverty and its association with health in the European Union both before and during the economic crisis. The study followed a consensual methodology and relied on self-reported, subjective indicators. Energy poverty was significantly linked to poor self-reported health, decreased well-being, and depression. The proponents of subjective energy poverty indicators base their case on the comprehensive nature of these measurements (Thomson et al., 2017). However, the study by Oliveras et al., 2021 focused primarily on heating and neglected other energy requirements, such as lighting and modern appliances.

Brown & Vera-Toscano (2021) provides further evidence for the interdependence of energy poverty and health by investigating the reciprocal relationship between health and energy poverty. The study concluded that subjective measures of energy poverty show more substantial evidence of interdependency than objective measures of energy poverty (LIHC), which portrayed no evidence of interdependency. This may be primarily attributable to the selection of an objective energy poverty measure (LIHC) that is biased toward affordability and omits other critical characteristics of energy poverty. On the other hand, the study reported a significant relationship between poor health and energy poverty when using univariate models.

These findings underline the necessity for methodological rigour when evaluating the link between energy poverty and health. Temperature extremes can intensify and worsen symptoms for people with health disorders such as cardiovascular, pulmonary, and respiratory diseases (Kahouli, 2020). Also, those with long-term medical conditions may be particularly vulnerable to insufficient power supply since they rely on energy-dependent gadgets to treat or maintain their condition. Dialysis and oxygen equipment, for example, are essential to patients with kidney disease, COPD, and cardiovascular disease, while those who are diabetic must refrigerate their insulin (Ikaheimo et al., 2014; Jessel et al., 2019).

Although studies on energy poverty in developing countries are limited, the few available studies show disparities with those from developed countries. Energy poverty in developing countries is primarily observed through the lens of cooking fuels. This is owing to the extensive use of biomass as a cooking fuel, as it is readily available and inexpensive relative to other cooking fuels. As a result, when adopting energy poverty measures in developing countries, cooking fuel becomes a vital factor to consider, which is not the case in developed countries. Researchers in China, for example, have examined the link between energy poverty and health by focusing on the accessibility and affordability of cooking fuels. Both Zhang et al., 2019 and Zhang et al., 2021 validated the negative relationship between energy poverty and health in China by employing multimodal approaches to energy poverty that primarily focused on the affordability and accessibility of cooking fuels. However, Xiao et al., 2021 likewise reached the same conclusions for China using the 10% criteria.

The development of modern, efficient energy sources increases life expectancy and decreases infant mortality rates (Banerjee et al., 2021). The study by Banerjee et al., 2021, was worldwide in scope, utilising macrodata from 50 developing countries in South America, Africa, Asia, and Europe. It relied on the human development index to develop a measure of energy poverty referred to as the energy development index (EDI). The EDI considers access to electricity, electricity consumption, renewable energy utilisation, and overall energy consumption as key metrics of energy development. Although this metric was designed in conjunction with human development index, that has been widely used, it does not consider important energy use in developing countries, such as biomass consumption. Its emphasis on electricity consumption as an indicator of energy poverty may not accurately depict energy poverty in developing countries. Nonetheless, the study demonstrated a statistically significant and robust negative effect of energy poverty on health.

2.5 Research Gaps

Although the link between household energy use and HAP is explicit in the reviewed literature, the quantitative aspect of the effect of HAP on human health has not been addressed. It is not known how unclean household fuels and technologies have exacerbated the disease burden or how the existing clean fuels and technologies have eased the disease burden. Evidence of cooking fuels and technologies' contribution to easing or exacerbating disease burden through HAP is necessary for effective decision making.

The literature is divided on the factors affecting household energy choices. The direction of influence of factors like age, gender, and education on household energy decisions is not yet the subject of widespread agreement (Meried, 2021). Furthermore, recent research has primarily concentrated on improved cookstoves in developing countries, ignoring other clean energy technologies and fuels utilised at the household level. This work addresses this deficiency by using a holistic approach, which considers all the energy options accessible to a household, unlike previous studies that have mainly focused on a particular fuel type or technology.

HAP concentrations vary widely between regions due to differences in stove design, fuel use, cooking habits, and kitchen characteristics. Consequently, information is required to estimate exposures across several research locations. While many cookstoves have been tested in a laboratory environment, previous research has found significant differences between laboratory and field data. Therefore, more field trials are required to determine the true exposures from various cookstoves.

Biomass cookstoves are still controversial despite design improvements to minimise emissions and increase fuel efficiency. Even though fuel efficiency may have been achieved (Sedighi & Salarian, 2017), the extent to which improved biomass cookstoves reduce emissions still requires further investigation. For instance, Kirby et al., (2019) found no evidence of reduced exposure to $PM_{2.5}$ concentration from improved biomass cookstoves. Most reviewed literature deduced the health benefits of improved biomass cookstoves rather than modelling the effects.

Most studies on energy poverty have been conducted in the global north, and they tend to analyse it from the context of affordability and the inability to maintain a sufficient room temperature. Other than China, very few studies have analysed energy poverty and health in the context of developing countries. For instance, Onyeneke et al., (2019) assessed the impact of improved cook-stoves on the environment and health in Nigeria, while Njiru & Letema, (2018) analysed the implications of energy poverty on living standards in Kenya. The study by Onyeneke et al., (2019) evades the whole concept of energy poverty, while that by Njiru & Letema, (2018) lacks empirical evidence on energy poverty. Moreover, the few available empirical studies on energy poverty in developing countries are motivated by environmental and economic sustainability. Examples of such studies include Ahmed & Gasparatos, (2020), Olang et al., (2018) and Sadath & Acharya, (2017). Conducting a study on the impact of energy poverty on human health requires primary data at the household level to capture individual characteristics. Unfortunately, this is lacking in the literature, particularly in sub-Saharan Africa.

Data requirements make assessing energy poverty and health at the household level challenging. Consequently, studies focusing on energy poverty and health status at the household level are limited. Moreover, previous studies only attribute deteriorating health status to energy poverty. There is limited evidence on causality. This study draws from the study by Nussbaumer et al., (2012) to construct and calculate energy poverty index at the household level. Second, unlike previous studies, the impact of energy poverty on health is investigated using quantitative techniques to establish cause and effect.

Despite biomass fuel being the most widely used fuel in rural areas, this sector has not attracted the attention of policymakers in Kenya. Providing sustainable energy solutions to rural communities has been left to non-governmental organisations. There are no clear policy guidelines on using different energy technologies and their effects at the household level. Rural electrification programs continue to draw more attention. However, rising electricity costs discourage most households from using electricity for cooking.

2.6 Theoretical Framework

2.6.1 Theory of Hierarchy of Needs

This study applied Abraham Maslow’s Hierarchy of Needs theory to evaluate links between need satisfaction (energy needs), HAP, and human health. In 1943, Maslow proposed the theory of human needs, which is now more commonly referred to as Maslow's needs hierarchy theory in the context of the human environment and the social structure. To investigate the fundamentals of HAP characteristics resulting from different fuels and technologies and determine the ensuing health outcomes according to different household energy characteristics, this study examined Maslow’s needs hierarchy theory in terms of basic household energy needs and choices. Maslow’s theory creates a five-category hierarchy of human needs based on the relative potency principle; physiological, safety and security, belongingness and love, esteem, and self-actualisation (Lester et al., 1983). Human needs, according to Maslow, are limitless, insatiable, interdependent, hierarchical, and correlated with the satisfaction or dissatisfaction of other needs (Maslow, 1948). In the needs hierarchical order, higher need levels are associated with less disease (good health), biological efficiency and require better external conditions (economic, political and educational) (Maslow, 1948).

Households’ preferences for energy sources can be categorised as either modern, such as electricity, LPG, and biogas, or traditional, such as all types of wood fuels and coal. Modern fuels are deemed superior or higher-level fuels in terms of efficiency, cleanliness, the convenience of use, and emissions per unit of fuel. They represent higher need levels. However, they require better economic conditions. On the other hand, traditional fuels meet only essential energy requirements, including cooking, lighting, and space heating. They are inefficient, less costly, more polluting, and represent lower needs (Figure 2.1). Low-income households will adopt modern energy sources and services as their income rises. Maslow's theory hypothesises that higher needs levels represent a general health ward trend. This study hypothesises that lower needs levels associated with traditional energy sources, and less efficient energy technologies, are characterised by HAP, leading to substantial effects on health. This theory conforms to the energy ladder and energy stack hypotheses outlined in Figure 2.1.

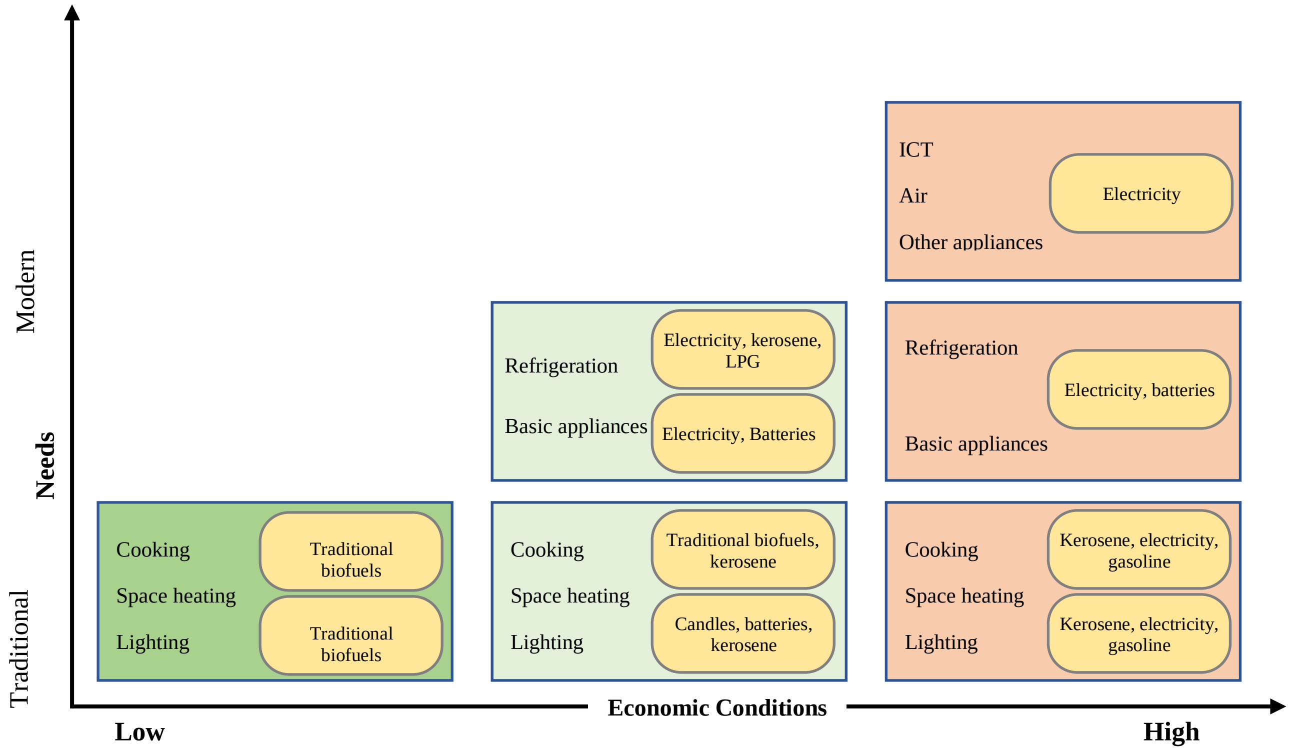


Figure 2.1: Illustration showing higher and lower energy needs levels demonstrating Maslow's need hierarchy theory. Adapted from (Kowsari & Zerriffi, 2011)

2.6.2 Energy Ladder and Energy Stack Hypothesis

The energy ladder and stack hypotheses present theoretical justifications for household fuel use patterns. The energy ladder hypothesis posits that households with lower income levels are more inclined to choose biomass fuel. In comparison, populations with higher income levels are more likely to pick more expensive, cleaner, and environmentally friendly energy sources, such as electricity and gas, as their primary fuel source (Waweru et al., 2022). As households improve their socioeconomic level, they abandon inefficient, less expensive, and polluting energy sources and shift from reliance on biomass to fuel such as charcoal, kerosene, and coal. Charcoal, kerosene, and coal are examples of transition fuels primarily consumed by households in the transitioning phase between traditional and modern cleaner, efficient fuels. The term "fuel switching" refers to the displacement of one type of fuel by another during the transitioning phase. Households that are in the process of transitioning to more sustainable energy sources are also more likely to use improved energy technologies. In the final stage, the third one, households transition to fuels such as LPG and electricity (van der Kroon et al., 2013). This process is illustrated in Figure 2.2.

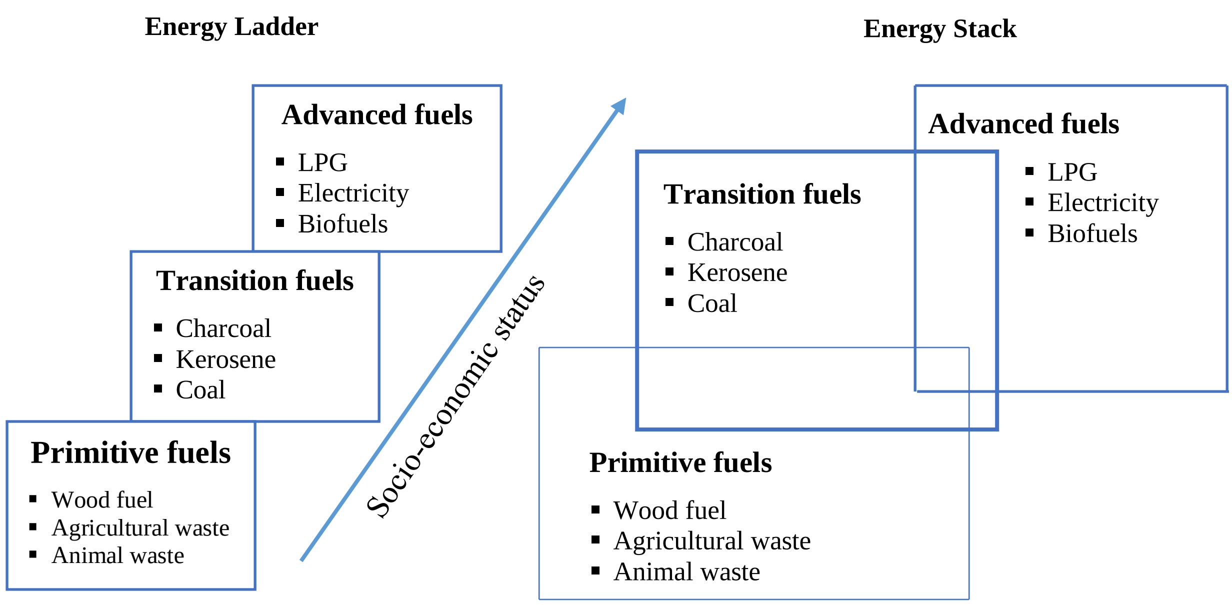


Figure 2.2. Energy ladder and energy stack framework.
Source: (van der Kroon, 2016)

Nonetheless, a rising number of empirical research on residential energy consumption demonstrate that the energy transition does not occur in a sequence of straightforward, distinct steps. In most cases, households do not immediately move to clean and efficient fuels; instead, they consume a combination of clean and unclean fuels. This is because households cannot completely abandon their previous energy sources, resulting in policy difficulties and contradictions in theories of energy transition (Yadav et al., 2021). As a result, the energy ladder idea has been refuted by the energy stacking (dual fuel use) hypothesis. Preferences, needs, costs, and budget are all major factors in the energy stack hypothesis (Waweru & Mose, 2022).

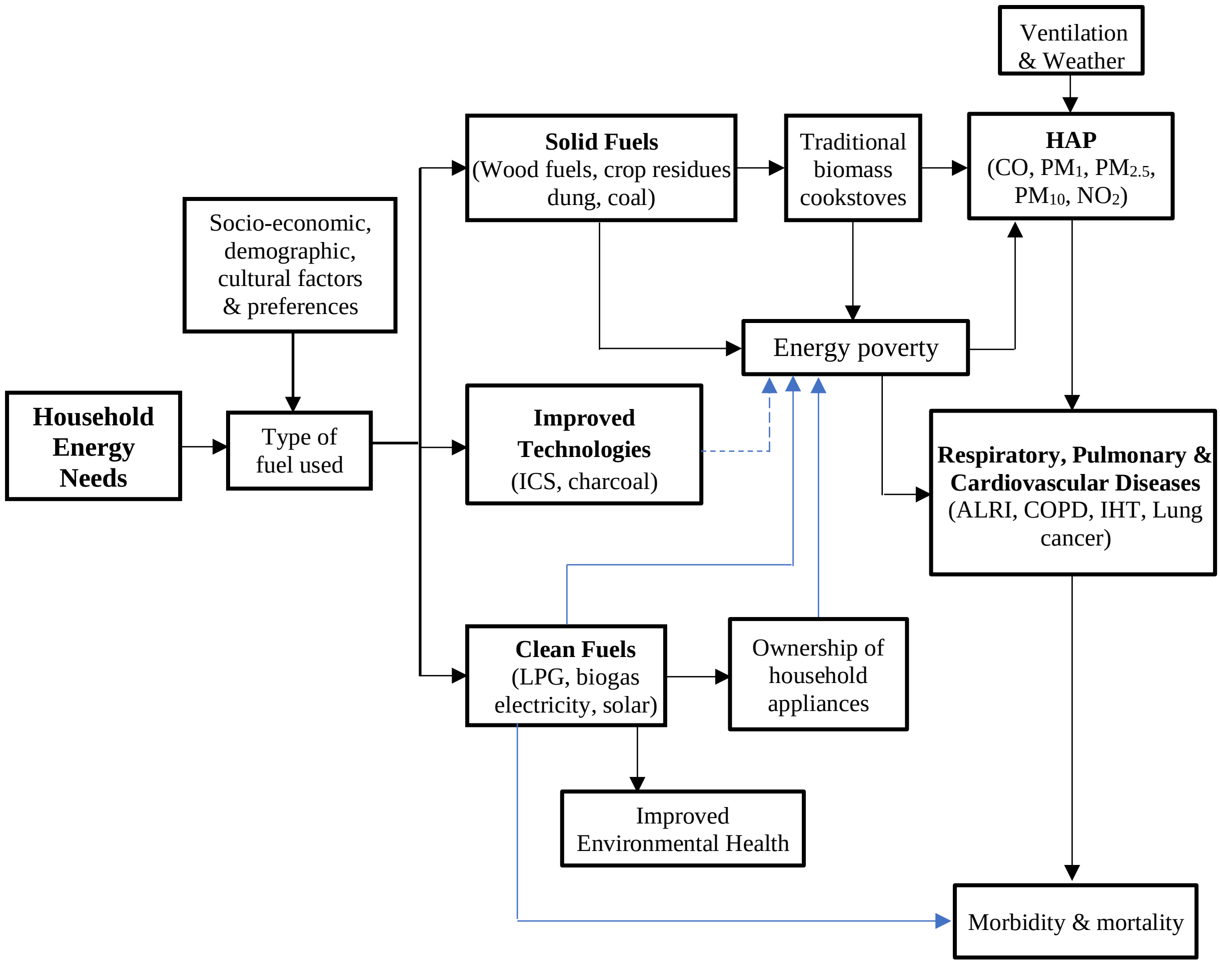
2.7 Conceptual Framework

This study's variables included household cooking and lighting fuel, such as wood, charcoal, kerosene, LPG, biogas, candles, solar energy, and electricity. Cooking methods and technologies were classified as traditional cookstoves, including three-stone, traditional *jikos*, ceramic *jikos*, sawdust *jikos*, and improved biomass stoves. Modern cooking technologies that were considered include gas stoves and electric stoves. Other variables considered include HAP, represented by PM_1, $PM_{2.5}$, PM_{10}, CO, and total volatile organic compounds (TVOC). For health assessment, several illnesses associated with HAP were considered, including respiratory diseases (acute lower respiratory infections - ALRI), pulmonary diseases (chronic obstructive pulmonary disease - COPD), and cardiovascular diseases (ischemic heart disease – IHD, and lung cancer). Other acute illnesses considered include phlegm, wheezing, cough, red itching eyes, nasal irritation, and burns.

In developing countries, the highest portion of energy consumption is used for cooking (Malla & Timilsina, 2014), where biomass is the primary fuel since it is the most readily available energy source. A substantial proportion of rural households in developing nations utilise inefficient cookstoves, exposing them to HAP and physical danger (World Bank, 2018). Since dependence on biomass cannot be eliminated entirely, improved cookstoves have been recommended as a transitional approach to minimise pressure on forests and reduce emissions (GHGs, PM, and CO). However, socio-economic, material, and cultural aspects influence the vulnerability outcome that prevents households from accessing modern, clean energy or embracing new energy technologies to abate the negative impacts of traditional energy practices.

Household energy characteristics are influenced by socio-economic status, culture, gender, age etc., which determine the type of fuels used by a household. The use of inefficient household energy can also be predicted by other social factors, including income, education, and employment status (Jessel et al., 2019). HAP results from unclean and inefficient energy sources and adversely affects human health. Besides socio-economic and cultural factors, HAP is also influenced by poorly ventilated spaces, overcrowding and insufficient living space, fuels used, tobacco smoking, and climatic factors (WHO, 2021a).

Depending on their roles, the variables investigated in this study can be classified as independent, confounding, or dependent variables. Human health and HAP are the primary dependent variables, but human health is the key outcome variable. Both HAP and human health are affected by the type of fuels and household energy technologies which form the independent variables for this study. Confounding variables include weather/climate, socioeconomic factors, smoking, and outdoor air pollution. Figure 2.3 provides a summary of the variables and their roles.



NB: Black arrows represent a positive relationship while blue arrows represent a negative relationship

Figure 2.3: Conceptual framework

CHAPTER THREE

MATERIALS AND METHODS

3.1 Description of the Study Area

This study was conducted in Kenya, situated in the easternmost part of Africa along the equator. Kenya’s latitude and longitude are shown to be within the range of 0.0236° S and 37.9062° E. Kenya is the 49^{th} largest country in the world, with an estimated total area of 580,367 km^2, 11,227 km^2 of water, and 580,140 km^2 of land (Mose, 2021). In particular, Vihiga County, located in the Lake Victoria Basin of Kenya’s western region, was the subject of the investigation. The county’s geographical location is 34°30’E, 35°0’E and 0°, 0°15’N (Figure 3.1) and covers an estimated area of 531.0 km^2.

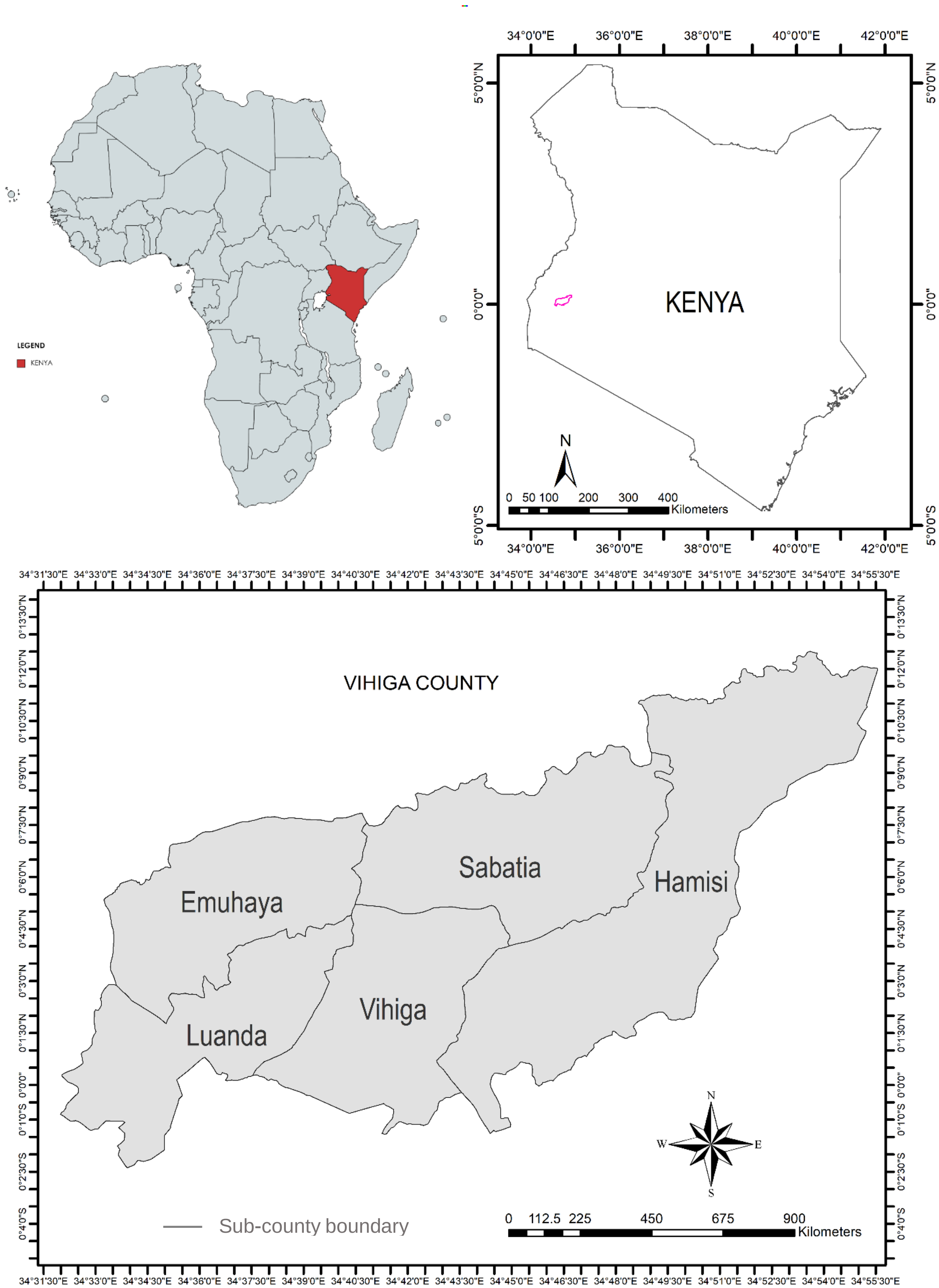


Figure 3.1: Map of the study area - Vihiga County.
Source: Authors

3.1.1 Socio-Demographic Characteristics

According to the 2019 Kenya population and housing census, Vihiga county has a population of 590,013 and a population density of 1,047 people/km^2 (KNBS, 2019). Males make up 47.8% of the population, while females make up 52.2%. The demographic profile shows a young population, with 46% of the population under the age of 15 years. It was projected that by the year 2022, Vihiga's population would have increased to 694,819 (CIDP, 2018). Only Nairobi and Mombasa, Kenya's two largest city counties, have a population density higher than 1,047 people/km^2. Vihiga's population density is significantly higher than the country's average, which is 66 people/km^2. Vihiga is thus the most densely populated rural area in Kenya. The high population density exerts pressure on available energy resources because as population size increases, so does energy consumption.

The county's Human Development Index (HDI) is 0.50 compared to 0.52 for the country. Life expectancy is 56.2 years, which is lower than the national average of 63.4 years. Infant mortality is approximated at 64/1000 while adult literacy is 93.8 % compared to 78% for the country. Compared to the national average of 45%, the County has a poverty rate of 39% (CIDP, 2018).

3.1.2 Physical and Topographic Features

The county's elevation ranges from 1300 metres to 1800 metres above sea level. It has gradually sloping hills and valleys that run from East to West. The streams run from the northeast to the southwest before emptying into Lake Victoria. River Yala is the sole significant river that flows through the county, and it has three major tributaries: *Edzava*, *Zaaba*, and *Garagoli*. The County experiences high riverine erosion due to its hilly landscape. Rocks of Kavirondian and Nyanzian origin make up the county's geological formation; prominent examples can be seen in the Tambua, Jepkoyai, Emabungo, and Maragoli Hills. The majority of the county's soils are sedimentary in composition, which enables a wide variety of agricultural pursuits to be carried out (CIDP, 2018).

3.1.3 Ecological Conditions

The county's primary agroecological zones can be divided into the upper and lower midlands (CIDP, 2018). The agro-ecological zones determine land use and settlement patterns within the county. The upper midland region, which includes the sub-counties of Hamisi, Sabatia, and a portion of Vihiga, is characterised by fertile, well-drained soils. The primary crops cultivated in this region are maize, beans, tea, bananas, and sweet potatoes. Emuhaya, Luanda, and sections of Hamisi sub-counties are located in the lower midland zone, characterised by predominantly red loamy sand soils formed from sedimentary and basalt rocks. Bananas, groundnuts, maize, cassava, sorghum, beans, and sweet potatoes are some of the crops cultivated in this zone. Both agroecological zones support the rearing of several livestock species (MoALFC, 2021). The county has a small forest area estimated at 2,800 ha of natural forest and 517 ha of community/private forest, making wood fuel supply relatively scarce (MEWNR, 2013).

The most common soil type in the county is acrisol, a deep, well-drained, slightly acidic soil topped with humic top layers that originated from volcanic and basement complexes. These soils are interspersed by yellowish-red loams produced from sediments and basements. Nitosols and humic ferrosols are also present, albeit to a lesser extent, particularly in the southernmost parts (MoALFC, 2021).

3.1.4 Climate

Vihiga county receives an average annual precipitation of 1900 mm, which falls within the equatorial climate type with generally evenly distributed rainfall across the year. The typical temperature is 23°C, with annual temperatures ranging from 14°C to 32°C. Monthly average temperatures in the past have ranged from 20°C to 35°C. March, April, and May are characterised by prolonged precipitation (typically referred to as the long rains season), whereas short rains characterise the months of September, October, and November. December, January, and February have average humidity of 41.8 %, making them the hottest and driest months of the year. Between January and February, relative dry spells with less than 100 mm of rainfall are common, yet these months may experience heavier rainfall of up to 250 mm. The county's north-eastern region receives an average of more than 2,000 mm of rain annually. Precipitation and temperature do not vary significantly across the county because of its modest size. The annual mean temperature trends indicate that temperatures have increased historically and will continue to increase (MoALFC, 2021).

3.2 Research Design

This research employed a quantitative design. The design is ideal for this study because the study sought to establish connections and causal relationships among different household energy technologies, HAP, and human health. Quantitative research designs are most frequently employed to investigate the relationships between variables (Creswell, 2014).

The experimental and non-experimental facets of quantitative research were employed in the study. The first facet of the quantitative design was non-experimental, involving survey research. The primary objective of survey research was to characterise the key features of the studied population. By studying responses from a representative sample of a population, survey research provides a quantitative or numerical account of the tendencies or opinions of a population (Asenahabi, 2019). Typically, surveys are conducted by administering questionnaires to a sample. Probability sampling was utilised in the sampling process to ensure that the sample represented the population. This study adopted a cross-sectional survey approach for objectives one and three. In a cross-sectional survey, the features and differences of a sample are measured at a single point in time (Rezigalla, 2020). The strengths of survey design lie in its ability to generalise results to large populations and versatility in terms of the topics and methods that can be explored.

The second part of this quantitative research design was experimental. Experimental research design is a collection of techniques in which the effects of various treatments or conditions on study participants are studied (Creswell, 2014). The fundamental purpose of an experimental design is to examine the effect of a treatment or intervention on a certain result, while controlling for any other variables that may influence that result. Several control procedures can be employed, including randomisation and having a control group.

Experimental research design is regarded as the most definitive of the types of research designs because of the researcher's capacity to vary the treatments and control for extraneous variables. It can be utilised to demonstrate cause and effect (Jongbo, 2014), and was chosen for this study's second objective. Experimental research design is only achieved if the following conditions are met; randomly selected participants and control groups, independent (treatment) variable, and dependent (effect variable).

3.3 Materials

3.3.1 Questionnaire

The household survey data was collected by administering questionnaires to household heads of each household. The questionnaire was divided into the following sections (Appendix II).

a) Section "A" was on biodata and demographic data
b) Section "B" contained questions on the determinants of the use of clean energy technologies
c) Section "C" contained questions on energy poverty indicators

d) Section “D” contained questions on household energy technologies and HAP

e) Section “E” contained questions on HAP on health outcomes

The questionnaire also contained simple health assessment questions. Self-Rated Health (SRH) has been widely used in health-oriented and non-health-oriented studies (Apouey & Clark, 2015; Churchill & Smyth, 2019; Hernández, 2016; Kuehnle & Wunder, 2017; Ronconi et al., 2012) and is more effective in predicting morbidity, functional limitations, mortality and utilisation of healthcare services (Bopp et al., 2012).

The questionnaire was predominantly closed-ended, however, there were a few open-ended questions that requested extra information. The questionnaires were administered face-to-face by trained research assistants from the local community and were fluent in the local language (*luhya*). The household survey was conducted between June 1, 2021, and June 8, 2021.

Validation of the Questionnaire

The questionnaire designed for the household survey was subjected to a validation process to check face and content validity. The concept of a questionnaire having “face validity” refers to the idea that the questionnaire should look superficially to test what it intended to test. The idea of content validity states that a test should represent the spectrum of behaviour in the theoretical topic being assessed (Connell et al., 2018). The ethical review committee from the University of Nairobi - Kenyatta National Hospital was consulted during the study’s validation phase, and copies of the proposal, which included the questionnaire and study objectives, were provided to them.

After completing the questionnaire’s validation process, the instrument underwent a round of pilot testing. Before administering the pilot test, research assistants participated in an intensive one-day training session on the methods, tools, and ethical issues involved in the data collection process. A pre-test survey of 36 households was done in one of the research area's villages.

This pilot test was carried out to understand how the respondents would react to the questions; establish whether the questions were understandable and clear; identify whether there were any questions they did not wish to answer; and evaluate the practicability of the proposed data analysis methods.

Following the pilot test, minor revisions were made to the questionnaire to address the issues identified, which included ambiguity in some questions. The village where the pilot test occurred was omitted from the actual data collection exercise to avoid bias.

3.3.2 Household Air Pollution Data

This section describes the procedures utilised to quantify HAP exposures resulting from various cooking techniques and kitchen conditions.

a) Pollutants considered and their characteristics

Fine particulate matter (PM_1 and $PM_{2.5}$), carbon monoxide (CO), and volatile organic compounds (VOCs) were used as HAP indicators in households. Other related pollutants included course particulate matter PM_{10}. $PM_{2.5}$ is a mixture of seven chemical components that comprise at least 79-85% of $PM_{2.5}$ mass. These include elemental carbon, sulphates, organic carbon, ammonium, sodium ion, nitrates, and silicon (Dominici et al., 2015). Particulate matter is measured in $\mu g/m^3$, representing mass concentration in an air volume. PM and CO are products of inefficient fuel combustion released during cooking activities. However, $PM_{2.5}$ accounts for the most impact on public health (Adetona et al., 2016). $PM_{2.5}$ that exceeds the WHO recommended threshold has been linked to cardiovascular and respiratory diseases, including lung cancer (Bruce et al., 2015; Gordon et al., 2014), obstructive pulmonary disease (Assad et al., 2015), stroke, and acute lower pulmonary infection (WHO, 2014).

Short-term exposure to CO is associated with acute symptoms, while chronic exposure has been linked with asthma and cardiovascular diseases. $PM_{2.5}$ and CO are included in the WHO's air quality guidelines for indoor fuel combustion and are essential to consider. WHO revised the air quality guidelines (AQGs) in the year 2021 as follows; the recommended maximum 24-hour $PM_{2.5}$ was revised to 15 μg/m^3 from 25 μg/m^3 set in 2005, PM_{10} was set to 45 μg/m^3 from 50 μg/m^3 of 2005, while CO for the first time entered the list of WHO AQGs with a recommended 24-hr maximum of 4 mg/m^3 (3.49 ppm). The WHO has not yet established PM_1 guidelines.

b) Outdoor Pollutants

Two energy-related pollutants were considered for the outdoor environment: CO and NO_2. The web-based application Giovanni, which has many archived distinct metrics for geophysical data, was used to extract monthly data on CO concentration from January 2010 to December 2021. MERRA-2 model was used to obtain the data at a spatial resolution of 0.5 x 0.625°, which is smaller than Vihiga county. The decision to utilise the monthly data was made because daily data for CO surface concentration were only available at a coarser spatial resolution (1°). According to the Giovanni measurement definitions, the results indicate the number of CO molecules in an atmospheric column extending from the planet's surface to the stratosphere's uppermost level, over a square centimetre above the surface (Acker & Leptoukh, 2007). The ozone monitoring instrument (OMI) on NASA's Aura satellite provided daily NO_2 data with a geographical resolution of 0.25° from January 2010 to December 2021. These data show the amount of NO_2 molecules present in the tropospheric column above a surface area of one square centimetre (1/cm^2).

The study utilised data on daily reported COVID-19 cases archived by the Ministry of Health from March 14, 2020 to August 30, 2020. The number of reported COVID-19 cases informed the government decision to impose more stringent preventive measures or ease some of the already imposed measures. In February 2020, before a single case was reported in Kenya, the

Ministry of Health advised maintaining basic hand and respiratory hygiene practices. However, with increased number of COVID-19 cases, the authorities in Kenya extended the measures to include the closure of schools (March 15, 2020), lockdown of hotspot zones and cessation of movement (May 6, 2020).

c) Experiment Setting

There are two methods of air pollution monitoring at the household level: stationary and personal monitoring. Personal monitoring requires equipment to be worn by a household member and carried throughout daily activities. This study sought to assess exposure to $PM_{2.5}$ and CO across the length of cooking duration. Hence, stationary monitoring was the most suitable technique. In stationary monitoring, equipment is set in a particular position to measure the levels of pollutants in a kitchen.

The monitoring equipment was positioned at the cook's breathing height. Assuming that the household member responsible for cooking spends the entire cooking time in the kitchen, this would represent the average concentration of pollutants to which the individual is exposed during that period. Only household members involved in cooking were targeted as respondents for this phase. Prior to initiating HAP monitoring in the target group, a baseline household survey had already been completed. The objective of the initial questionnaire-based survey was to collect essential data and to understand the household kitchen structure, fuel usage, and cooking behaviours in the area. Based on this survey's findings, the cooking fuels and cookstoves that best represented the local context were chosen. The biomass cookstoves sampled are shown in plate 3.

Three stone | *ICS (Chepkube)* | Sawdust *jiko* | Ceramic *jiko*

Plate 1: Types of biomass cookstoves sampled. *Source*: Author

Kitchen PM and CO monitoring were done using the Multifunctional Air Quality Detector EGVOC-180 (Figure 3.2) and Carbon Monoxide Meter AS8700A (Figure 3.3), respectively.

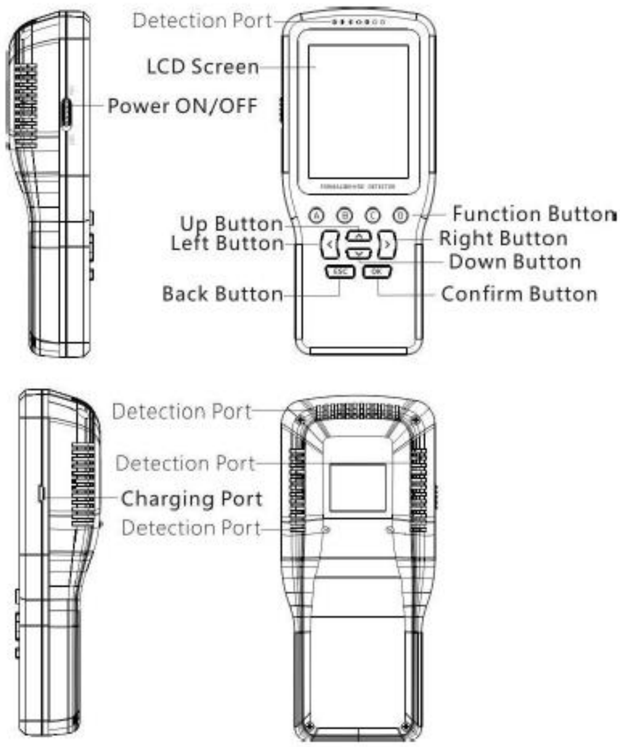


Figure 3.2. Schematic illustration of the Multifunctional Air Quality Detector EGVOC-180

Figure 3.3. Diagram illustrating the various parts of the Carbon Monoxide Meter

From the user manual, the Multifunctional Air Quality Detector allows real-time monitoring of PM_1 (in µg/m^3), $PM_{2.5}$ (in µg/m^3), PM_{10} (in µg/m^3), total volatile organic compounds (TVOC) (in mg/m^3), temperature (in degree Celsius) and relative humidity (in %) using advanced sensor technology. It consists of a built-in fan that rapidly draws in ambient air with a laser sensor for measuring dust particles, while a second in-built electrochemical semiconductor sensor tests air quality for TVOC. Measurements from optical monitoring sensors have been found to correlate significantly with those from gravimetric methods (Shi et al., 2017). The Carbon Monoxide Meter uses an electrochemical sensor to detect CO in parts per million (ppm) and temperature (in degrees Celcius). Calibration and ground truthing were carried out before the onset of each experiment. This involved placing the instruments in clean air for at least 30 minutes until zero readings were attained. Clean air locations were identified outside in the open, with free air circulation.

Indoor PM and CO concentrations are affected by emission levels resulting from indoor fuel combustion, which are further affected by the type of cookstove in use. For instance, there could be a reduction in emissions from household fuel combustion due to efficient technologies and practices, thus changing the level of PM and CO. Other factors include structural factors, e.g., rates of ventilation; fuel factors, e.g., fuel type; behavioural factors including the tendency to open or close windows and/or doors; household characteristics such as the size of the family; weather factors such as temperature, wind, rainfall, and relative humidity; and other pollution sources including tobacco smoking and presence of kerosene lamps.

Each household completed a simple questionnaire (Appendix III) during the monitoring period to record any factors unique to that particular household. This included, for instance, the number of people being cooked for or multiple cooking instances within the same kitchen. If a significant departure from the normal was noted, the monitoring session was repeated, or that particular household was excluded from the final sample. The sampled households were asked to follow their routine activities while cooking without altering their cooking techniques and stove operations. Kitchen monitoring was carried out for at least 65 continuous minutes during a cooking episode. The average cooking time of 65 minutes was determined from the baseline household survey. The cooking duration was similar throughout the tests for uniformity.

Background PM, CO, and VOC concentrations in the kitchens were measured at least 10 minutes immediately before each monitoring event and subtracted from those measured during the monitoring period. In the event of $PM_{2.5}$ and CO exceeding 25 μg/m^3 and 0 ppm, respectively, before the tests, the monitoring was delayed until a lower value of background concentration was observed.

d) Control experiment

This study recognised that other types of intervention, such as improved ventilation or behaviour changes, could contribute to reduced HAP levels and affect the observed variation in households. It was also anticipated that HAP and exposure levels would greatly vary between households because of variability in household energy use patterns, housing type, and weather/climatic factors. To control for these factors, HAP monitoring was also done in the same kitchen for all the cooking technologies and fuels considered. This was performed three times using the same cooking method and fuel at different times of the day (morning, afternoon, and evening), representing different atmospheric stability conditions. This experiment was referred to as the 'control group' throughout the rest of the work, while HAP monitoring for the sampled households was referred to as the 'field group'. To avert the differences attributed to the type of meal prepared, this was fixed to water boiling for the control group, while there were no restrictions on the kind of meal for the field tests. The kitchen selected for the control experiment represented the kitchen characteristics of most kitchens in this region. These characteristics include; mud walls, one window, one door, a corrugated iron sheet roof, and earthen floors. In addition to the pollutants of interest in this study, temperature, and humidity were also measured concurrently.

3.4 Methods

The approaches described in this section cover the methods used to achieve each objective. The first objective on the determinants of household energy choices was investigated using the probit model. The second objective on HAP and associated health risks was addressed by modelling the health impacts of HAP using the AirQ+ model. The third objective on the impact of energy poverty on health was addressed using the multidimensional energy poverty framework, inverse probability of treatment weighting (IPTW), and marginal structural models. Below is a detailed discussion of these methods.

3.4.1 Sampling

Considering the likelihood of extraneous variables' effects, the sampling technique was carefully designed to ensure that observed differences were due to a characteristic of the population and not by chance. This stage was critical in ensuring that statistical significance and cause and effect were achieved. The first step in this sampling procedure was to define the study's target population, which consisted of the entire household population in Vihiga county. According to the 2019 Kenya population and housing census, the number of households in Vihiga county was 143,365 (KNBS, 2019). This was the targeted population. The sampling frame comprised households situated at least 5 kilometres from major highways or polluting industries. The basic sampling unit was the household, targeting the household heads.

3.4.1.1 Sampling Technique

The study adopted the probabilistic sampling technique. Probability or random sampling was preferred because it ensures that each household in the study population had equal probability of being sampled (Taherdoost, 2016). Probability sampling provides advantages over other sampling techniques because it minimises sampling biases and ensures a minimal likelihood of systematic errors. Inferences drawn from the sample can also be generalised to the population (Sanjoy, 2018). Probability sampling is the foundation of every study that aims to generalise findings from a sample to the entire population of interest.

In particular, the study utilised systematic random sampling. At intervals of five (5), households were randomly selected from a random point to draw a random sample from the target population. Due to the homogeneity of the research population, systematic random sampling was an ideal sampling strategy. Madow and Madow were the first researchers to investigate the theory of systematic random sampling in 1944.

The study was focused on rural communities with a high number of wood fuel users. This was necessary to ensure that users of different energy technologies were identified. Users of other fuels or technologies such as electricity, kerosene, biogas, and solar would also suffice within this population.

3.4.1.2 Sample Size Determination for the Survey Study

This estimation aimed to determine an appropriate sample size capable of estimating outcomes for the entire population with good precision. The estimated sample size must be sufficient to make inferences or generalisations about the entire population. Therefore, to make inferences about the population based on a sample, the sample must conform to certain criteria. One of the essential considerations is the requirement that the sample must accurately reflect the whole population (Taherdoost, 2017).

There are several methods available for calculating sample size. However, for all methods, the fundamental elements to be considered for a suitable sample are the necessary precision level, the desired confidence level, and the degree of variability. The level of precision is the error margin between the sample estimate and the actual value of the population. The distribution of traits or attributes in the population is referred to as the degree of variability and is dependent upon the homogeneity or heterogeneity of the population (Singh & Masuku, 2014). For instance, the greater a population's heterogeneity, the higher the sample size needed to achieve a certain degree of precision.

One of the essential approaches that have garnered the support of many academicians is the application of several formulae for determining required sample sizes in various contexts. Different formulas are available for determining appropriate sample sizes for probabilistic sampling methods, but the most outstanding ones are Cochran and Yamane formulas.

Cochran's formula was utilised to arrive at an estimate sample size necessary for the household survey research (equation 1).

$$n_o = \frac{z^2pq}{e^2} \qquad (1)$$

Cochran, (1977) developed the above formula to estimate the representative sample for proportions. n_o represents the sample size, z is the critical value of the confidence level, p is the proportion estimate of an attribute present in the population, $q = 1 - p$, and e is the level of precision. This formula assumes a large study population. This study assumed maximum variability in the study population, 50% (p = 0.5) and 95% confidence level hence $\pm$5% precision level. At 95% confidence level, z = 1.96.

$$\text{Therefore, } n_o = \frac{(1.96)^2(0.5)(1-0.5)}{0.05^2} = 384 \qquad (2)$$

3.4.1.3 Sample Size Determination for the HAP Study

The study on HAP adopted a cross-sectional (unpaired) design to evaluate HAP exposure from the baseline cooking fuels and technologies using a systematic random sampling approach. Systematic sampling using the equal-probability method was preferred for this because of the homogeneity in the population in terms of cooking fuels and housing characteristics. Data for HAP monitoring was collected from a sub-sample of the baseline household survey. Based on Cochran's formula, the minimum sample size for baseline studies is 384. However, the maximum number of samples that may be used is unrestricted. A sampling interval, k, was determined, where every k^{th} element in the sampling frame was selected. The value of k was determined as follows.

$$k = \text{Sampling frame size (N) / Sample size (n)}$$

Sample size estimation was based on statistical approaches for HAP and health studies provided by (Anenberg et al., 2017; Smith et al., 2014). The variability in the study's sample and the detectable difference are critical parameters in determining the sample size. The detectable difference represents the estimated size of the difference in HAP that will become statistically significant. This affects the sample size because, for instance, a much larger sample size is required to justify that a more negligible difference is statistically significant than the sample size required to demonstrate the statistical significance of a larger difference. The Coefficient of Variation (COV) determines the variation within the HAP measurements. COV is standard deviation (SD) divided by the mean (SD/Mean). More variability in HAP requires a more significant number of samples to show statistical differences. COV varies depending on fuel type, stove type, HAP type to be estimated, and location. The sample size was computed based on COV, detectable difference, and other statistical parameters such as confidence level, p-value, and the number of tails in the test. The study adopted the standard convention of a p-value of 5% and a 2-tailed test. However, it is upon the researcher to determine the confidence and precision level upon which to base the effect of different energy technologies on HAP. A 90/30 confidence/precision level is sufficient for studies on HAP exposure for both paired designs (before and after) and cross-sectional (unpaired designs) (Appendix IV). This criterion presupposes a minimum sample of 30 households for such studies. This study sampled 42 households, higher than the minimum threshold of 30, and fell within the range of similar studies (Adhikari et al., 2020; de la Sota et al., 2018; Jayarathne et al., 2018).

3.4.1.4 Criteria for inclusion/exclusion

Among the goals of this study was to investigate the health effects of HAP and energy poverty. Respondents were pre-screened for inclusion/exclusion to ensure that the study questions were answered and that potential confounders were minimised. Exclusion was based on the following factors: those under medication, pregnant women, those with a family history of TB or asthma, those who smoke (regularly or sometimes), and those who work in the transport sector. To minimise the effect of traffic pollution, the respondents were selected from households located away (not within a 5km radius) from the main highway (Adhikari et al., 2020). There were no polluting industries within the study area, so the effect of industrial pollution can be ignored. Those who used diesel generators were also excluded from the sample. Additionally, the HAP monitoring study excluded those near burning activities or likely to experience other polluting sources.

3.4.2 Ethical Considerations

For every household participating in the study, a written informed consent (Appendix I) was administered that guaranteed low risk from their involvement in the study, the ability to withdraw from the exercise, and non-responsibility for equipment damage. Before the study began, the University of Nairobi - Kenyatta National Hospital (UoN-KNH) ethics and research committee granted ethical approval (protocol number P34/01/2021, Approval date: 21 May 2021). It was made clear to those who participated in the study that their participation was entirely voluntary.

3.4.3 Probit Model Specification

The first objective was to evaluate factors affecting household decisions toward clean fuels and technologies. Household fuel choice was hypothesised to be influenced by socio-economic status and demographic characteristics. A household's decision to utilise clean fuels or technologies is binary, with two possible mutually exclusive outcomes; a household uses either clean or unclean fuels or technologies. In instances of fuel stacking, the primary fuel used was prioritised. The appropriate econometric approach for this situation is the binary choice model. The paradigm for such analysis assumes households' rational choice when selecting an energy source (Amoah, 2019). Households have preferences on utilizing clean or unclean fuels and technologies and opt for whichever that maximises their utility. Thus, a stimulus that pushes past a certain reaction threshold triggers a reaction that is dependent on socio-economic status and demographic characteristics.

A binary dependent variable y_i can be defined with two possible values: $y_i \in [0,1]$, where $y_i =$ 1, if a household uses clean fuels as a primary energy source, and 0, otherwise.

Thus, a household's probability of using clean fuels is given by;

$$\Pr\left(y_i = \frac{1}{x_i\beta_i}\right) = 1 - F(-x_i\beta_i) \qquad (3)$$

F is the cumulative distribution function, x_i is a vector of independent variables described in table 3.1, and β_i is a vector of model estimate coefficients.

Since the response variable is binary, the probability associated with the alternative event (using unclean fuels) is expressed as.

$$\Pr\left(y_i = \frac{0}{x_i\beta_i}\right) = 1 - F(-x_i\beta_i) \qquad (4)$$

The interaction of the dependent and independent variables is given by:

$$y_i = \beta + \beta_i x_i + \mu_i \qquad (5)$$

where μ_i is the random error term.

The default approaches for panel data modelling and nonlinear modelling, in general, are the probit and logit models for binary choice. The primary distinction between logit and probit models is that logit assumes a logistic distribution of the error component, while probit assumes normal error distribution (Greene & Zhang, 2019). However, the outcomes of both models are identical. In this work, the choice of probit model was informed by its capacity to deal with heteroscedasticity. In addition, the logistic model's major limitation is the independence of irrelevant alternatives (IIA) assumption. Similar prior studies have employed the probit model (Amoah, 2019; Guta, 2020; Onyeneke et al., 2019; Rahut et al., 2018; Salisu, 2016).

The probit model is represented by;

$$P_i = P(y_i^* < y_i) \qquad (6)$$

$$P_i = P\left(y_i^* < \beta_o + \beta_i x_{ji}\right) = F(y_i) \qquad (7)$$

$$P_i = F(y_i) = \frac{1}{\sqrt{2\pi}}\int_{-\infty}^{z_i} e\,\frac{S^2}{2}\,ds \qquad (8)$$

P_i represents the probability of using either clean or unclean fuels, y_i represents the choice of either clean or unclean fuels (dependent variable), y_i^* represents the threshold value for y_i, while S represents the random term which is normally distributed.

The cumulative distribution function's inverse can be written as.

$$y_i = F^{-1}(P_i) = \beta_0 + \beta_i x_i + \mu_i \qquad (9)$$

The probit model coefficients (β_i) show the direction of effect. Their applicability is restricted, however, because they do not indicate how changes in the independent variables affect the probability of the dependent variable (whether a household chooses clean or unclean fuel). The marginal effect measures how each independent variable affects a household's probability of choosing clean fuels. It is expressed as follows.

$$\frac{\partial P_i}{\partial x_{ij}} = \beta_{ij} f(Z_i) \qquad (10)$$

Where P_i is the mean dependent variable, expressed as;

$$f(Z_i) = F^{-1}(P_i) \qquad (11)$$

For independent binary variables, marginal effects quantify discrete change.

Table 3.1: Description of variables used in the probit model.

Variable name	Description	Expected sign	Sources
Dependent variables			
Clean cooking energy	Dummy, 1 = if a household uses clean energy for cooking, 0 = otherwise		
Clean lighting energy	Dummy, 1= if a household uses clean energy for lighting, 0= otherwise		
Explanatory variables			
Household size	Number of members in a household, continuous variable	±	Mekonnen & Abera, (2019)(-), Narasimha Rao & Reddy, (2007)(+) , Ouedraogo, (2006)(+), Kulindwa et al., (2018)(-), Baiyegunhi & Hassan, (2014)(-), Gitone, (2014)(-)
Gender	Dummy, 1= male, 0 = female	±	Zeru & Guta, (2021) (+), Link et al., (2012a)(-), Rahut et al., (2018)(-)
Age	Age of the household head. Dummy, 0 = 21-30yrs, 1 = 31-40yrs, 2 = 41-50yrs, 3 = 51-61yrs, 4 = above 60yrs	±	Abate & Chawla, (2016)(+), Baiyegunhi & Hassan, (2014) (+), Guta, (2012)(-) , (Jan et al., 2017)(-)
Education	Education level of the household head. Dummy, 0 = no formal education, 1 = primary, 2 = secondary, 3 = tertiary	+	Abate & Chawla, (2016), Twumasi et al., (2020), Kulindwa et al., (2018), Puzzolo et al., (2016), Joshi & Bohara, (2017)
Marital status	Marital status of the household head. Dummy, 1=married, 0=otherwise	±	Onyeneke et al., (2019)(+), Anteneh, (2019)(+)

Income	Monthly income in Kshs. Dummy, 0 = Less than 10000, 1 = 10000-20000, 2 = 21000-30000, 3 = 31000-50000, 4 = 51000-100000, 5 = Above 100000	±	Shen et al., (2015)(+), Mekonnen & Abera, (2019)(+), Gebreegziabher et al., (2012)(+), Beyene & Koch, (2013)(+), Mamuye et al., (2018)(+), Rahut et al., (2014)(-)
Income Activity	Dummy, 1= farming, 0 = otherwise	±	Onyeneke et al., (2019) (-)
Employment sector	Dummy, 0 = public, 1 = private, 2 = unemployed	±	Author
Number of rooms	Household rooms, Continuous variable	+	Nlom & Karimov, (2015), Mekonnen & Abera, (2019)
Credit	Dummy, 1= a household with access to credit, 0 = otherwise	+	Onyeneke et al., (2019), Onyeneke et al., (2018), Gebreegziabher et al., (2012), Beyene & Koch, (2013)
Membership of an association	Dummy, 1= member of an association, 0=otherwise	+	Onyeneke et al., (2019), Link et al., (2012b)
Prior information	Knowledge of clean energy technology initiatives within their locality. Dummy, 1=Yes, 0=otherwise	±	Zeru & Guta, (2021), Shen et al., (2015), Adepoju & Akinwale, (2019)
Decision making	Who decides on cooking/lighting fuel in a household? Dummy, 0=husband, 1=wife, 2=jointly (husband and wife), 3=children, 4=other	±	Author
Stove preference	Why the household prefers the current cook-stove. Dummy, 1=lack of other options, 0=otherwise	-	Author

3.4.4 Health Risk Analysis and Impact Assessment using AirQ+ Model

World Health Organization's European centre developed AirQ+ model to aid in estimating the health burden attributed to air pollution from exposure to six atmospheric pollutants (CO, PM_{10}, $PM_{2.5}$, O_3, NO_x, and SO_x). The model estimates the health burden for both short-term and long-term exposures to air pollution for five major diseases; chronic obstructive pulmonary disease (COPD), acute lower respiratory infection (ALRI), ischemic heart disease (IHD), lung cancer (LC), and stroke. AirQ+ also enables risk analysis and analysis of air pollution impacts on the entire population under different emissions scenarios (Conti et al., 2017; WHO Regional Office for Europe, European Centre for Environment and Health, 2019).

The tool is powerful compared to similar tools since its estimation is based on the mortality and morbidity for the specified area for different population sizes, making it applicable to any region, country, or city. It offers flexibility for simulation of health burdens arising from a particular pollutant for a specified disease within a given age group. AirQ+'s underlying methods and algorithms have been validated by different epidemiological studies (Conti et al., 2017; Ghozikali et al., 2015, 2016; Miri et al., 2016). Notably (Conti et al., 2017) comprehensively discusses how AirQ+ works and the improvements realised since its inception. The model's health impact estimation is based on the attributable proportion (AP), representing the portion of a health outcome in a population attributed to a given air pollutant.

This study used the AirQ+ v 2.1 model to answer the following: What is the extent of COPD, ALRI, IHD, and LC attributed to $PM_{2.5}$? What health benefits can be attributed to clean cooking fuels and technologies? The model input parameters include the following: pollutant's mean value (or data set), location (latitude and longitude), the total population for the specific area, area (in km^2), source of measured air pollution data, number of measurements conducted, the population at risk, and the annual death incidence per 100,000 people. Data on annual death incidence were sourced from the Institute for Health Metrics and Evaluation IHME, (2020), Vos et al., (2020), and Health Effects Institute (2020). For Kenya, IHME provides both country and county-specific data. The AirQ+ model was run for different scenarios using 2020 IHME data on the annual death incidence per 100,000 people attributed to COPD (48.57), ALRI (67.75), IHD (66.06), and LC (5.34)

Pearson's moment correlation was used to determine the associations between reported COVID-19 cases and CO and NO_2 concentration levels. Pearson's product-moment correlation measures the degree of the relationship between continuous variables (Zaid, 2015). The variables under investigation are continuous, hence the decision to use Pearson's product-moment correlation.

3.4.5 Multidimensional Energy Poverty Framework (MEP)

The multidimensional energy poverty framework employs measures such as household energy use, appliances, HAP, and energy deprivation. As a result, it provides a technique for focusing on individuals who fall within the energy poverty bracket in the context of environmental sustainability. It considers energy deprivations that are likely to affect an individual, such as quality of energy services, reliability, accessibility, and the aspect of affordability. This is analogous to the multidimensional poverty measures, which emphasise the need to consider poverty from the absence of opportunities and choices (Alkire et al., 2010; Alkire & Foster, 2009). Identifying energy deprivation variables is a crucial aspect of this metric.

An algorithm based on indicators of energy poverty was used in this investigation. Recognising that the deprivation variables are not of equal importance, relative weights are assigned to these dimensions and indicators according to the framework developed by Nussbaumer et al., (2012). The framework comprises five dimensions (cooking, lighting, services provided through household appliances, entertainment/education, and communication) for essential energy services and six indicators (Tables 3.2 and 3.3).

Table 3.2: MEP dimensions, indicators, and variables with their relative weights and cut-offs

Dimension	**Indicator**	**Weight**	**Variables**	**Deprivation cut-off (energy poor if)**
Cooking	Modern cooking fuel	0.2	Type of cooking fuel	Uses any fuel besides electricity, LPG, kerosene, natural gas, or biogas
	Indoor pollution	0.2	Food cooked on stove or open fire (no chimney), indoor, if using any fuel beside electricity, LPG, natural gas or biogas	True
Lighting	Electricity access	0.2	Access to electricity	False
Services provided by means of household appliances	Household appliance ownership	0.13	Fridge ownership	False
Entertainment/education	Entertainment or education appliance ownership	0.13	Radio or Television ownership	False
Communication	Telecommunication means	0.13	Phone landline or mobile phone ownership	False

Source: (Nussbaumer et al., 2012)

Table 3.3: MEP indicators used in the study

Indicator	**Description**	**Effect on energy poverty**	**Significance for inclusion**
Modern cooking fuel	Gets the value 0 if a household uses modern fuels	Negative	Indicates a household's exposure to indoor pollution
Traditional stoves	Gets the value 0.2 if food is cooked on open fire/stove, indoor, without a chimney, using fuels besides beside electricity, LPG, natural gas or biogas	Positive	Indicates a household's exposure to indoor pollution
Electricity access	Gets the value 0 if a household has access to electricity	Negative	Indicates a household's exposure to indoor pollution
Fridge ownership	Gets the value 0 if a household has a refrigerator	Negative	Indicates the ability to preserve food, therefore, saving productive time that could have been spent in the kitchen. It also reduces pollution exposure time
Radio or Television ownership	Gets the value 0 if a household has a television or radio	Negative	Increases awareness of various programs and opportunities for living a decent life. Represents initial assets acquired by a household after electrification.

Assuming that the number of variables is *d*, and the sample surveyed comprises *n* households,

$$Y = \left[y_{ij}\right] \tag{12}$$

represents n x d matrix of household energy deprivation scores for i households across j variables.

A weighting factor represented by weighting vector, w, is applied to the variable j. The variable weight w_j, is defined and the deprivation cut-off (set of conditions to be met) in variable j, z_j such that,

$$\sum_{j=1}^{d} w_j = 1 \qquad (13)$$

Also, $g = [g_{ij}]$ represents the deprivation matrix whose elements g_{ij} are defined by

$$g_{ij} = w_j, \text{ when } y_{ij} < z_j \qquad (14)$$
$$g_{ij} = 0, \text{ when } y_{ij} \geq z_j$$

Each entry of the matrix g is equivalent to the variable weight w_j, when household i is deprived in variable j, otherwise it is zero.

Deprivation counts are represented by a vector c such that,

$$c_i = \sum_{j=1}^{d} g_{ij} \qquad (15)$$

is the sum of weighted deprivations for household i.

To identify the multidimensional energy poverty for each household, i, a cut-off (k > 0) was defined and applied across the vector c_i, i.e., $c_i(k)$. The following boundary conditions were set.

$$\begin{cases} c_i > k, c_i(k) = 1, \; energy\,poor \\ c_i \leq k, c_i(k) = 0, \; not\,energy\,poor \end{cases} \qquad (16)$$

If a household is not classified as being energy poor, $c(k)$ counts zero deprivation for that household. It is thus different from the deprivation count vector c. If q is the number of households that were found to be energy poor (i.e., where $c_i > k$), and n the total number of households surveyed, the energy poverty ratio H, is expressed by,

$$H = \frac{q}{n} \quad (17)$$

Thus, H represents the incidence of energy poverty, while the intensity of energy poverty I, is expressed by,

$$I = \sum_{i=1}^{n} \frac{c_i(k)}{q} \quad (18)$$

The multidimensional energy poverty index is thus defined by $H \times I$ and incorporates information on energy poverty incidence and intensity. The censored deprivation of the energy poor were further categorised into three levels c(k) > 0.7, acute, c(k) 0.3 ≤ 0.7), moderate, and c(k) < 0.3), low. This was done to enable comparison across different socio-economic statuses.

Energy poverty is a function of geographical, socio-cultural, and lifestyle energy use patterns. Therefore, this study carried out a restricted dominant analysis that involved varying the weights of the indicators from the original MEP (Table 3.4). This was necessary to achieve the study's objective of the impact of energy poverty on health. Moreover, the MEP framework allows for variation in weights of indicators under different scenarios (Nussbaumer et al., 2012). The indicator weights used for the alternate scenarios have been employed in prior studies (Ahmed & Gasparatos, 2020).

Table 3.4: Alternative scenarios of MEP indicators

Variable	**Original scenario** (Nussbaumer et al., 2012)	**Alternative scenario 1** (Equal weighting)	**Alternative scenario 2** (80% for Indoor air pollution factors)
Cooking: modern cooking fuel	0.200	0.166	0.300
Cooking: Indoor air pollution	0.200	0.166	0.300
Lighting: electricity access	0.200	0.166	0.200
House appliance ownership: refrigeration	0.130	0.166	0.100
Entertainment/education: Owns TV/radio	0.130	0.166	0.100

Telecommunication means: Owns a telephone	0.130	0.166	N/A
Total weight	1.000	1.000	1.00

Source: Authors' estimation

3.4.5.1 Causal Inference – Effect of Energy Poverty on Health

Various statistical methods for assessing causal relationships between interventions and outcomes under certain assumptions exist. However, confounding factors usually lead to biased estimates of causal effects in observational research. For a long time, this problem was addressed using conventional methods such as multivariate regression and stratification. In addition, a growing body of research have used propensity scores in their approach, such as the inverse probability of treatment weighting (IPTW). Despite randomization being used in the data collection process, the IPTW approach was employed for this study's analysis because of its robustness. Due to its ability to restore randomization balance and provide an unbiased estimate of the causal effect of intervention/treatment, IPTW was selected over other statistical methods (Pezzi et al., 2016).

Inverse probability of treatment weighting is a stepwise procedure that entails estimating the probability (propensity score) of exposure, given the characteristics of an individual and potential confounders. The Propensity Score (PS) summarises information from potential confounders into a unique balancing score variable. Given a vector of observed covariates, PS is the conditional probability of getting treatment or intervention.

$$p(X) = \Pr(Z = 1|X) \qquad (19)$$

Where p denotes the propensity score, Z = {0,1}, represents the exposure to treatment (1=energy poor, 0 = not energy poor), and X is a vector of covariates. Therefore, the PS alone can eliminate biasness and confounding effects instead of modelling each covariate separately.

The average treatment effect is the expected difference at $p(X)$.

$$E\{r_1|p(X), Z = 1\} - E\{r_0|p(X), Z = 0\} = E\{r_1 - r_0|p(X)\} \tag{20}$$

Where r = {0,1} indicates the resultant response, given the conditions that the individual had received or not received treatment (for this case, it is whether energy poor or not).

Since the propensity score is unknown from the onset, it is estimated based on the observed covariates (X) and the binary treatment variable (Z). In order to estimate propensity scores, logistic regression is the most commonly employed model. Since the treatment variable (Z) is binary, we parameterise the logistic model by,

$$\beta = (\beta_0, \beta_1, \dots \beta_p)^T \tag{21}$$

So that,

$$\log\left(\frac{p(X)}{1 - p(X)}\right) = X^T\beta \tag{22}$$

Where β is a vector of regression coefficients. The fitted propensity score model for each individual, i, can be expressed as.

$$\hat{p}_i = \hat{p}(X_i) = \frac{exp(X_i^T\hat{\beta})}{1 + exp(X_i^T\hat{\beta})} \tag{23}$$

The propensity score has been found to boost precision and eliminate bias in large data samples (Williamson et al., 2014). There are several ways PS can be used to reduce confounding effects, including covariate adjustment, PS matching, IPTW (inverse probability of treatment weighting), and PS stratification. This study adopted the IPTW because the focus is on estimating the average effect of the treatment in the study sample. Moreover, IPTW estimates have low mean squared errors and are less subject to information loss compared to the other methods (Pezzi et al., 2016). When IPTW is used with PS, it is referred to as inverse propensity score weighting (IPSW). In PS weighting, each individual's weight is computed as the inverse of the probability of receiving their actual exposure level (Chesnaye et al., 2021). Simply put, individuals are assigned weights by the inverse of their PS. For instance, participants who are energy poor were weighted by $w_i = 1/\hat{p}_i$, while those who were not energy poor were weighted by $w_i = 1/(1 - \hat{p}_i)$. i.e.,

$$\begin{cases} w_i = \dfrac{1}{\hat{p}_i}, if\ Z_i = 1 \\ w_i = \dfrac{1}{1 - \hat{p}_i}, if\ Z_i = 0 \end{cases} \quad (24)$$

Where w_i is the IPTW for i. Inclusion of weights renders 'assignment' to either the exposed (energy poor) or unexposed (non-energy poor) group, independent of the variables included in the propensity model. Therefore, IPTW reduces selection bias by creating a 'pseudo population' where the exposure is independent of the confounders. Thus, the treatment effect in the weighted sample will be less biased (Xu et al., 2010). In the IPTW pseudo population, the sum of the weights represents the number of observations. The number of observations, N_w, in the pseudo population is always greater than that of the original sample.

$$N_w = \sum_{i=1}^{n} w_i \quad (25)$$

A marginal structural model (MSM) that is a linear function of the treatment (energy poverty) was fit using the IPTW.

$$E(Y_i^a) = g^{-1}(\psi_0 + \psi_1 a) \quad (26)$$

Where a is the explanatory variable (energy poor vs non-energy poor). MEP is the key explanatory variable. The MEP cut-off k was set to 0.3, thus, it takes the value 1 if MEP was found to be higher than 0.3, and 0 otherwise.

Y is the outcome (facing at least a respiratory or physical health-related problem or not, including cough, wheeze, phlegm, nasal irritation, red itching eyes or burns).

$g()$ is the link function.

The model was executed in R programming environment, first using log link to get a causal relative risk (CRR), followed by an identity link to get a causal risk difference (CRD).

3.5 Data Analysis

3.5.1 Quantitative Data Analysis

MS Excel and R program for statistical computing and graphics were used to compile and analyse the quantitative data collected from household surveys and HAP measurements. Several statistical measures, primarily inferential statistics, were computed from the data. Data summaries were created using descriptive statistics. Inferential statistics included non-parametric tests such as the t-test, chi-square, Mann-Whitney tests, and regression models, including probit, logit and marginal structural models. The analysed data was presented in graphs, figures, and tables.

3.5.2 Analysis of Statistical Differences between Variable

The t-test was used to test for significant differences in means of pollutants concentration of different cooking technologies at a 0.05 significance level. This method was selected because it is ideal for quantitative data compared to alternative non-parametric tests such as the Mann-Whitney U test. Paired t-test is a parametric test based on the assumption of normality. Consequently, all the data were checked for normality using the Shapiro-Wilk normality test. The test yielded p-values greater than 0.05 for $PM_{2.5}$ and CO datasets, indicating the presence of normality. For categorical data, chi-square and Mann-Whitney tests were used. All this work’s statistical tests and presentations were carried out in R programming environment.

3.5.3 HAP Data Verification

Prior to doing the analysis, the collected data were screened for outliers. The outliers were identified using box plots and interquartile range and carefully examined for mistakes and any unusual circumstances that may have arisen from data recording. Any data points appearing individually on the box plot (Figure 3.4) were treated as outliers and removed or investigated further. Data points that were 1.5 times greater than the interquartile range (IQR) from the upper (third quartile) or those that were 1.5 times less than the IQR from the lower (first quartile) were also treated as outliers. However, no data points fell beyond the prescribed limits.

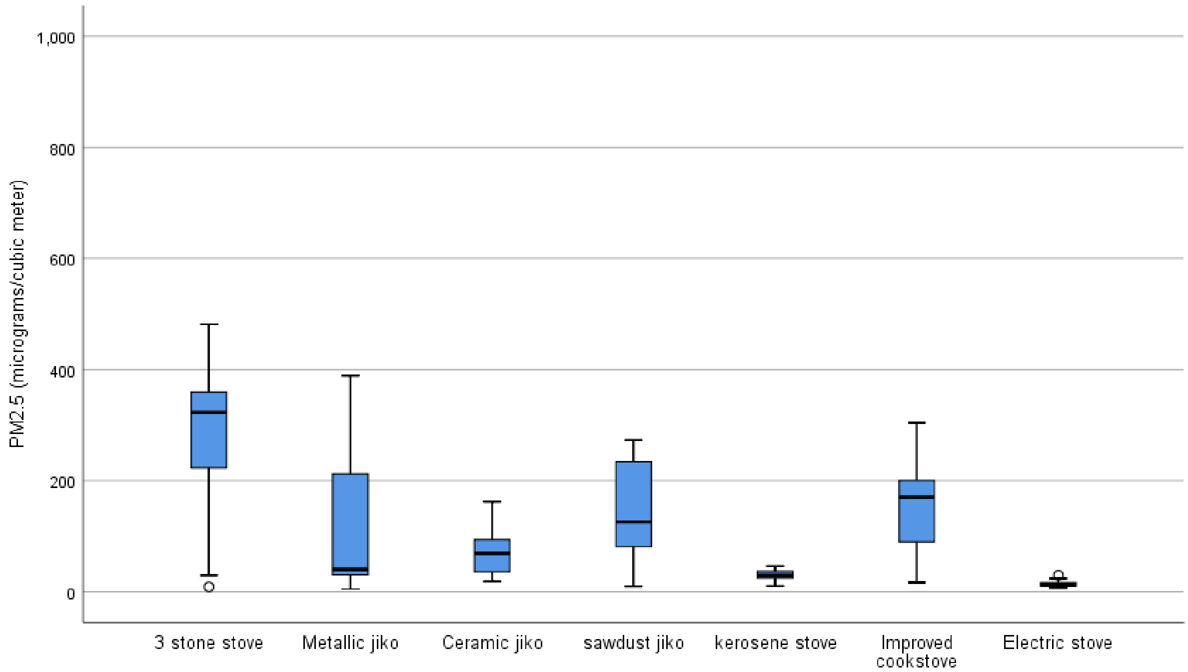


Figure 3.4: $PM_{2.5}$ Box plot for different cookstoves

CHAPTER FOUR

RESULTS AND DISCUSSIONS

4.1 Introduction

This chapter presents and discusses the findings in accordance with the study's objectives. The chapter is broken into four sections, reflecting results and discussions of objectives one, two, and three. In this chapter's opening section, results and discussions on the factors that affect a household's fuel choices are presented, with specific emphasis on clean and unclean fuels and technologies. This is followed by a discussion on HAP and the associated health disorders. The third section presents results and discussions on the impact of energy poverty on human health.

In the original household survey, 487 households were sampled, 483 of which were valid due to incomplete data on questionnaires from four (4) households. The data was collected from three sub-counties within Vihiga county, as shown in Table 4.1. This data has been primarily utilised in sections one and three of this chapter.

Table 4.1: Population and sample size distribution in the study area

Sub-county	**Population (2019)**	**Population density (2019)**	**No. of Households**	**Sample obtained**	**Valid sample**
Hamisi	159,241	1,013	37,986	246	245
Sabatia	131,628	1,181	31,422	142	141
Vihiga (sub-county)	95,292	1,058	23,375	99	97
Total				487	483

Source; KNBS (2019) and Authors

4.2 Factors Affecting Household Decisions Towards Clean Fuels and Technologies in Vihiga county

4.2.1 Socioeconomic, Demographic, and Energy Use Characteristics

This subsection describes socioeconomic and demographic factors that were hypothesised to affect household energy decisions. Household primary energy choices are also described. This sub-section describes these factors using basic statistical measures such as mean, standard deviation, and percentages. This analysis was done in two parts (cooking and lighting) and further disaggregated into users and non-users of clean energy fuels. Households participating in this study were randomly recruited throughout the study area, which also helped to eliminate selection bias (Ngombe et al., 2014). A clean energy user was considered to be a household that uses at least any of the following: biogas, electricity, LPG, improved cookstove, or solar as the primary energy sources or technologies for cooking or lighting. Non-users were households that use either wood fuel, kerosene, or traditional cookstoves as their primary energy sources/technologies for cooking/lighting. The decision to include variables hypothesised to influence users' energy decisions was based on the variable's persistence in the literature. In addition, new variables such as the employment sector, income activity, and decision making regarding household energy use were incorporated.

Females comprised 64% of the respondents, with males making up the remaining 46%. About 25.7% and 79.7% of the sampled females were users of cooking and lighting, while 29.7% and 84.9% of the sampled males were users, respectively. The household head's age was divided into four strata: 21-30yrs, 31-40yrs, 41-50yrs, 51-60yrs and above 60yrs. On average, 28% of users (cooking) were between the ages of 41 and 50, whereas 33% of non-users (cooking) were over 60 years old. Non-users had a comparatively low level of education. For instance, only 5% of the non-users (lighting) and around 13% of the non-users (cooking) had tertiary education. In contrast, 29% of users (cooking) and 20% of users (lighting) had completed post-secondary education.

The average household size for the entire sample was approximately five people. Non-users had an average household size of 5.8 members, whereas users had an average of 5.1 members in their households. A household's income has been reported to influence its energy use decisions. For instance, high LPG prices result in varying fuel use among socio-economic levels (Dalaba et al., 2018; Karimu, 2015; Ma et al., 2019). Approximately 66% of the households earned less than Kes 10,000 (USD 100) a month. For the non-users, 72% and 90% for cooking and lighting, respectively, earned less than Kes 10,000 (USD 100). This pattern was also observed in the users category, where approximately 55.5% of users earned less than Kes 10,000 (USD 100). Farming was the primary source of revenue for both users (cooking) and non-users (cooking), accounting for 34% and 50%, respectively. For lighting users and non-users, the proportion of households with farming as their primary source of income was 42% and 60%, respectively. Overall, more non-users participate in farming than users.

Previous research has also cited credit facilities as an important factor in utilising clean fuels and technologies (Mishra & Mishra, 2018; Twumasi et al., 2020). Approximately 42% and 22% of the non-users (cooking and lighting) had access to credit facilities, respectively. In contrast, credit facilities were available to 63% of cooking users and 53% of lighting users. In terms of membership in an association, more users (cooking) (59%) than non-users (cooking) (47%) belonged to at least one community association. A similar trend was observed for users (lighting), 53%, and non-users (lighting), 38%. Decision making on household energy choices was mainly a reserve of the females in 64% and 70% of the households that were users (lighting) and non-users (cooking), respectively. About 52% of non-users (cooking) preferred their current cookstoves due to a lack of alternatives.

Biomass is the principal source of cooking fuel. This was utilised by 90% of the households, followed by LPG (8%) and kerosene (1%). The primary lighting energy sources were grid-connected electricity (60%), solar (22%), and kerosene (12%). Approximately 7% of the households used wood for lighting (Table 4.2).

Table 4.2: Socio-economic, demographic, and energy use characteristics of users and non-users of clean energy technologies

Characteristic		Overall sample	Cooking		Lighting	
			Users (n=131)	Non-users (n=352)	Users (n=394)	Non-users (n=89)
		Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)	Mean (SD)
Age		2.55 (1.26)	2.37 (1.32)	2.62 (1.23)	2.49 (1.26)	2.83 (1.20)
Gender		0.36 (0.48)	0.39 (0.49)	0.34 (0.48)	0.37 (0.48)	0.29 (0.46)
Marital status		0.71 (0.45)	0.73 (0.45)	0.71 (0.46)	0.74 (0.44)	0.6 (0.49)
Level of education		1.54 (0.89)	1.84 (0.90)	1.43 (0.86)	1.63 (0.90)	1.17 (0.77)
Employment sector		1.39 (0.70)	1.20 (0.72)	1.46 (0.69)	1.36 (0.72)	1.53 (0.62)
Income Activity		0.46 (0.50)	0.34 (0.48)	0.50 (0.50)	0.42 (0.49)	0.6 (0.49)
Income (Kshs)		0.60 (1.04)	0.86 (1.12)	0.51 (0.99)	0.68 (1.07)	0.24 (0.80)
Household size (persons)		5.20 (2.37)	5.06 (2.53)	5.25 (2.30)	5.06 (2.36)	5.82 (2.30)
Number of rooms		3.78 (0.99)	3.89 (1.04)	3.74 (0.96)	3.83 (0.98)	3.53 (0.99)
Access to credit facilities		0.48 (0.50)	0.63 (0.49)	0.42 (0.49)	0.53 (0.50)	0.26 (0.44)
Membership of an association		0.50 (0.50)	0.59 (0.49)	0.47 (0.50)	0.53 (0.50)	0.38 (0.49)
Prior information		0.34 (0.48)	0.40 (0.49)	0.32 (0.47)	0.36 (0.48)	0.26 (0.44)
Household member responsible for decision making regarding fuel type to be used		1.24 (0.76)	1.24 (0.84)	1.24 (0.72)	1.22 (0.73)	1.33 (0.87)
Stove preference		0.39 (0.49)	0.03 (0.17)	0.52 (0.50)		
Primary Energy technologies and sources	Biogas		0.21%		N/A	
	Electricity		0.41%		59.83%	
	LPG		7.66%		N/A	
	Improved cook-stove		18.84%		N/A	
	Kerosene		1.24%		11.60%	
	Traditional 3-stone stove		71.64%		N/A	
	Solar		0.00%		21.74%	
	Wood fuel		_		6.83%	

NB: Refer to table 3.1 for variable definition

4.2.2 Probit model

The effect of the aforementioned socioeconomic and demographic characteristics on household energy choices for cooking and lighting are discussed in this section. The socio-economic and demographic variables included in the models indicate reasonably good predictions of fuel choices for cooking and lighting. The likelihood ratio, Wald chi^2 of the overall model in both cases was significant ($p<0.000$ and $p<0.024$) at 5% level, suggesting strong explanatory power. This analysis used the variance inflation factors (VIF) to test for multicollinearity. All the variables had VIFs less than 5, demonstrating the absence of multicollinearity. Among the thirteen explanatory variables included in the model (cooking), eight turned significant at 5% level. For lighting, seven out of twelve explanatory variables were significant at 5% level. A number of the explanatory variables positively and significantly affected household energy decisions towards cleaner fuels: (a) household size; (b) gender; (c) age; (d) education level; (e) household income; (f) access to credit facilities; (g) membership of community association; (h) number of rooms; and (i) marital status. Variables that had significant negative effects include: (a) employment sector; (b) stove preference (household lacking other energy options); and household size (for lighting).

The estimate coefficients of the probit model only provide information about the direction of the effect of the explanation factors on the outcome factor, but do not explain the probabilities of change. Therefore, the marginal effects from the probit model for the statistically significant variables were also computed.

The marginal effect measures the expected change of the probability of a household making a particular choice for a unit change in the independent variable (continuous) or switching pattern for dummy variables. The purpose of marginal effect was to enable the comparison of both the magnitude and direction of impact. Computations indicate that gender, education, income and access to credit facilities have the greatest impact.

4.2.2.1 Determinants of household cooking fuel and technology choice

This sub-section discusses the factors that affect cooking fuel choices (Table 4.3).

Table 4.3: Probit model estimates of household primary cooking fuel choices

Variable	**Estimate coefficient**	**Std. Error**	**z-value**	**p-value**	**VIF**
Household size	0.1466	0.0747	1.963	0.0497*	1.1964
Gender	1.7568	0.6753	2.601	0.0093**	1.1238
Age	0.3474	0.1742	1.994	0.0461*	1.2930
Education	0.9808	0.3120	3.143	0.0017**	1.9442
Marital status	-0.3897	0.2051	-1.900	0.0575 .	1.2082
Income	0.7774	0.3560	2.1840	0.0290*	2.0623
Income Activity	0.0312	0.1845	0.1690	0.8656 NS	1.4167
Employment sector	-0.6647	0.2826	-2.3520	0.0187*	1.7418
Access to credit facilities	0.7921	0.2311	3.427	0.0006***	1.9305
Membership of an association	0.7231	0.3815	1.8950	0.0581 .	1.7967
Prior information	-0.2982	0.3364	-0.8860	0.3754 NS	1.1045
Decision making	-0.2736	0.1534	-1.7830	0.0745 .	1.0557
Stove preference	-2.5603	0.5007	-5.1130	0.0000***	1.0263
Number of observations: 483					
Wald Chi^2 = 29.4					
Prob > Chi^2 = 0.0000					
AIC = 448.09					

Note:
*** statistical significance at 0.1% probability level,
** statistical significance at 1% probability level,
* statistical significance at 5% probability level,
. statistical significance at 10% probability level,
NS – Not statistically significant

(a) Income and access to credit

Income and credit are critical drivers of cooking fuel choice. According to this study's findings, households with higher incomes are more likely to utilise cleaner cooking fuels. The marginal effect suggests that a household's likelihood of using clean cooking fuel rises by 14% as monthly income increases from one income group to the next (Table 4.4).

Table 4.4: Marginal effects of the probit model statistically significant variables on household fuel choices

Variable	**Cooking**	**Std. error**	**Lighting**	**Std. error**
Household size	0.0236 (0.1535)	0.0165	-0.0212 (0.0029)**	0.0071
Gender	0.5562 (0.0014)**	0.1739		
Age	0.0792 (0.0534)*	0.0409		
Education	0.2247 (0.0026)**	0.0746	0.0896 (0.0040)**	0.0311
Marital status			0.0586 (0.1470)	0.0404
Income	0.1396 (0.0868).	0.0815	0.1887 (0.0241)*	0.0837
Number of rooms			0.0369 (0.0305)*	0.0170
Stove preference	-0.4272 (0.0000)***	0.0494		
Income Activity				
Employment sector	-0.0650 (0.3704)	0.0725		
Access to credit facilities	0.1012 (0.0775).	0.0573	0.1126 (0.0100)*	0.0437
Membership of an association			-0.0139 (0.7375)	0.0417

For households with access to credit, there is a 10% increase in the probability that they will choose clean cooking fuels. Increasing household income is associated with increased electricity consumption (Ali et al., 2021; Cayla et al., 2011). Guta, (2018) argued that a rise in household income improves its ability to finance the costs of solar energy, increasing the likelihood of embracing the technology. Similar results have been reported for LPG adoption among households with high incomes (Soltani et al., 2019). Access to credit eliminates the financial barriers and up-front costs that prevent rural residents from accessing clean energy technologies. This finding validates the energy ladder proposition, which states that an increase in household income causes a shift from unclean to clean fuels. Therefore, income and credit are major enablers for the sustained use of modern clean fuels/technologies in developing countries. In situations where there has been high uptake of LPG, such as in the peri-urban household of Ecuador, the fuel was heavily subsidised (Gould et al., 2020).

(b) Education

There were four categories for the household head's education: no formal education, primary, secondary, and tertiary. This variable was found to positively affect a household's decision to use clean cooking fuels at 1% probability level. Due to their increased understanding and increased career prospects, household heads with higher education attainment are more inclined to prefer clean cooking fuels like LPG, biogas, and electricity over unclean fuels (Cho et al., 2019; Guta, 2018). From the marginal effect, an increase in the education of the household head from one level to the next increases the probability of the household adopting clean cooking fuels by 22.5%. In general, the positive effect of education on clean cooking fuels relates to increased awareness of the health, societal, and economic benefits of clean fuels. In addition, educated female members of a household may lack time to collect wood for fuel and would therefore resort to alternative clean fuels. However, other factors such as income may influence education, with higher education typically leading to higher living standards.

(c) Employment status

Though closely connected to income, the inclusion of this variable was based on the theoretical background that those employed in the formal sector may be more acquainted to clean energy initiatives than those who are jobless or in the informal sector. This variable was statistically significant at the 5% level and had a negative effect on a household's decision to switch to cleaner fuels. The marginal effect suggests that as one shifts from public to private to unemployed, the probability of choosing clean cooking fuels decreases by 6.5%. Unemployed individuals are less likely to use cleaner fuels than those employed in the public or private sectors.

(d) Gender

In numerous distinct social and demographic contexts, gender roles can be shown to play considerably varied functions. In some societies, women are often the principal users and beneficiaries of modern, clean cooking technologies. As a result, women may profit more from these technologies than men. The findings show that gender has a significant, positive effect on household decisions toward clean fuels. This contradicts the findings of some previous studies that found females to be more likely than men to adopt clean fuels. However, this finding corroborates with Link et al., (2012a) and Rahut et al., (2018), who found that households with more female adult populations are more likely to choose wood fuel than those with more males. The marginal effect indicates that male-headed households are 55.6% more likely to adopt clean cooking fuels. Culturally, wood fuel collection is seen as a female affair in the African context. Males may therefore be more willing to use alternative fuel sources than engage in wood collection. Soltani et al., (2019) also reported that male-headed households had a higher probability of using LPG than female-headed households.

(e) Age

The age of the household head presents mixed outcomes in past studies. This study found that households with older heads are more likely to use cleaner fuels. This finding agrees with Guta, (2012) and Jan et al., (2017). The marginal effect demonstrates that an increase in the age of the household head from one age stratum to the next increases the probability of using clean cooking fuels by 7.9%. This is due to elder household heads' greater familiarity with the advantages of cleaner fuels compared to their younger counterparts. In addition, in the absence of younger family members, older household members might not be able to carry out chores such as wood fuel collection, thus preferring alternative fuel sources. Aged people are also likely to have more savings and be able to afford cleaner fuels.

(f) Household size

The effect of household size on the choice of cooking fuel is positive and statistically significant at 5%, but small in marginal effect. The marginal effect indicate that an increase in household size by one member increases a household's probability of adopting clean cooking fuel by 2.4%. This suggests that larger households are more likely to choose LPG, improved cookstoves, and electricity and less likely to select kerosene and the conventional 3-stone cookstoves. The findings accord with (Rahut et al., 2014; Shen et al., 2015) and can be attributed to a range of factors, including observance of energy efficiency measures in larger households compared to smaller ones. Baiyegunhi & Hassan, (2014) and Thomas et al., (2016) also reported similar results where larger households tend towards cleaner fuels. Large households take a considerable amount of time and wood for cooking. Thus, they would prefer more efficient cooking methods than smaller households.

(g) Stove preference

Stove predilection had a significant and negative effect on the decision to use cleaner fuels. From the marginal effect, the lack of other options increases the probability of a household choosing unclean cooking fuels by 42.7% and reduces the probability of choosing clean cooking fuels by the same percentage. The majority of households used their current cooking fuels/technologies due to a lack of alternatives. The lack of other viable options pushes households into unclean fuels that are cheap and readily available.

Three other variables (marital status, membership of an association, and decision making) that were hypothesised to affect cooking fuel decisions were significant at the 10% level, while income activity (farming = 1) and prior information did not portray any significant effects.

Since the respondents may not have been unfamiliar with the clean fuels and technologies under consideration, prior knowledge had no bearing on their decision to forgo them.

4.2.2.2 Determinants of household lighting fuel and technology choice

This sub-section discusses the factors that affect a household's energy choice for lighting (Table 4.5).

Table 4.5: Probit model estimates of household primary lighting fuel choice

Variable	**Estimate coefficient**	**Std. Error**	**z-value**	**p-value**	**VIF**
Household size	-0.0801	0.0308	-2.5990	0.0094**	1.1567
Gender	0.17507	0.3790	0.462	0.6441 NS	1.1023
Age	0.23732	0.13613	1.743	0.0813 .	1.3951
Education level	0.73048	0.27081	2.697	0.0070**	1.8440
Marital status	0.34712	0.16144	2.150	0.0315*	1.1436
Monthly Income	0.9816	0.3693	2.6580	0.0079**	1.7734
Number of rooms	0.18049	0.07589	2.378	0.0174*	1.1300
Income Activity	-0.1906	0.1703	-1.1190	0.2630 NS	1.4311
Employment sector	0.1229	0.1400	0.8780	0.3797 NS	1.6955
Access to credit facilities	0.5477	0.2004	2.7330	0.0063**	1.7969
Membership of an association	0.2892	0.1474	1.9630	0.0497*	1.6859
Decision making	-0.1096	0.0924	-1.1860	0.2357 NS	1.0676
Number of observations: 483					
Wald $Chi^2 = 9.5$					
Prob > $Chi^2 = 0.024$					
AIC = 419.84					

Note:
*** statistical significance at 0.1% probability level,
** statistical significance at 1% probability level,
* statistical significance at 5% probability level,
. statistical significance at 10% probability level,
NS – Not statistically significant

Several of the factors addressed in the previous section were also found to affect household lighting energy decisions. These include education, income, and access to credit facilities. This section addresses variables that have not been previously mentioned and those previously discussed but have taken on a different form.

(a) Room count

At a 5% probability level, the coefficient estimate for the number of rooms is positive and statistically significant. It follows that households with fewer rooms are less likely to choose solar or electricity over kerosene or wood fuel. The marginal effect suggests that for each additional room, the likelihood of a household selecting electricity or solar increases by 4%. This finding is supported by similar studies, including Mekonnen & Abera, (2019) on determinants of lighting energy transitions in rural Ethiopia and Soltani et al., (2019) on household energy choice and consumption. Large houses (with more rooms) may be associated high-income earners, as opposed to smaller homes. Moreover, installing electric lights in numerous rooms is more convenient and cost-effective than using kerosene lamps or wood fuel to illuminate numerous rooms.

(b) Household size

The model results show that households with fewer members are more likely to choose solar and electricity for lighting, while those with more family members prefer kerosene and wood fuel. This is partly because expenditure on other household commodities is likely to increase in larger households than smaller ones, limiting their ability to invest in solar and electricity. Mekonnen & Abera, (2019) opines that large households have a high probability of choosing kerosene over solar. Other studies that have reported similar results include Baiyegunhi & Hassan, (2014) and Gitone, (2014).

(c) Marital status

The estimated coefficient for marital status is positive and statistically significant, implying that households whose head is a couple are more likely to choose electricity and solar over kerosene and fuelwood. Decision making among couples is likely to be more consultative and, therefore, result in better choices regarding clean energy adoption. This result agrees with Anteneh, (2019) and Onyeneke et al., (2018) for household adoption of solar energy and improved cookstoves, respectively.

(d) Membership of community association

The coefficient for membership of a community association is also positive and statistically significant for a household's decision to use electricity or solar over kerosene or wood fuel. The marginal effect indicates that those belonging to a community association are 1.4% more likely to utilise electricity or solar energy for lighting. Local entrepreneurs and organisations promoting new technologies and innovations typically target community institutions such as community-based associations. As a result, members of these associations receive information about new technologies earlier than non-members. It is also easy for members of these associations to obtain credit and other financial aid. Other studies have reported similar findings, including Link et al., (2012b), who concluded that exposure to community organisations increases the use of alternative fuels. Vulturius & Wanjiru, (2017) and Onyeneke et al., (2019) have reported similar findings.

Gender, age, education, monthly income, and access to credit were other factors that affected household decisions toward clean energy for lighting.

Similarities and distinctions can be drawn from this study's findings with other more recent similar studies in Kenya. Waweru & Mose, (2022), using secondary data and logistic regression, found that income, education, and gender (male) favourably influence household decisions towards clean cooking fuels (electricity and LPG). The study also reported that large family size and increasing age of the household head were key determinants of the adoption of firewood as the primary cooking fuel. Although the study by Waweru & Mose, (2022) was conducted in Kenya’s urban areas, their findings are congruent with this study, other than for the age of the household head variable.

4.3 Household Air Pollution and its Impact on Human Health

This section's findings are based on data collected in October/November 2021, which included quantifying emissions (PM, CO, and TVOC) from various household cooking fuels and technologies and modelling their effects on human health.

4.3.1 Pollutants Concentrations from different Cookstoves

In all the monitoring sessions, data were collected at a single point at a distance (x) of 0.5 metres from the stove and height (z) of 0.6 metres to 1 metre, depending on the cook's sitting position. This was done from October 22, 2021, to November 20, 2021. Tables 4.6 and 4.7 present housing characteristics for the control and field experiments, while Table 4.8 presents details on cookstove characteristics, including cookstove type, body material, fuel, and elevation of the sampled seven stoves.

Table 4.6. Housing characteristics for the control experiment

Characteristic	**Description/Dimension**
Length x Width x Height	312cm x 161cm x 200cm
Wall material	Wood and mud
Floor material	Dung
Roof material	Steel (iron sheets)
Internal divisions	Yes (wood and mud)
Doors	One (167cm x 61cm)
Windows	One (45cm x 38cm)

Table 4.7. Housing characteristics for the field group

Kitchen variables	Characteristic		Frequency (%)
Housing type	Mud wall (iron roofing)		42 (100)
Ventilation	Number of doors	1 door	41 (97.6)
		2 doors	1 (2.4)
		3+ doors	0 (0.0)
	Number of windows	No window	5 (11.9)
		1 window	31 (73.8)
		2 windows	5 (11.9)
		3+ windows	1 (2.4)
Cooking place	Kitchen type	Partition inside the main house	8 (19.0)
		Separate kitchen	34 (81.0)

Table 4.8. Stove characteristics and fuel combinations

Cookstove	Material		Fuel	Cooking duration (minutes)	Elevation	Sample (n)
	Body	Liner				
Traditional three-stone	Stone	NA	Firewood	65	Ground	10
ICS (*Chepkube*)	Ceramic	NA	Firewood	65	48 cm	9
Ceramic *jiko*	Metal	Ceramic	Charcoal	65	Ground	5
Sawdust *jiko*	Metal	None	Wood pellets (Sawdust)	65	Ground	7
Kerosene stove (wick type)	Metal	N/A	Kerosene	65	Ground	6
LPG stove	Metal	N/A	Liquefied petroleum gas	65	45 cm	3
Electric cooker	Metal	N/A	Electricity	65	43 cm	2
Total						42

In at least 74% of the sampled households, firewood, charcoal, or wood pellets were used for cooking, highlighting the significance of biomass as the primary cooking fuel. The seven cookstoves identified were the three-stone, ICS (*chepkube*), the ceramic *jiko*, sawdust *jiko*, kerosene stove, LPG stove, and electric cooker.

The three-stone was the most widely used cookstove, followed by ICS (*chepkube*). There is no standard design for traditional biomass cookstoves in Kenya and across Africa. Users design them based on their preferences, the availability of construction materials, and available space. The classic traditional three-stone cookstove configuration, in its most basic form, consists of three stones placed on the ground, with biomass lit inside the barrier. However, ICSs are designed using scientific principles and are available in various forms and combinations (Sharma & Dasappa, 2017). They may have chimneys or not. The ICS (*chepkube*) is constructed using locally available materials by local artisans. The average PM, CO, and TVOC concentrations for the seven cookstoves are presented in Tables 4.9 and 4.10 for the control and field groups, respectively.

Table 4.9. The average mass concentration of PM_1, $PM_{2.5}$, PM_{10}, CO, and TVOC concentrations from different cookstoves (control group) over the cooking period

Stove	**PM_1 (μg/m^3)**		**$PM_{2.5}$ (μg/m^3)**		**PM_{10} (μg/m^3)**		**CO (ppm)**		**TVOC (mg/m^3)**	
	Mean	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**
Traditional three-stone	290.3	182.7	382.6	240.4	441.0	275.6	12.78	7.6	0.518	0.314
ICS (*Chepkube*)	100.3	82.2	132.7	108.1	152.8	125.7	8.39	3.5	0.342	0.091
Ceramic jiko	57.7	37.2	76.5	48.9	88.8	56.4	54.17	52.1	0.419	0.219
Sawdust jiko	87.6	44.6	115.7	58.6	133.9	68.1	10.24	4.5	0.869	0.228
Kerosene stove	16.2	8.3	19.9	10.1	22.5	11.7	10.41	4.3	0.790	4.275
LPG stove	16.8	4.9	22.8	6.5	26.0	7.6	6.43	3.8	0.097	0.044

Table 4.10. The average mass concentrations of PM_1, $PM_{2.5}$, PM_{10}, CO and TVOC concentrations from different cookstoves (field group) over the cooking period

Stove	**PM_1 (μg/m^3)**		**$PM_{2.5}$ (μg/m^3)**		**PM_{10} (μg/m^3)**		**CO (ppm)**		**TVOC (mg/m^3)**	
	Mean	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**	**Mean**	**Std.dev**
Traditional three-stone	216.5	88.5	279.7	119.9	315.7	137.4	14.5	6.7	0.588	0.213
Improved cookstove (*Chepkube*)	118.4	66.7	160.2	82.7	173.3	92.6	6.5	2.7	1.005	0.060

Ceramic jiko	65.5	37.0	71.9	40.3	83.2	46.4	95.7	79.2	0.435	0.293
Sawdust jiko	145.9	79.0	147.8	84.9	223.7	122.7	18.7	9.4	1.072	0.531
Kerosene stove	24.4	10.3	32.3	14.3	37.3	15.9	18.6	12.6	1.222	0.671
Electric cooker	10.1	3.7	14.4	5.6	15.4	5.8	0.0	0.0	0.171	0.018

For the control group (Table 4.9), the average PM_1, $PM_{2.5}$, and PM_{10} indoor concentrations for biomass cookstoves were about 15-20 times higher than those for non-biomass cookstoves. However, CO concentrations showed less variation between biomass and non-biomass cookstoves and less variation between individual cookstoves except for the ceramic *jiko*. Table 4.11 shows statistical differences in $PM_{2.5}$ and CO concentrations between various cook stoves.

Table 4.11: Statistical significance (p-value) of $PM_{2.5}$ and CO concentrations between different cook stoves

	Traditional three-stone	ICS (*Chepkube*)	Ceramic jiko	Sawdust jiko	Kerosene stove	LPG stove	Electric cooker
Traditional three-stone	-	0.00	0.00	0.00	0.00	0.00	0.00
ICS (*Chepkube*)	0.00	-	0.04	0.35	0.00	0.00	0.00
Ceramic jiko	0.00	0.12	-	0.01	0.00	0.00	0.00
Sawdust jiko	0.05	0.00	0.00	-	0.00	0.00	0.00
Kerosene stove	0.12	0.01	0.00	0.85	-	0.41	0.00
LPG stove	0.00	0.04	0.00	0.01	0.00	-	0.00
Electric cooker	0.00	0.00	0.00	0.00	0.00	0.00	-

The difference in PM and CO variation can be attributed to both dilution and deposition of PM and differences in their chemical composition. The chemical constituents of PM from biomass combustion include hygroscopic elements such as semi-volatile aerosols in liquid form, which are highly deposited than CO that has zero hygroscopicity (Snider et al., 2016; Stockwell et al., 2016). Particulate matter aerosols deposition is visible on kitchen roofs and walls.

Figures 4.1 and 4.2 illustrate the range of values recorded for the average $PM_{2.5}$ and CO mass concentrations produced by various cookstoves.

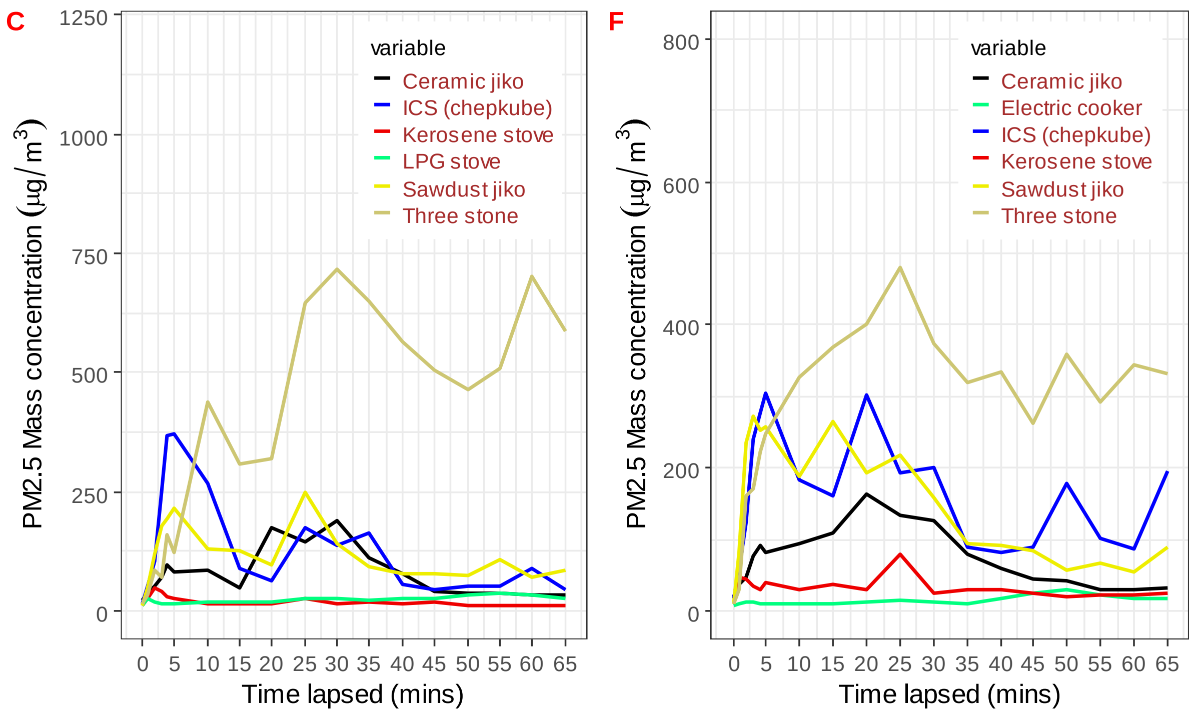


Figure 4.1: **(C)** Shows averaged time-series $PM_{2.5}$ mass concentration for different cookstoves from the control group tests. **(F)** Shows averaged time-series $PM_{2.5}$ mass concentrations for different cookstoves from the field group tests.

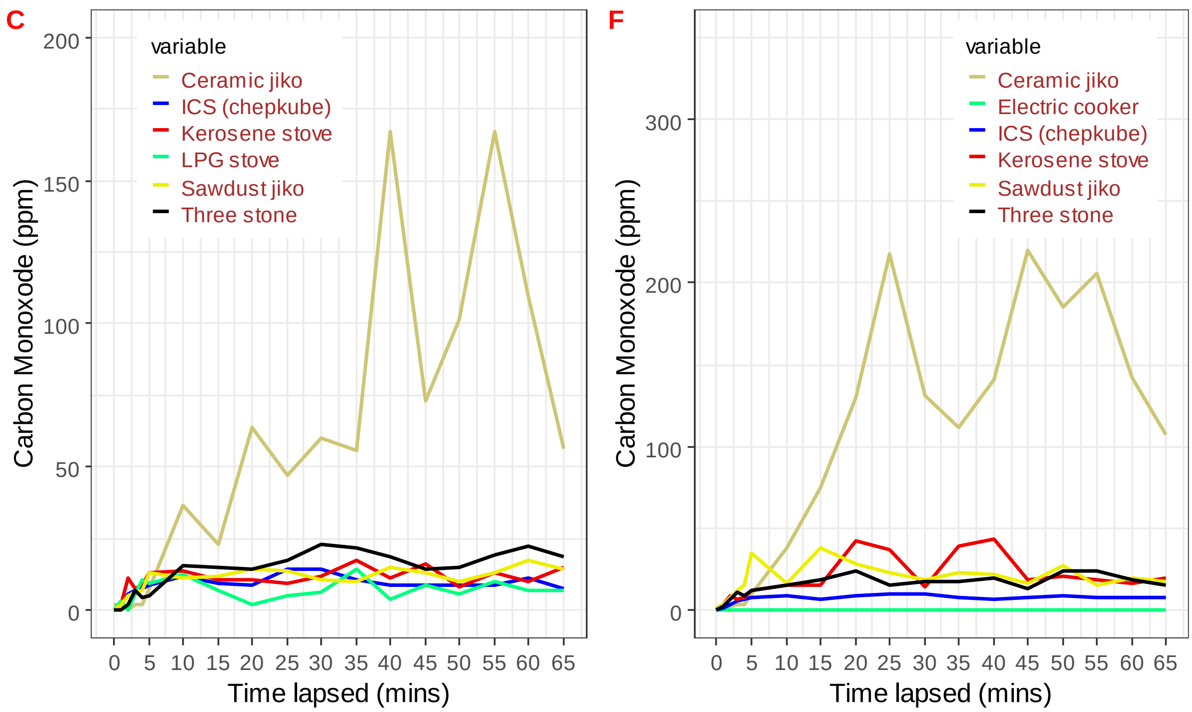


Figure 4.2. **(C)** Shows averaged time-series CO concentration in parts per million (ppm) of different cookstoves from the control groups tests. **(F)** Shows averaged time-series CO concentration in parts per million (ppm) for different cookstoves from the field group tests.

The three-stone cookstove recorded the highest average $PM_{2.5}$ in mass concentration (715.3 μg/m^3 ±240.4 μg/m^3) for the control group. This is followed by the ICS (*chepkube*) (371.3 μg/m^3 ±108.1 μg/m^3), sawdust *jiko* (247.3 μg/m^3 ±58.6 μg/m^3), ceramic *jiko* (189.0 μg/m^3 ±48.9 μg/m^3), kerosene stove (46.3 μg/m^3 ±10.1 μg/m^3), and LPG stove (36.3 μg/m^3 ±6.5 μg/m^3). A similar trend was observed for the field group where the three-stone cookstove recorded the highest (481.2 μg/m^3 ±119.9 μg/m^3) average $PM_{2.5}$ mass concentration, followed by the ICS (*chepkube*) (304.3 μg/m^3 ±82.7 μg/m^3), sawdust *jiko* (273.1 μg/m^3 ±84.9 μg/m^3), ceramic *jiko* (162.4 μg/m^3 ±40.3 μg/m^3), kerosene stove (80.2 μg/m^3 ±14.3 μg/m^3) and the electric cooker (29.5 μg/m^3 ±5.6 μg/m^3). This trend was also observed for PM_1 and PM_{10}. The ceramic *jiko* recorded the highest average CO concentration (167.0 ppm ±52.1 ppm), while the LPG stove recorded the least (14.0 ppm ±3.8 ppm) in the control group. The ceramic *jikos* also recorded the highest average CO concentration (220.4 ppm ±79.2 ppm) for the field group, while the electric cookers recorded zero CO concentrations (0.0 ppm).

Comparing biomass and non-biomass cookstoves, the variability of PM_1, $PM_{2.5}$, and PM_{10} tends to be higher for the former (Figures 4.1 and 4.2) because biomass stoves require refilling feedstocks regularly as the fire repeatedly and quickly dies off. This is reflected by the repeated peaks and troughs in the PM_1, $PM_{2.5,}$ and PM_{10} concentration profiles of the three-stone stove, the ICS (*chepkube*), the ceramic and sawdust *jikos.* In contrast, the non-biomass stoves had steady emissions concentration profiles reflecting constant fire without ripples throughout the cooking period.

The variance in PM_1, $PM_{2.5}$, PM_{10}, and CO concentrations is also influenced by the different combustion conditions. These include kitchen structure and size, type of biomass, cooking style, kitchen temperatures, emission factors, fuel moisture and carbon content, and the prevailing meteorological conditions (Adhikari et al., 2020). Lowden & Hull, (2013) reported that fuel combustion temperature below 225^{o}C is a recipe for high emission and concentration of organic matter, which forms part of PM_1, $PM_{2.5,}$ and PM_{10}. In contrast, other PM_1, $PM_{2.5,}$ and PM_{10} constituents, such as elemental carbon, are exacerbated under fuel combustion temperatures that exceed 300^{o}C (Akagi et al., 2011). However, this study did not control these factors in the field group since the aim was to measure the typical day-to-day pollutants exposure.

The concentration profiles in Figures 4.1, 4.2, 4.3, and 4.4 show that the bulk of PM_1, $PM_{2.5}$, and PM_{10} concentrations occurred during the early smouldering stages when the fire was lit.

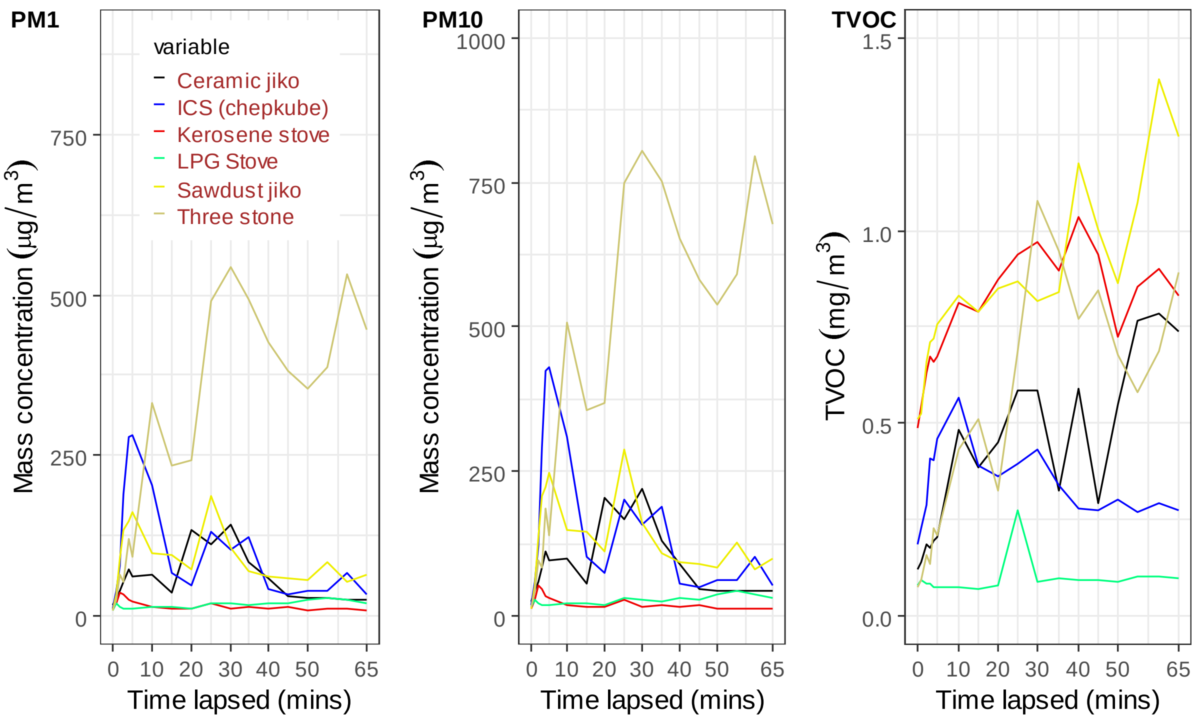


Figure 4.3: Shows averaged time series of PM_1, PM_{10}, and TVOC for different cookstoves during a cooking event for the control group

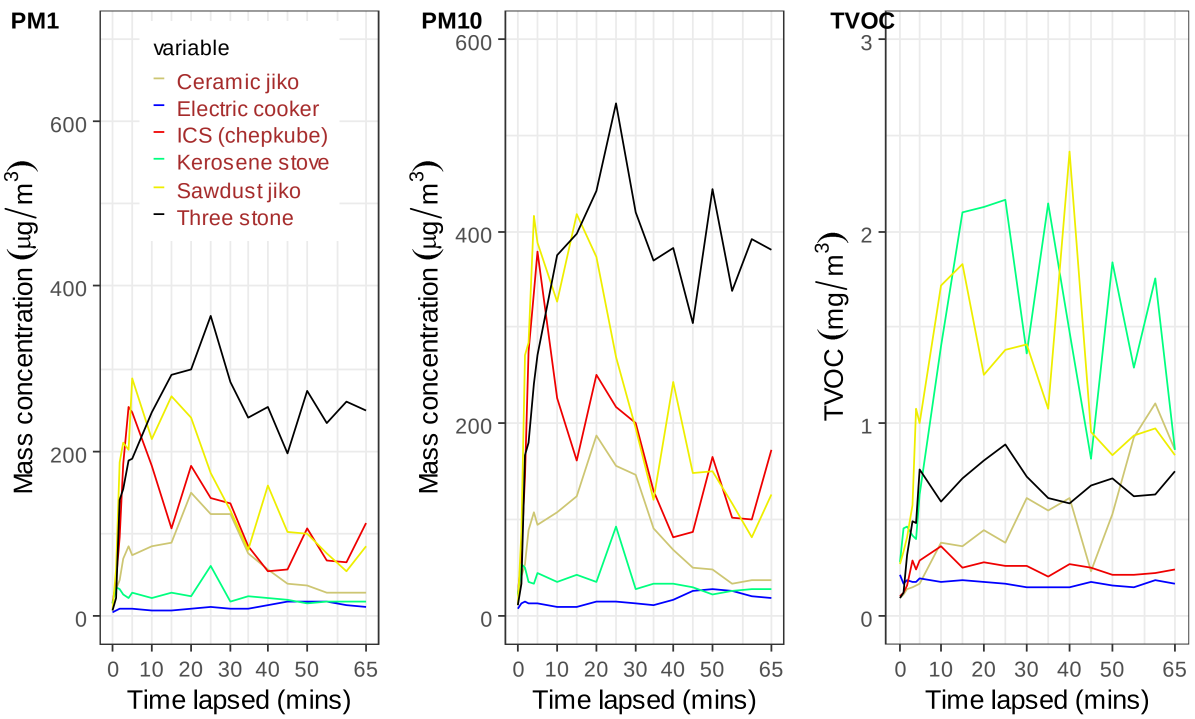


Figure 4.4: Shows averaged time series of PM_1, PM_{10}, and TVOC for different cookstoves during a cooking event for the field group.

This can be attributed to the excess smoke released during the lighting stage for biomass fuels and the use of other materials, such as newspapers, to ignite charcoal and sawdust. This increased PM_1, $PM_{2.5}$, and PM_{10} concentrations within the first 10 minutes, while CO concentration increased gradually. However, towards the end, while the fire was dying, modest PM_1, $PM_{2.5}$, and PM_{10} were observed for the majority of the cookstoves as they flattened off the emissions curve other than the three-stone cookstove, whose emissions profile remained high. The three-stone cookstove did not efficiently utilise fuel (wood), and at no point during the test did it produce a uniform fire.

On the other hand, higher CO concentration levels were recorded during the final phase. The distributions of PM_1, $PM_{2.5}$, and PM_{10} portrayed a relatively similar pattern in shape and spread of emissions concentration profiles for all the stoves. The shape of graphs of the pollutants concentrations profiles implies that a few major events of the entire cooking process contributed the most to the cumulative emissions concentration of each cookstove. Total pollutants concentration could be significantly reduced if these occurrences can be avoided or minimised during the cooking process. On average, $PM_{2.5}$, PM_{10}, and CO mass concentration levels exceeded the WHO indoor AQGs exposure limits for all the biomass cookstoves. Particulate matter and CO from LPG and electric cookers were way below WHO indoor AQGs exposure limits. Kerosene stove also recorded PM_{10} below WHO AQGs, but the average CO concentration was above WHO AQGs.

4.3.2 Indoor Air Pollution and Meteorology

The control group's average $PM_{2.5}$ and CO concentrations portrayed significant variation with time. The experiments were conducted at three distinct times of the day, morning (07h00 – 08h30), afternoon (12h30 – 15h00), and evening (18h30 – 21h00). These represent not only the cooking times but also different atmospheric stability conditions. All the times presented in this analysis are in the East Africa Time zone (UTC+03:00). The morning hours represent stable atmospheric conditions, afternoon unstable, while evenings are usually associated with unstable/neutral conditions within the tropical regions (Muhsin et al., 2016). The average $PM_{2.5}$ for the three-stone cookstove during a cooking event that started at 07h36 (04/11/2021) was 532.4 μg/m^3 ±119.9 μg/m^3 compared to 360.7 μg/m^3 ±119.9 μg/m^3 and 254.7 μg/m^3 ± 119.9 μg/m^3 that were recorded in the afternoon (from 13h40) and evening (from 18h42), respectively, on the same day (Figure 4.5).

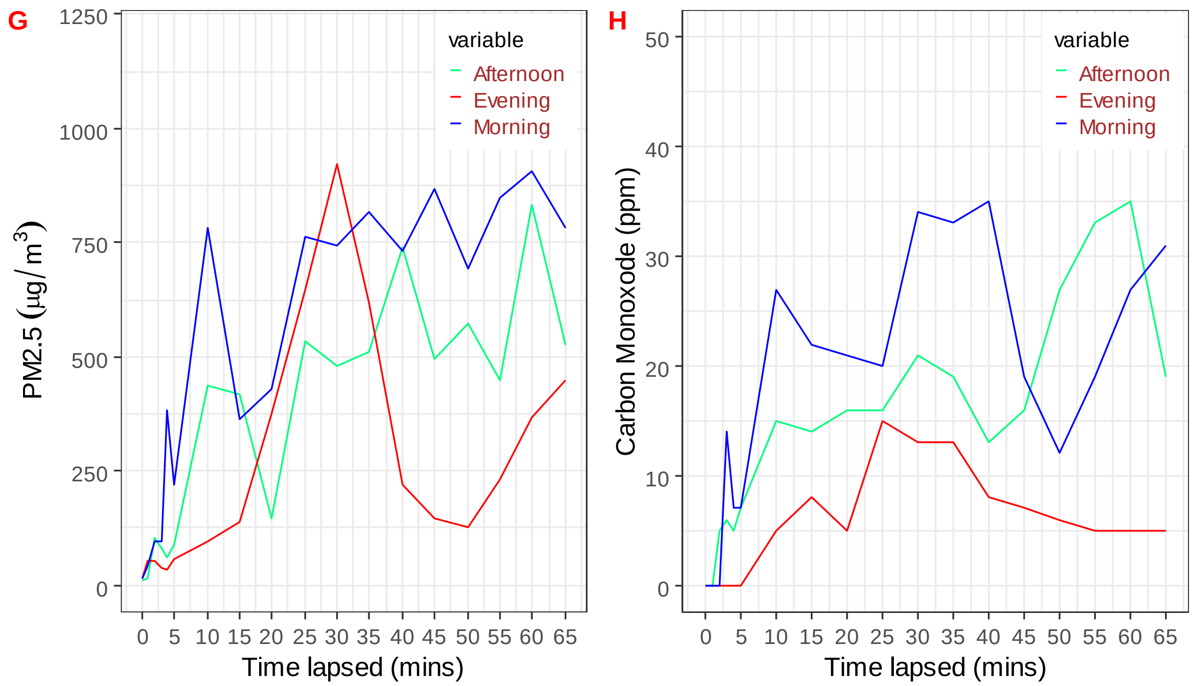


Figure 4.5. **(G)** Shows averaged time-series $PM_{2.5}$ mass concentration for the three-stone cookstove at different times of the day (morning, afternoon, and evening). **(H)** Shows averaged time-series data CO concentration in parts per million (ppm) for the three-stone cookstove at various periods of the day (morning, afternoon, and evening)

The test for the ICS (*chepkube*) conducted on 16/11/2011 also recorded significant variation in $PM_{2.5}$ mass concentration for the three different times of the day (Figure 4.6).

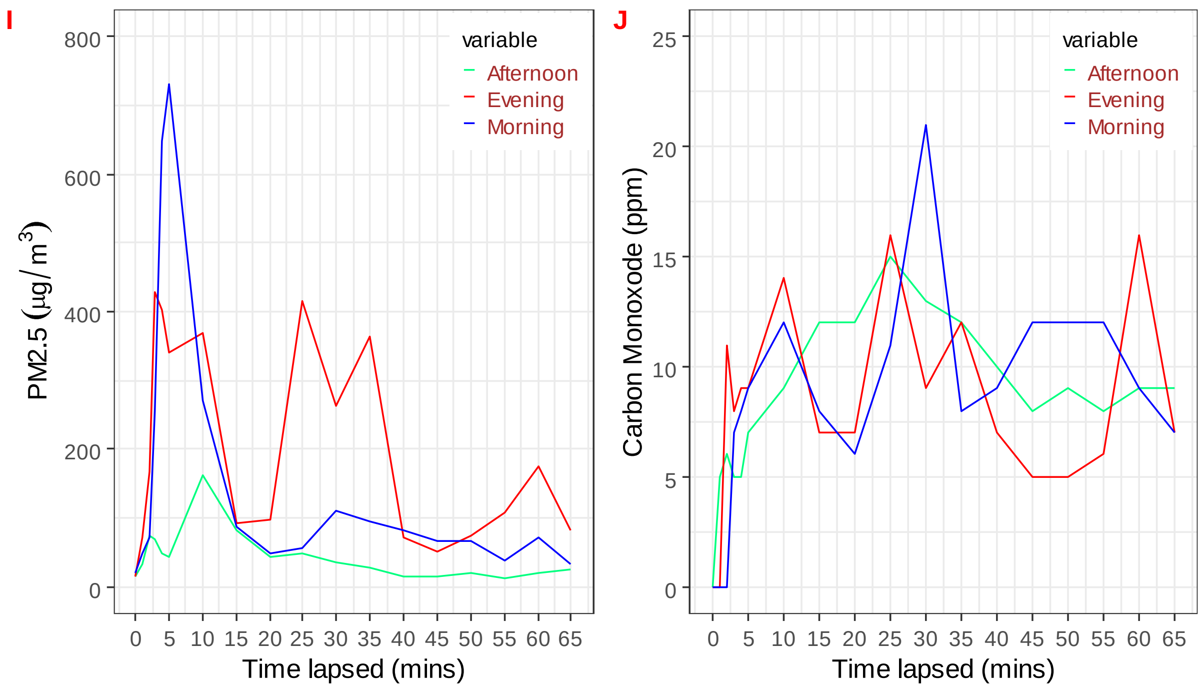


Figure 4.6. **(I)** Shows averaged time-series $PM_{2.5}$ mass concentration for the ICS (*Chepkube*) cookstove at different times of the day (morning, afternoon, and evening). **(J)** Shows averaged time-series data CO concentration in parts per million (ppm) for the ICS (*Chepkube*) at various periods of the day (morning, afternoon, and evening)

This translated to 155.7 µg/m^3 ± 82.7 µg/m^3 (07h30), 43.5 µg/m^3 ±82.7 µg/m^3 (13h36), and 198.8 µg/m^3 ±82.7 µg/m^3 (18h34). Similar trends were observed for CO concentration for both three-stone cookstove and ICS (*chepkube*), although the latter recorded slight variation.

An unstable atmosphere increases vertical air mixing, enhancing smoke and particulate matter dispersion. On the other hand, a stable atmosphere inhibits vertical motion, decreasing air inflow and the dispersion of smoke and particle matter. A neutral atmosphere neither suppresses nor facilitates smoke and particulate matter dispersion (Muralikrishna & Manickam, 2017). These results indicate that atmospheric stability conditions resulting from temporal changes in temperature, wind, and other weather variables play a role in PM and CO variation.

Indoor kitchen temperature and humidity were recorded simultaneously with particulate matter, CO, and TVOC. For all the experiments performed, indoor temperatures ranged from 20.2°C to 34.7°C. Therefore, the outcomes were not likely to be impacted by temperature. The average temperature increased gradually throughout the cooking period for individual cookstoves except for the kerosene stove, which recorded an almost constant temperature (Figure 4.7-T). No extreme values of temperature and humidity were recorded by the cookstoves considered. This implies that the kitchen environment is safe for occupancy while cooking.

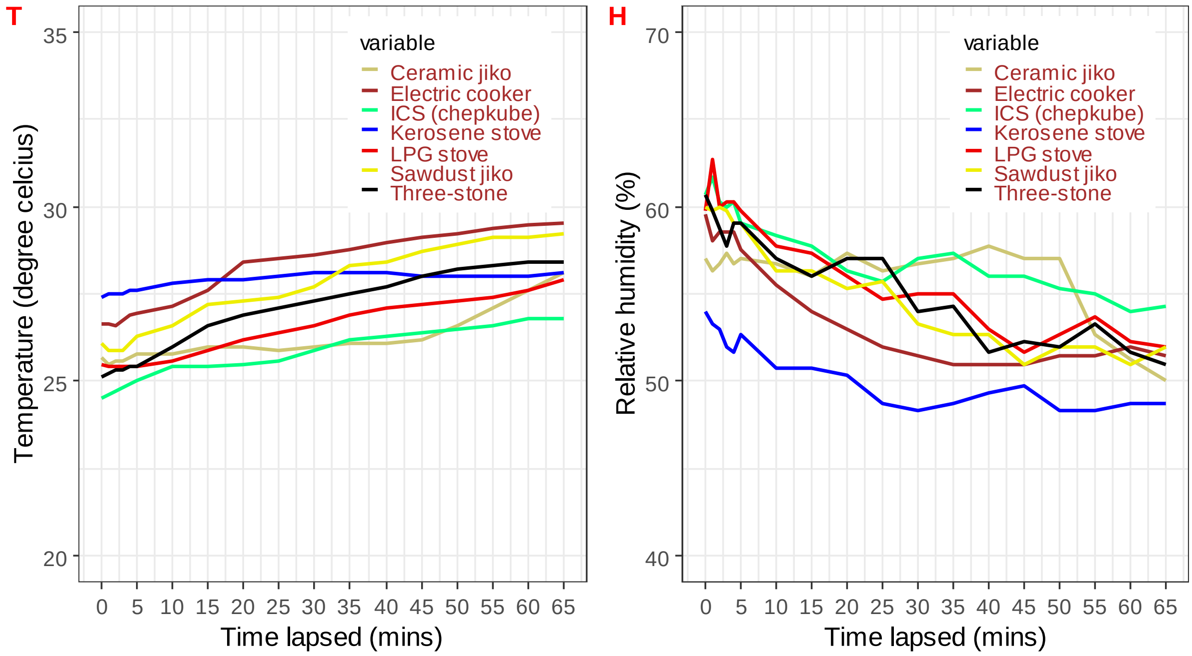


Figure 4.7. (**T**) Average temperature profiles of different cookstoves during a cooking event. (**H**) Average relative humidity (RH) profiles of different cookstoves during a cooking event.

The average relative humidity recorded during the tests was 35-69%, which was not so high to cause hygroscopic growth in the particulate matter. Relative humidity exceeding 75-80% has been reported to be the deliquescence relative humidity for particulate matter (Hernandez et al., 2017; Jayaratne et al., 2018). In contrast to the temperature profiles, the average relative humidity for individual cookstoves steadily fell during the monitoring period. This trend was observed across all the cookstoves (Figure 4.7-H).

4.3.3 Outdoor Air Pollutants

The outdoor pollutants considered were CO and NO_2. There was no adequate PM data for the specific location. In addition, household energy use is not a major contributor of outdoor particulate matter. A comparative study was performed where CO and NO_2 values in Vihiga county were compared with those from Nairobi and Tana River counties. Nairobi County depicts an urbanised environment, whereas Vihiga and Tana River represent dense and sparsely populated rural environments, respectively. Additionally, the COVID-19 pandemic season (2020/2021), which was the season during which the data used in this study were collected, was given special consideration.

Outdoor CO levels were generally higher in Vihiga County than in Nairobi County and Tana River County. Due to heavy road traffic, CO concentrations are spatially heterogeneous in urban places such as Nairobi. Due to the considerable CO emissions produced by kerosene stoves and biomass burning, indoor air in rural regions may be contaminated with high amounts of CO, affecting outdoor pollution. Peak seasonal variation of CO in Vihiga County occurs between June and August (Figure 4.8 and Figure 4.9).

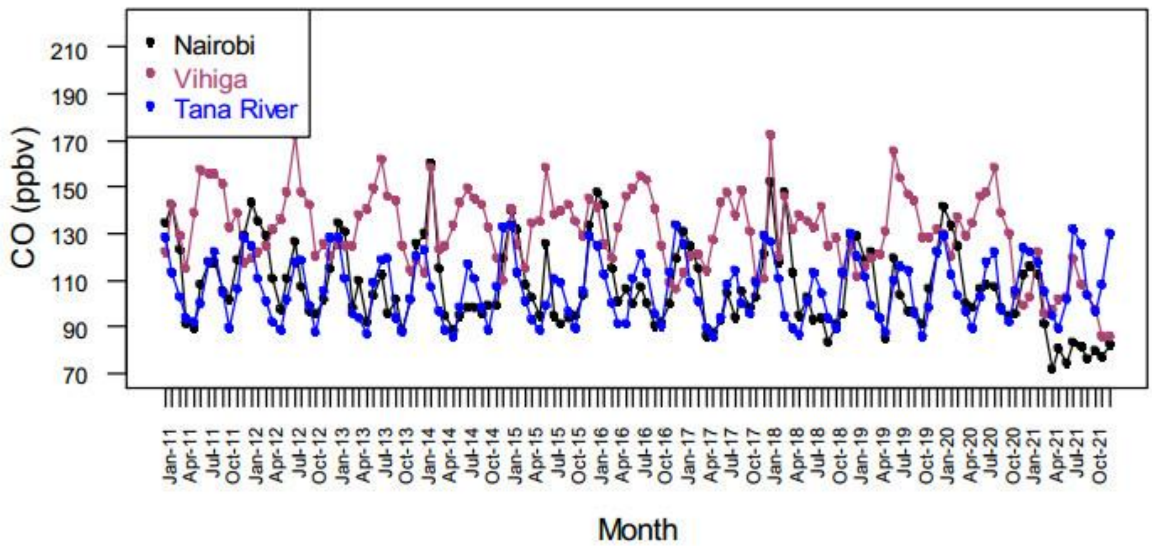


Figure 4.8: Time series of monthly surface CO concentrations for Nairobi, Vihiga and Tana River

Data Source: MERRA-2 model M2TMNXCHM v5.12.4

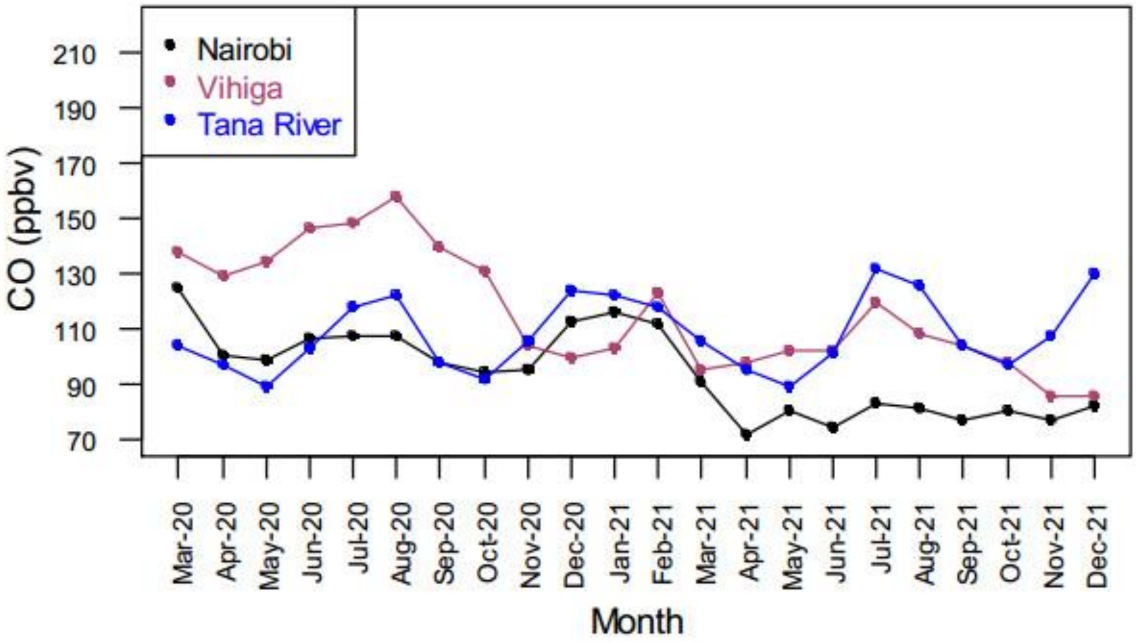


Figure 4.9. Time series of monthly surface CO concentrations for Nairobi, Vihiga and Tana River during the COVID-19 period

Data Source: MERRA-2 model M2TMNXCHM v5.12.4.

Analysis of the correlation between COVID-19 cases and CO concentration levels in Vihiga county showed a negative correlation, - 0.45 (*p*-value, 0.05). The correlation between NO_2 and COVID-19 cases was insignificant (-0.075) for Vihiga county. These findings highlight a reduction in outdoor CO concentration levels in Vihiga county during the COVID-19 pandemic. Outdoor NO_2 troposphere column concentrations in Vihiga county fluctuated from March 2020 to December 2021, as shown in Figure 4.10.

It has been established that population density influences CO and NO_2 emission rates (Ribeiro et al., 2019). While rural households rely on biomass, most urban dwellers can access clean energy alternatives for their household energy requirements. It is estimated that biomass burning is the second largest producer of tropospheric trace and primary carbonaceous particles after fossil fuel combustion (Neto et al., 2012).

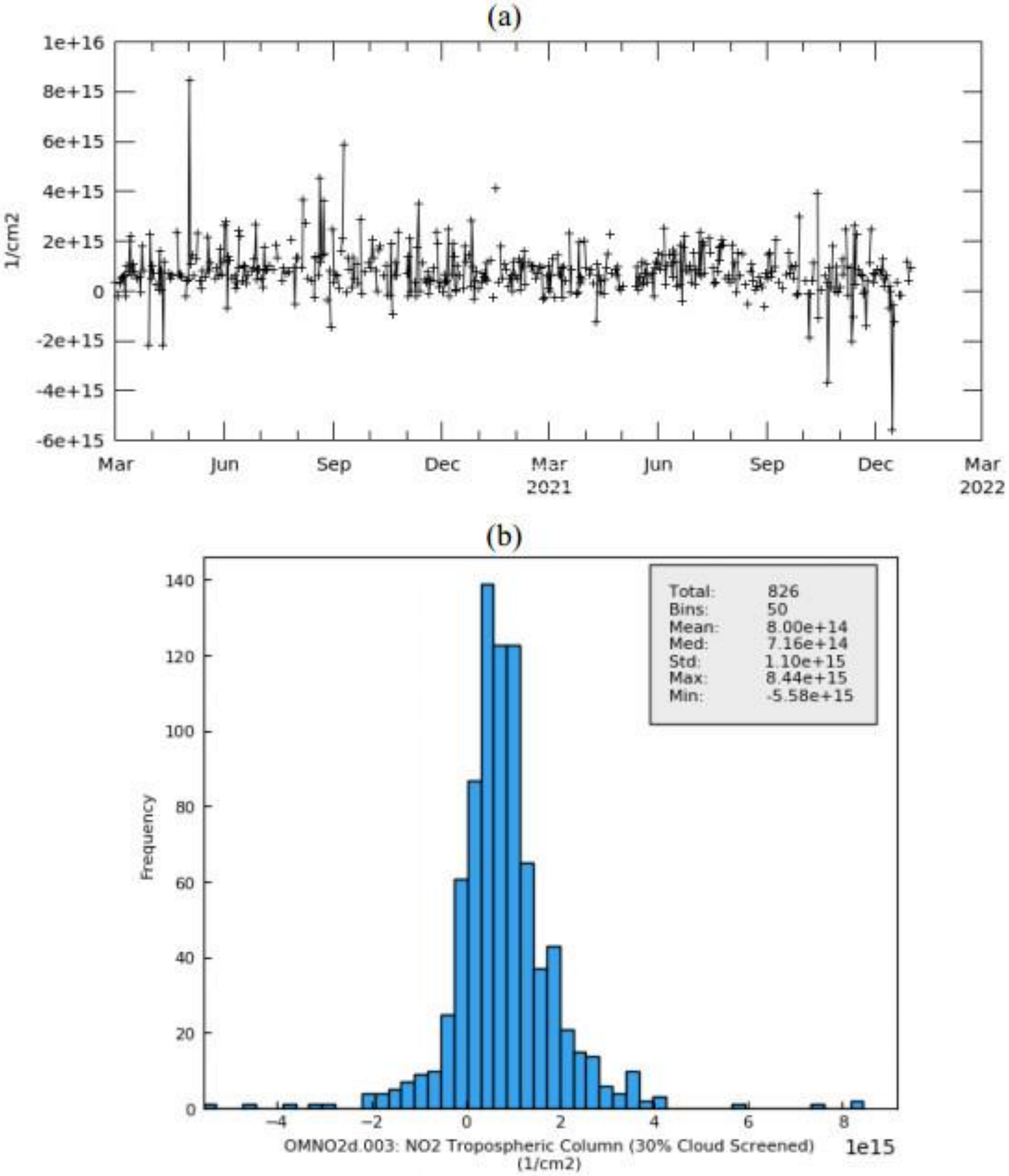


Figure 4.10. (a) Area-averaged time series and (b) histogram of NO_2 tropospheric column (30% cloud-screened) over Vihiga county

Data source: OMI OMNO2d v003

4.3.4 Health Risk Assessment

As shown in the preceding sections, biomass cookstoves produce considerable amounts of PM_1, $PM_{2.5}$, PM_{10}, and CO, necessitating further research to determine their health effects. This sub-section estimated health risks due to HAP from different cooking fuels and technologies using the AIRQ+ model. Cross-sectional design has been used to estimate HAP and related health impacts in comparable past studies (Agarwal et al., 2018; Nicolaou et al., 2022; Wafula et al., 2022). Furthermore, this study's results are within the range of other similar studies. For instance, studies in western Kenya have reported $PM_{2.5}$ concentration values of 319 μg/m^3 – 518 μg/m^3 and a geometric mean of 586 μg/m^3 for HAP from different cookstoves (Pilishvili et al., 2016; Yip et al., 2017). Other studies elsewhere have reported similar values of HAP due to biomass use, including 158-507 μg/m^3 in India and Guatemala (Liao et al., 2021), 376 ± 573 μg/m^3 and 288 ± 397 μg/m^3 for $PM_{2.5}$ and PM_1 in North China (Huang et al., 2017), and 417.6 μg/m^3 in Nepal (Bartington et al., 2017). This gives strong evidence that the results of this study can be used to research both the short- and long-term health impacts attributable to HAP.

The model results indicate that if clean cooking technologies are adopted, approximately 185 (representing 84.9%) mortality cases due to ALRI could be averted annually in children aged 0-5 years in Vihiga county (Table 4.12).

Table 4.12: Modelled $PM_{2.5}$ long-term mortality impact due to different diseases arising from the use of unclean cooking technologies and the averted mortality from the use of clean cooking technologies

Mortality due to	**Mortality from the use of solid fuel cookstoves (three-stone).**		**Mortality from the use of clean cooking technologies (LPG, electricity)**		**Averted mortality**
	Estimated number of attributable cases	**Estimated attributed proportion (%)**	**Estimated number of attributable cases**	**Estimated attributed proportion (%)**	
Acute Lower Respiratory Infection, ALRI (in children aged 0-5yrs)	Lower – 153 Central – 218 Upper – 256	Lower – 38.2 Central – 54.6 Upper – 64.1	Lower – 22 Central – 33 Upper – 45	Lower – 5.4 Central – 8.2 Upper – 11.2	185 (84.9%)
Chronic obstructive pulmonary disease, COPD (in adults, 25+ years)	Lower – 123 Central – 157 Upper – 218	Lower – 42.9 Central – 54.9 Upper – 76.1	Lower – 12 Central – 21 Upper – 31	Lower – 4.0 Central – 7.2 Upper – 10.8	136 (86.6%)
Ischemic Heart Disease, IHD (in adults, 25+ years)	Lower – 148 Central – 181 Upper – 262	Lower – 37.9 Central – 46.3 Upper – 67.2	Lower – 20 Central – 34 Upper – 70	Lower – 5.2 Central – 8.7 Upper – 17.9	147 (81.2%)
Lung cancer, LC (in adults, 25+ years)	Lower – 16 Central – 18 Upper – 20	Lower – 50.9 Central – 57.9 Upper – 63.4	Lower – 1 Central – 2 Upper – 3	Lower – 3.2 Central – 5.5 Upper – 8.1	16 (88.9%)

By switching to LPG or electricity, a significant reduction in mortality due to COPD, IHD, and lung cancer in adults is observed. This can be achieved by reducing the average kitchen $PM_{2.5}$ concentration levels from the current 382.6 $\mu g/m^3$ ±240.4 $\mu g/m^3$ due to biomass burning on three-stone cookstoves to an average of 18.6 $\mu g/m^3$ ±6.5 $\mu g/m^3$ from LPG and electric cookers. If the observed $PM_{2.5}$ concentration can be lowered to WHO recommended exposure limit of 15 $\mu g/m^3$, the annual mortality can be reduced by 197 cases for ALRI in children in Vihiga county. Approximately 144, 164, and 17 mortality cases due to COPD, IHD, and LC can be averted in adults.

These estimates indicate that households switching to cleaner fuels and technologies can tremendously increase health benefits by averting significant mortality cases associated with ALRI, COPD, IHD, and LC. However, in the absence of any intervention, persistence in the current situation in HAP levels could lead to 218 (153-256), 157 (123-218), 181 (148-262), and 18 (16-20) mortality cases due to ALRI, COPD, IHD and LC, respectively (Table 4.12). Other studies have shown that reducing the use of solid biomass fuels, improving ventilation, and improving biomass cookstoves can help reduce mortality (Po et al., 2011).

4.4 The Effects of Energy Poverty on Human Health

The impact of energy poverty on human health is discussed in this sub-section. The screen sample utilised in this section is summarised in Table 4.13.

Table 4.13: Population and sample size distribution in the study area showing valid cases

Sub-county	Population (2019)	Population density (2019)	No. of Households	Sample	Incomplete	Excluded	Valid
Hamisi	159,241	1,013	37,986	246	14	36	196
Sabatia	131,628	1,181	31,422	142	0	33	109
Vihiga (sub-county)	95,292	1,058	23,375	99	1	19	79
Total				**487**	**15**	**88**	**384**

Source; KNBS (2019) and Authors

4.4.1 Extent and Intensity of Energy poverty

The multidimensional energy poverty was computed for the 384 households that passed the inclusion criteria. MEP was also calculated for the entire sample by multiplying the energy poverty ratio (proportion of households identified as multidimensionally energy poor) and the intensity of energy poverty among those categorised as multidimensionally energy poor. The MEP, therefore, reflects both the proportion of people and their degree of energy poverty. The study conducted a robustness test of the MEP by varying the weights of different indicators as described in chapter 3 (Table 3.4). The incidence of energy poverty was not affected by weight variation, as there were no significant differences across the three scenarios. This translated to 0.9302, 0.9302 and 0.9281 for the original scenario, scenarios 1 and 2, respectively. Energy poverty intensity was 0.6239, 0.5713 and 0.7823 for the original scenario, scenarios 1 and 2, respectively. The MEP for the original scenario, scenarios 1 and 2, was 0.5803, 0.5314 and 0.7261, respectively.

Nussbaumer et al., (2012) estimated the original MEP for the western region of Kenya at 0.8, using secondary macro-level data. The difference between this study's MEP and that of

Nussbaumer et al., (2012) is attributed to two things. First, the time interval between the two studies is sufficient to necessitate significant changes in modern energy access, especially electricity access. Second is the differences brought about due to the different data types used (macro-level and micro-level). The number of households classified as energy poor remained the same across the three scenarios. As shown in Table 4.14, about 32.6% of the households live in acute energy poverty (MEP > 0.7), while 58.3% recorded moderate energy poverty ($0.3 < MEP \leq 0.7$). Lack of access to modern cooking fuels largely contributes to the high MEP. Firewood is the most common cooking fuel used because it is cheap and easily accessible in rural areas.

The MEP was compared among different socio-economic and demographic factors. In most of these factors, significant differences were recorded between those classified as multidimensional energy-poor and those who were not (Table 4.14). Previous studies have reported significant relationships between household size, income, gender, education level, age, and energy poverty (Abbas et al., 2020; Romero et al., 2018). Consequently, this study included these socio-economic and demographic factors as energy poverty covariates in the next section. Respiratory health factors, including cough, nasal irritation, phlegm, and wheeze, were more prevalent among those categorised as multidimensional energy poor. The same was true for other health risk factors such as burns and red itching eyes (Table 4.14). Alternative scenario 2 was chosen as the explanatory variable in impact estimation between energy poverty and health since it reflects high reliance on traditional (unclean) cooking fuels associated with indoor air pollution. Therefore, alternative scenario 2 carries more information on those exposed to health risks than the other two scenarios.

Table 4.14. Baseline characteristics disaggregated by MEP status

Characteristic		Baseline characteristics (n=384) (%)	MEP Acute (n=125, 32.6%)	MEP Moderate (n=224, 58.3%)	MEP Low (n = 35, 9.1%)	Difference (p-value)
Age bracket	21-30yrs	7.8	6.4	6.3	22.9	0.004**
	31-40yrs	17.2	14.4	17.9	22.9	
	41-50yrs	24.0	16.8	28.1	22.9	
	51-60yrs	20.8	23.2	20.5	14.3	
	>60yrs	30.2	39.2	27.2	17.1	
Gender	Male	31.3	25.6	31.7	48.6	0.054*
	Female	68.8	74.4	68.3	51.4	
Education level	No formal Education	41.2	55.2	37.1	14.3	0.000***
	Primary	30.5	21.6	37.5	17.1	
	Secondary	19.0	4.8	19.6	68.6	
	Tertiary	9.4	18.4	5.8	0.0	
Household size	1-3	22.9	23.2	18.3	51.4	0.000***
	4-5	42.7	36.8	47.3	34.3	
	6-9	30.7	35.2	30.4	14.3	
	10-12	3.6	4.8	3.6	0.0	
Income (kshs.)	<10,000	84.1	98.4	0.9	57.1	0.000***
	10k-20k	5.7	1.6	7.6	8.6	
	21k-30k	7.6	0	8.9	25.7	
	31k-50k	2.6	0	3.1	8.6	
	51k-100k	0.0	0	0.0	0.0	
	>100000	0.0	0	0.0	0.0	
Income activity	Farming	45.1	61.6	42.0	5.7	0.000***
	Other	55.0	38.4	58.0	94.3	
Household member responsible for decision making regarding fuel type to be used	Husband	5.2	5.6	4.0	11.4	0.083
	Wife	68.0	82.4	62.1	54.3	
	Jointly (husband and wife)	21.6	4.8	29.5	31.4	
	Children	2.6	4.8	1.3	2.9	
	Other	2.6	2.4	3.1	0.0	
User preferences	Lack of other options (0)	39.1	49.6	38.4	5.7	0.000***
	Uses less fuel (1)	15.9	8.8	20.5	11.4	
	Is convenient to use (2)	27.6	22.4	26.8	51.4	
	Cooks fast (3)	15.6	17.6	12.5	28.6	
	Produces less smoke (4)	1.3	0.8	1.3	2.9	
	Prefers test of food cooked by the stove (5)	0.5	0.8	0.4	0.0	
			Acute (n=125, 32.6%)	Moderate (n=224, 58.3%)	Low (n = 35, 9.1%)	Difference (p-value)
Cough		30.0	24.8	37.1	2.9	0.000***
Wheeze		5.2	4.8	5.8	2.9	0.219
Red itching eyes		47.4	58.4	47.8	5.7	0.000***
Nasal irritation		38.8	40.0	43.8	2.9	0.000***
Burns		14.8	12.8	17.4	5.7	0.157
Phlegm		2.6	0.8	2.2	11.4	0.004**

NB: Wilcoxon-Mann-Whitney test was used for continuous variables, Chi-square test was used for categorical variables

4.4.2 Effect of Energy Poverty on Health

The propensity score (PS) was used to control for the measured confounders by balancing the characteristics of the energy poor and non-energy poor groups. The PS accounted for differences in the measured baseline characteristics through the IPTW, eliminating any bias that may have occurred during the sampling process. All the possible baseline characteristics that could act as confounders were included in the model as covariates; age, gender, education level, income, occupation, household size, decision making and preferences. The covariates were selected based on existing literature, while others, such as user preferences and decision making were informed by expert knowledge on the topic. The PS was calculated using logistic regression.

The IPTW achieved its intended purpose since the pseudo-population was bigger (n=759) than the original sample (n=384), with a reasonably equal mean distribution between the energy poor and non-energy poor (Table 4.15).

Table 4.15. Standardised differences of the weighted data (pseudo population) stratified by the energy poverty

	MEP		SMD
	Non-energy poor (Weighted Mean ± SD)	Energy poor (Weighted Mean ± SD)	
n	377	382	
Age	3.49 ± 0.99	3.50 ± 1.28	0.009
Gender	0.13 ± 0.34	0.31 ± 0.46	0.432
Education level	1.92 ± 0.81	1.96 ± 0.99	0.047
Income	1.21 ± 0.67	1.29 ± 0.73	0.113
Occupation	0.34 ± 0.48	0.45 ± 0.50	0.224
Household size	4.09 ± 1.31	4.54 ± 1.56	0.313
Decision making on energy use	0.88 ± 0.33	0.69 ± 0.46	0.492
User preferences	0.40 ± 0.50	0.39 ± 0.49	0.029

The original sample for non-energy poor and energy poor categories were 35 (9.11%) and 349 (90.89%), respectively, compared to 377 (49.67%) and 382 (50.33%) for the weighted data. Therefore, covariate balance was achieved. To obtain balance after weighting, the propensity model was adjusted by including interaction terms (Austin, 2011). Results of the logistic model of energy poverty and its covariates are presented in Table 4.16.

Table 4.16. Logistic model of energy poverty and its covariates

Variable	***Coeff.***	***Std. Error***	***P>|z|***	***95% (z=1.96)***
Age	0.1904	0.1679	0.2565	-0.2131
Gender	-0.3390	0.4481	0.4494	0.3363
Education level	-0.5421	0.2972	0.0681	0.0403
Income	-0.4447	0.2420	0.0661	-0.0678
Occupation	1.6148	0.7845	0.0395	0.9954
Household size	0.3777	0.1496	0.0115	-0.2489
Decision making on energy use	0.2622	0.4387	0.5500	0.3177
User preferences	2.1436	0.7697	0.0053	0.9666
Constant	1.3354	1.0187	0.1898	1.4545

The covariates were included in the model regardless of their p-values since basing inclusion of variables on prognostic methods may lead to the exclusion of essential confounders (Chesnaye et al., 2021; Wyss et al., 2013). Thus, the confounders were included even if their p-values were greater than 0.05.

The calculated weights were then used to fit marginal structural models to obtain adjusted estimates, hence the average effect of energy poverty on the entire population. To properly account for weighting, the asymptotic variance was used. The causal relative risk (CRR) point estimate was 1.88, with 0.56 and 6.24 as the lower and upper bounds, respectively (Table 4.17). The CRR value was greater than 1, indicating a higher health risk for those who live in energy poverty. The causal risk difference (CRD) estimate was 1.40, with 0.42 and 4.65 as lower and upper bounds, respectively. A CRD greater than 1 also implies a greater health risk in the energy poverty group. These findings are consistent with Awaworyi & Smyth, (2021) and Liddell & Morris, (2010), who, among other methods, employed propensity score matching to examine how energy poverty affected individuals' health..

Table 4.17: Marginal structural models (MSMs) estimate of the impact of energy poverty on health

Log link					
	Coeff.	*Std. Error*	*P>|z|*	*Lower 95%*	*Upper 95%*
Energy poverty	0.6329	0.0654	$<2\text{x}10^{-16}$	0.4905	0.7754
Intercept	-0.9593	0.0727	$<2\text{x}10^{-16}$	0.5048	0.7610
Causal relative risk (CRR)	Lower confidence limit		CRR	Upper confidence limit	
	0.5683		1.8831	6.2405	
Identity Link					
	Coeff.	*Std. Error*	*P>|z|*	*Lower 95%*	*Upper 95%*
Energy poverty	0.3384	0.0340	$<2\text{x}10^{-16}$	0.1959	0.4809
Intercept	0.3832	0.0251	$<2\text{x}10^{-16}$	0.2102	0.4665
Causal risk difference (CRD)	Lower confidence limit		CRD	Upper confidence limit	
	0.4233		1.4027	4.6483	

Kenya has made significant progress in electricity access, from just 19% in 2010 to about 75% in 2020 (World Bank Group, 2021). Key factors for the significant increase include government programs such as rural electrification and Last Mile connectivity program. However, despite tremendous improvement in electricity access, 90% of households in Vihiga are still trapped in energy poverty. This trend is because of unaffordable electricity costs, which drive many rural households to use cheap and readily available traditional biomass.

4.5 Assumptions

These results are to be interpreted under the following assumptions (Chesnaye et al., 2021); 1) exchangeability - the exposed (energy poor) and unexposed (non-energy poor) groups are exchangeable, i.e., the outcome risk would be the same if either group were to be exposed; 2) correct specification of the propensity score model; 3) positivity and consistency – there are both exposed (energy poor) and unexposed (non-energy poor) individuals at all levels of the confounders.

5. CONCLUSION AND RECOMMENDATIONS

This section summarises the study's key findings and proposes several recommendations. This study achieved its objectives as outlined below.

5.1 Conclusions

The study used household survey data to systematically address concerns regarding household energy choices for cooking and lighting. The evidence indicates that the anticipated transition from traditional fuels and technologies to modern, environmentally friendly ones is still modest. This is because wood remains the primary cooking fuel in the majority of rural households. This study provides strong empirical evidence on the effects of socio-economic and demographic factors on household energy decisions by employing the probit model to describe causes and effects. Household decisions on cooking and lighting fuels and technologies are affected by socio-economic and demographic characteristics. Demographic factors affecting household energy choices include gender and age, where male gender was associated with utilisation of cleaner fuels and technologies than females. Older household heads were also more likely to utilise clean fuels and technologies than younger ones. Socio-economic factors such as increasing household income, higher education attainment, access to credit, employment, and membership of community associations increase the likelihood of utilising clean fuels and technologies for cooking and lighting.

Pollutants concentrations were estimated for the most commonly used biomass and traditional cookstoves in the area, including the three-stone cookstove, a locally made ICS (*chepkube*), the ceramic *jiko*, sawdust *jiko,* and kerosene stove. Also tested were two modern, environmentally friendly cooking technologies: LPG and electric stove. The study sought to estimate pollutants concentration in real household conditions to quantify the overall pollutants exposure. However, a control test was set up to account for variations in the individual kitchens due to design and other natural factors. Modern cooking technologies (LPG and electric cooker) recorded the least PM_1, $PM_{2.5}$, PM_{10}, CO, and VOC mass concentration values and had the least variability. AirQ+ model results indicate that using solid biomass fuels for cooking was responsible for approximately 218 deaths annually due to ALRI in children aged 0-5 years in Vihiga County. In adults, an estimated 157 deaths due to COPD were attributed to HAP from solid biomass fuels, while IHD and lung cancer accounted for 181 and 18 mortality cases, respectively. Shifting from solid biomass cookstoves to modern, cleaner fuels and technologies (LPG or electricity) at the household level could help to avert 185 (84.9%), 136 (86.6%), 147 (81.2%), and 16 (88.9%) annual premature mortality cases due to ALRI, COPD, IHD, and LC, respectively in Vihiga county. This study's findings indicate that exposure to HAP and associated health concerns in rural areas is mostly attributed to the use of solid biomass for cooking.

Energy poverty intensity and incidence remain high (90.9%) in rural households and is significantly affected by different socio-economic factors, including occupation, income, household size, and household preferences. A majority of the households had moderate energy poverty status. This study demonstrated that energy poverty plays a critical role in public health. Empirical results from marginal structural models suggest a negative impact of energy poverty on human health, especially poor respiratory health (cough, wheeze, nasal irritation), mainly attributed to HAP from traditional biomass fuels. Health ought to be mainstreamed in national energy policies and other related policies. This study's findings will provide the much-needed empirical evidence that will aid the identification of vulnerable groups for targeted support.

5.1.2 Contribution to Knowledge

This work's main contribution to knowledge is that;

- Shifting from solid biomass cookstoves to modern, cleaner fuels and technologies (LPG or electricity) at the household level can help to avert 185 (84.9%), 136 (86.6%), 147 (81.2%), and 16 (88.9%) annual premature mortality cases due to ALRI, COPD, IHD, and LC, respectively
- Energy poor households are associated with a greater risk of health complications including persistent cough, nasal/eye irritations and burns than households that are not classified as energy poor.
- Despite design improvements on the available biomass cookstoves in Vihiga county, they are not currently at the level to lower $PM_{2.5}$, PM_{10} and CO to WHOs recommended thresholds of 15 $\mu g/m^3$, 45 $\mu g/m^3$, and 3.49 ppm, respectively.

5.2. Recommendations

This study puts forward the following recommendations and important policy alternatives.

a) Eradicating poverty and economic growth are crucial components of the energy transition matrix. However, this usual strategy of focusing on household income as the primary predictor of energy choice for cooking and lighting ought to be reconsidered. Designing effective interventions will benefit from a thorough understanding of the various factors influencing household energy decisions for lighting and cooking. These include socio-economic and demographic factors such as age, gender, household size, marital status, stove preferences, education, access to credit, and employment status.

b) This study has demonstrated that no one energy source can meet a household’s cooking and lighting energy requirements. This is true for the majority of developing countries, particularly in Africa. As a result, switching to new cooking or lighting fuel/technology may not eliminate the need for the existing ones altogether. This explains why biomass remains the predominant cooking fuel of choice despite increasing grid connection rates in Kenya over the past decade. In resolving household energy issues, concerned parties should pay more attention to both cooking and lighting instead of focusing on one aspect of energy use. For instance, decreasing consumer electricity prices could be a potential fix allowing electricity usage for cooking and lighting.

c) Programs seeking to popularise clean fuels and technologies among rural households should consider local contexts and other distinct factors such as economic situations, household demographics, and community governance systems. It is critical to properly comprehend and consider human behaviour to design appropriate strategies and technologies for the sustainable development of energy resources. This will aid governmental and non-governmental rural energy access initiatives to develop focused intervention strategies for tackling the pervasive issue of energy access in Kenya’s rural areas.

d) Although the improved cookstoves and modern biomass cookstoves such as the ceramic *jiko* are usually perceived to be efficient in both performance and emissions reduction, this study recommends that further design considerations are required to stabilise their emission levels. The emission levels from these improved biomass stoves are still significantly higher than the WHO's air quality standards. These findings will benefit policymakers in understanding the adverse health effects of solid biomass use and the health benefits of transitioning to clean energy at the local, national, and regional levels.

e) The production of biogas from smaller digesters that may be used in homes is a developing technology that shows promise in environments where there is ready availability of animal waste that can be used to feed digesters. The key concern of this initiative has been the maintenance of digesters as noted by the multi-national East Africa Biogas initiative, which started in 2009 (Quinn et al., 2018). However, if such programmes are adequately implemented and follow-up services provided, biogas is a viable solution to the challenges rural households face regarding cooking fuels.

f) In general, two distinct yet complimentary strategies can be utilised to deal with the significant issue of household air pollution and associated health complications: (a) by encouraging the use of solid fuels in a more sustainable, efficient, and less polluting way, and (b) easing the transition to modern, clean and environmentally friendly cooking fuels and technologies. The first strategy has traditionally been emphasised. However, the evidence presented by this work shows that improved biomass cooking technologies do not deliver the levels of improvement required to reduce HAP load to recommended thresholds significantly. To obtain significant health benefits, lowering HAP to extremely low levels will necessitate promoting the use of truly clean fuels such as LPG, biogas, solar, and electricity. It is still possible to promote improved biomass stoves as "interim" technology, and they may be able to perform well enough to provide some health benefits.

Proposed Future Work

Further research in this area should consider gender inequalities in the prevalence of energy poverty and its impact on health. A longitudinal study on this topic would be helpful. Finally, future research should also consider estimating outdoor air pollution in addition to indoor air pollution

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APPENDIX I: PARTICIPANT INFORMATION AND CONSENT FORM

FOR PARTICIPATION IN THE STUDY

(To be administered in English or any other appropriate language e.g Kiswahili translation)

Title of Study: Assessment of the Impact of Clean Energy Technologies on Energy Poverty in Vihiga County

Student\and institutional affiliation: Cohen Ang'u, University of Nairobi

Introduction:

I would like to inform you of a study being undertaken by the researcher named above. This consent form's goal is to provide you with the details you need to make a decision about whether or not to participate in the study. Please ask questions that you might have concerning the study's goals, what will happen if you join, the potential risks and rewards, your rights as a volunteer, and anything else that is unclear about the study or this form. Once we have properly answered all of your questions, you will have the option to join in the study or not. This procedure is known as "informed consent.". I'll ask you to sign this form once you understand and consent to participating in the study. You should be aware of the fundamental guidelines that all participants in social research must follow: i) Your participation is completely voluntary ii) At any time, you may withdraw from the study without providing a reason.

You will receive a copy of this document for your files.

May I continue? YES / NO

The Kenyatta National Hospital-University of Nairobi Ethics and Research Committee has approved this study, protocol No. **P34/01/2021**

WHAT IS THIS STUDY ABOUT?

The researcher in possession of this form is interviewing individuals **who reside in Vihiga County**. The interview's aim is to **find out the household fuels and technologies in use, household air pollution and associated human health complications**. Participants in this study will be questioned about **their energy uses, household demographics and design, and**

respiratory health status. Participants will also have the choice to **participate in the monitoring of Household Air Pollution (HAP) in their homes**.

The individuals to take part in this research will be chosen at random, and there will be about **500** total. In order to consider having you participate in this study, we need your consent.

WHAT WILL HAPPEN IF YOU DECIDE TO BE IN THIS RESEARCH STUDY?

The following things will happen if you consent to take part in this study:

A qualified interviewer will speak with you in a quiet setting where you feel at ease answering questions. The interview is expected to take about **10 minutes**. The interview will cover topics such as **your bio-information, demographic information, household energy use, kitchen characteristics and health**.

ARE THERE ANY RISKS, HARMS DISCOMFORTS ASSOCIATED WITH THIS STUDY?

This study may pose psychological, social, emotional, and physical risks. However, every effort is made to minimise the dangers. Loss of privacy is one potential risk of participating in the study. Everything you tell us will be kept as private as possible. An encrypted computer database will have a unique code number that serves as your identification, and all our paperwork will be stored in a secured filing cabinet. However, no mechanism for maintaining your privacy can be 100% safe, therefore it is still possible that someone could discover that you were a participant in this study and obtain your information.

Additionally, it is possible that responding to some interview questions will make you feel uncomfortable. You are free to ignore any of the questions that you do not wish to provide an answer to. You are within your rights to decline to participate in the interview as well as to refuse to answer any questions posed by the interviewer.

You could find it embarrassing to have your **culinary operations monitored**. We shall use every effort to keep this a private matter. Additionally, all research personnel and interviewers have received specialised training in conducting these interviews.

In the event of a research-related accident, illness, or complication, please call the study personnel immediately at the number listed at the end of this publication.

ANY BENEFITS OF PARTICIPATING IN THIS STUDY?

There are no expected immediate benefits for you. There are, however, benefits to the society and for households in future arising from the study results. Additionally, the information you offer us will aid in our understanding of household energy use, indoor air pollution, and respiratory health. This information is a scientific contribution that will aid in the formulation of relevant policies.

WHAT WILL YOUR PARTICIPATION IN THIS STUDY COST YOU?

Your participation in this study will not have any financial costs to you. You will also not be required to use your physical resources beyond your routine daily operations. The only cost to you will be the time you will spend in this interview.

WILL YOU RECEIVE A REFUND FOR ANY MONEY SPENT ON THIS STUDY?

You will not spend any money on this study

WHAT IF YOU HAVE QUESTIONS IN FUTURE?

In the event that you have any more inquiries or concerns regarding taking part in this research project, the staff conducting it can be reached through phone or text message (the relevant number is provided below).

You can get in touch with the Secretary or the Chairperson of the Kenyatta National Hospital-University of Nairobi Ethics and Research Committee if you would like further information about your rights as a participant in this study. Telephone No. 2726300 Ext. 44102 email uonknh_erc@uonbi.ac.ke.

If you make a call to one of these numbers for the purpose of communicating about the study, the staff members will reimburse you for any fees you incur.

WHAT ARE YOUR OTHER CHOICES?

It is entirely up to you whether or not you choose to take part in the research. Participation in the study is not compulsory and you can opt out at any moment without suffering any harm or losing benefits.

CONSENT FORM (STATEMENT OF CONSENT)

Participant's statement

I have either read this consent form myself or had it read to me. I had the chance to speak with a study counsellor about this research study. My inquiries were addressed in a language I can comprehend. The risks and advantages have been outlined to me. I am aware that taking part in this research is entirely optional and that I am free to discontinue my involvement at any point. I consent to taking part in this research on my own free will.

I am aware that every possible measure will be taken to protect the confidentiality of information pertaining to my personal identification.

My signature on this permission form does not signify a release of my legal rights as a research subject.

I consent to participate in this research:	YES	NO
I consent to have (define specimen) preserved for later study:	YES	NO
I consent to providing my contact details for follow-up:	YES	NO

Participant name: ____

Participant signature _______________________ **Date** _____________________

Researcher's statement

I, the undersigned, firmly think that the participant in question has comprehended and voluntarily given his or her consent after I properly described the study's pertinent contents to them.

Researcher's Name: _____________________________________ Date: ______________

Signature:____

Role in the study: ___________________________ *[i.e. study staff who explained informed consent form.]*

For more information contact **Cohen Ang'u** at **+254704739039**

Witness Name *(if a witness is required, A witness is someone who is acceptable to both the participant and the researcher)*

Name: ______________________________ **Contact information:** ____________________

Signature: ___________________________ **Date**; ___________________________________

APPENDIX II: QUESTIONNAIRE

Assessment of the Impact of Clean Energy Technologies on Energy Poverty in Vihiga County

County:			
Sub-County:		**Division:**	
Date:		Start Time:	End Time:
A. Biodata and demographic data			
1.1	Gender:	Male [ ] Female [ ]	
1.2	Age bracket:	21-30 [ ] 31-40 [ ] 41-50 [ ] 51-60 [ ] Above 60 [ ]	
1.3	Education level:	No formal Education [ ] Primary [ ] Secondary [ ] Tertiary [ ]	
1.4	Employment sector:	Public sector [ ] Private sector [ ] Mixed [ ] Own business [ ] Unemployed [ ]	
1.5	Marital status	Single [ ] Married [ ] Separated [ ] Widow/Widower [ ]	
1.6	Employment status	Both parents working [ ] Only Male Working [ ] Only Female Working [ ] None working [ ]	
1.7	Household size:	1 person [ ] 2 people [ ] 3 people [ ] 4 people [ ] 5 people [ ] 6-9 people [ ] 9-12 people [ ] More than 12 people [ ]	
1.8	Approximate monthly income (Kshs.)	Less than Kshs.10000 [ ] 10k-20k [ ] 20k-30k [ ] 30k-50k [ ] 50k-100k [ ] Above 100k [ ]	
B. Determinants of the use of clean energy technologies			
2.1	What is the primary fuel type used for heating/cooking?	Electricity [ ] LPG [ ] Kerosene [ ] Biogas [ ] Wood-fuel [ ] Solar [ ] Other: ________________________________	
2.2	What is your primary source of light?	Electricity [ ] Solar [ ] Kerosene [ ] Wood-fuel [ ] Candles [ ] No light [ ] Other: ________________________________	

2.2.1	If wood-fuel, what is the primary source of wood:	
2.3	What type of cookstove do you use for typical day to day cooking?	[ ] Traditional 3-stone stove without a chimney [ ] Traditional 3-stone stove with chimney [ ] Improved cook-stove without chimney [ ] Improved stove with chimney [ ] Kerosene stove [ ] LPG stove [ ] Biogas stove [ ] Electric Cooker
2.4	For how long have you had this stove?	
2.5	How many meals do you prepare in a day using the above cookstove?	1 [ ] 2 [ ] 3 [ ] More than 3 [ ]
2.6	What is the average time you take to prepare a meal?	0-30 mins [ ] 30min – I hr [ ] 1 hr – 2 hrs [ ] More than 2 hrs [ ]
2.7	If using ICS, do you think it is designed to meet your needs?	[ ] It's very well designed [ ] It's just fine [ ] I don't know [ ] It's not the best design for my daily needs [ ] It's not designed based on my needs
2.8	If using a traditional 3-stone stove, would you like to transede to ICS?	[ ] Very likely [ ] Likely [ ] Neutral [ ] Unlikely [ ] Very unlikely
2.9	Among your relatives, friends, or acquaintances, are there people who have ICS	[ ] Yes [ ] Probably [ ] Possibly [ ] No [ ] I do not know
2.10	Are you/have you been a member of any community association (e.g. women group)?	[ ] Always a member [ ] Often a member [ ] Sometimes a member [ ] Rarely a member [ ] Never been a member
2.10.1	If yes, what is the association/group about?	
2.11	Do you have access to credit facilities?	[ ] Always [ ] Usually [ ] Occasionally

		[ ] Never
2.12	Do you know/have heard any NGOs/government initiatives dealing with ICS in your area	[ ] To a great extend [ ] To some extend [ ] Rarely [ ] Never
2.13	Why do you prefer your current cookstove?	[ ] Uses less fuel [ ] Produces less smoke [ ] Cooks fast [ ] Is convenient to use [ ] I prefer the taste of food cooked by the stove [ ] Lack of other options [ ] I don't know
C. Energy Poverty Indicators		
3.1	Uses modern cooking fuel (electricity, LPG, natural gas, biogas)	[ ] Yes [ ] No
3.2	Has access to electricity	[ ] Yes [ ] No
3.3	Indoor pollution	Food is normally cooked on stove or open fire with no hood/chimney, indoor, with fuel other than electricity, LPG, natural gas or biogas: [ ] True [ ] False
3.4	Household appliance ownership	Has a fridge: [ ] Yes [ ] No
3.5	Entertainment/education appliance ownership	Has a radio or Television: [ ] Yes [ ] No
3.6	Telecommunication means	Has a phone landline or mobile phone: [ ] Yes [ ] No
D. Household energy technologies and household-level indoor air pollution		
4.1	How many rooms does the household have?	[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] More than 4
4.2	Kitchen type	[ ] Open-air kitchen [ ] Indoor kitchen with partition inside the main house [ ] Indoor kitchen without partition inside the main house [ ] Separate indoor kitchen outside the main house

4.3	What time do you usually cook?	[ ] Morning (before noon) [ ] Afternoon (noon to 6 pm) [ ] Evening (After 6 pm) [ ] All the above
4.4	Other than cooking, do you ever use your stove for space heating?	[ ] Very frequently [ ] Frequently [ ] Occasionally [ ] Rarely [ ] Very Rarely [ ] Never [ ] This is done concurrently
4.5	How many external doorways are there in the house/kitchen?	[ ] 1 [ ] 2 [ ] 3 [ ] More than 3
4.6	How many windows or major openings are there in the house/kitchen?	[ ] 1 [ ] 2 [ ] 3 [ ] 4 [ ] More than 4
4.7	When do you find the air in the kitchen most polluted?	[ ] Before cooking [ ] While cooking [ ] After cooking [ ] It is ever polluted [ ] It is hardly polluted
4.8	Rate the obscurity in the kitchen during cooking	[ ] Highly obscured [ ] Moderately obscured [ ] Low [ ] None
4.9	What is the cause of the obscurity above?	Smoke [ ] Wood particles [ ] Ash [ ] Dust particles [ ] Soot [ ] Other: ___________________________
4.10	How frequent are the kitchen walls painted?	[ ] Very frequent [ ] Frequently [ ] Occasionally [ ] Rarely [ ] Never
4.11	Please rate the ventilation of your kitchen	[ ] Very poor [ ] Poor [ ] Moderate [ ] Good [ ] Very good
4.12	Do you burn mosquito coils and/or incense?	[ ] Always [ ] Often [ ] Sometimes [ ] Never

E. Household-level indoor air pollution on health outcomes		
5.1	How long have you lived in this locality?	
5.2	What kind of work do you do most of the time?	[ ] Heavy manual work [ ] Office work [ ] Transport sector [ ] House chores [ ] Other
5.3	Do you smoke cigarettes?	[ ] Always [ ] Often [ ] Sometimes [ ] Rarely [ ] Never
	If yes, for how long have you smoked cigarettes??	
5.4	Are you or is anyone in the household suffering from tuberculosis (TB)?	YES [ ] NO [ ]
5.5	Have you or has anyone in the household ever received medical treatment for TB?	YES [ ] NO [ ]
5.6	Are you or anyone in the household asthmatic?	YES [ ] NO [ ]
5.7	Do you exhibit any of the following (tick appropriately)	[ ] cough, [ ] wheeze, [ ] phlegm, [ ] nasal irritation
5.7.1	If Yes, how often?	[ ] Very frequently [ ] Frequently [ ] Sometimes [ ] Rarely

END

APPENDIX III: QUESTIONNAIRE:

Household Air Pollution Monitoring

Experiment No.__________________

A1. Housing type (kitchen)

[ ] Mud wall (Roof - iron sheets) [ ] Mud wall (grass thatched) [ ] Wooden (iron sheets)

[ ] Wooden (grass thatched)   [ ] Permanent

A2. Kitchen type

[ ] Indoor kitchen with partition inside the main house

[ ] Indoor kitchen without partition inside the main house

[ ] Separate indoor kitchen outside the main house

A3. Ventilation type

[ ] Door and window Door only

A4. Number of doors _________   **A5. Number of windows ___________**

A6. Fuel type used.

[ ] Wood fuel   [ ] Charcoal   [ ] Wood particles/sawdust

[ ] Kerosene   [ ] Gas   [ ] Electricity

A7. Type of stove used

[ ] Traditional three-stone   [ ] Metallic *jiko*   [ ] Ceramic *jiko*   [ ] Sawdust *jiko*

[ ] Kerosene stove   [ ] Improved cookstove (*chepkube*)   [ ] LPG stove

[ ] Biogas stove   [ ] Electric stove

A8. Cookstove has a chimney

[ ] Yes   [ ] No

A9. Practice of opening door/window while cooking

[ ] Always opens door and window

[ ] Always opens door only (window closed/no window)

[ ] Always opens window only (door closed)   [ ] Sometimes opens door and window

[ ] Sometimes opens only door (window closed)

[ ] Sometimes opens only window (door closed)

[ ] Closes both door and window while cooking

A10. Type of meal prepared

[ ] Vegetables Starches (maize meal, potatoes etc.)

[ ] Grains (beans, green grams etc)

[ ] Water/tea/porridge

[ ] Meat   [ ] Others

A11. Number of people cooked for:_____________

APPENDIX IV: SAMPLE SIZES AND PRECISION RULES

Precision rule	**95/5**	**90/10**	**90/15**	**90/20**	**90/25**	**90/30**	**90/35**	**90/40**
COV								
0.10	16	3	2	1	1	1	1	1
0.20	62	11	5	3	2	2	1	1
0.30	139	25	11	7	4	3	2	2
0.40	246	44	20	11	7	5	4	3
0.50	385	68	31	17	11	8	6	5
0.60	554	98	44	25	16	11	8	7
0.70	753	133	59	34	22	15	11	9
0.80	984	174	77	44	28	20	15	11
0.90	1245	220	98	55	36	25	18	14
1.00	1537	271	121	68	44	31	23	17
1.10	1860	328	146	82	53	37	27	21
1.20	2213	390	174	98	63	44	32	25
1.30	2597	458	204	115	74	51	38	29
1.40	3012	531	236	133	85	59	44	34
1.50	3458	609	271	153	98	68	50	39
1.60	3934	693	308	174	111	77	57	44
1.70	4441	783	348	196	126	87	64	49
1.80	4979	877	390	220	141	98	72	55
1.90	5548	977	435	245	157	109	80	62
2.00	6147	1083	482	271	174	121	89	68

COV = std dev/mean