Energy for Sustainable Development 82 (2024) 101545

Contents lists available at ScienceDirect

Energy for Sustainable Development

journal homepage: www.journals.elsevier.com/energy-for-sustainable-development

Determinants of household cooking fuel choices: Does proximity to mine site matter?

Eliasu Ali [a,*], Kodzo Yaotse [a], Eric Osei-Bonsu Obeng [a], Samuel Gyamfi [b], Mohammed Saani Osman [a], Theophilus Adoko [c], Satyanarayana Narra [d]

[a] Africa Centre for Energy Policy (ACEP), Accra, Ghana
[b] University of Energy and Natural Resources (UENR), Sunyani, Ghana
[c] African Minerals Development Centre (AMDC), Addis Ababa, Ethiopia
[d] University of Rostock, Rostock, Germany

ARTICLE INFO

Keywords:
Cooking fuel
Indoor air pollution
Multinomial Logit
Mining
Energy transition

ABSTRACT

The attainment of the United Nation's Sustainable Development Goal 7 is significantly impeded by the slow pace of clean cooking fuel adoption in Ghana and most parts of Sub-Saharan Africa. Despite continuous government efforts, firewood and charcoal remain the dominant cooking fuel choice in Ghana, posing health risks to households through indoor air pollution. Researchers have identified households' economic status, family size, the educational level of household heads, and access to fuel as factors that influence household cooking fuel choices in rural and urban areas. However, there is a dearth of research on the determinants of household cooking fuel choices in mining host communities despite the peculiarity of socio-economic, environmental and cultural factors in these settings. Using descriptive statistics and a multinomial logit regression model of 426 randomly surveyed households in the Newmont Ahafo Mines catchment areas in Ghana, this study showed that every unit increase in households' income index was associated with a 65 % higher chance of choosing Liquified Petroleum Gas (LPG) for cooking over charcoal. Conversely, larger families are less likely to choose electricity over charcoal but more likely to choose firewood over charcoal for cooking. Notably, the study found that households closer to the mine site were less likely to choose either LPG or kerosene over charcoal for cooking, suggesting that host communities in closer proximity to mine sites might have limited access to clean fuel options such as LPG. Based on these findings, the study suggests subsidies for clean fuels, and improving access to infrastructure for LPG distribution as a means to advance the transition to clean cooking fuels in mining host communities.

Introduction

Energy is an essential input for economic development. Domestic cooking and heating constitute at least 20 % of the total energy use of countries within the Organisation for Economic Co-operation and Development (OECD) (Dongzala & Adams, 2022) and nearly 80 % of the total primary energy consumption in sub–Sub-Saharan Africa (SSA) (Ohimain, 2012). In SSA, a greater proportion of this energy (about 83 %) is still supplied by Firewoods, as compared to 43 % in developing Asia, and 11.4 % in central and southern America (IEA, 2022). Biomass-based cooking fuel sources contribute to climate change and depleting forest covers (Beek et al., 2020; Bensch et al., 2021). Bensch et al. (2021) projects that at this pace of slow clean cooking fuel transition in SSA, Greenhouse Gas (GHG) emissions from polluting fuel usage in the region will match Germany's 2015 total CO_2-e emission level by 2050. The use of biomass for cooking also poses respiratory health risk (Kumar et al., 2023). Even with improved cooking stoves, the levels of particulate matter resulting from cooking with Firewood are still above the WHO health threshold (Quinn et al., 2018).

In Ghana, reforms in clean cooking have been tailored towards increasing the use of fossil-based liquid fuels. One of the earliest of these reforms was the National LPG Promotion Programme, launched in 1990 and aimed at achieving a 50 % LPG penetration for domestic cooking and heating. Following the LPG promotion programme, the government launched the Rural Kerosene Distribution Programme to improve access to and promote the use of kerosene for domestic cooking in rural

* Corresponding author.
E-mail address: eliasuali@acep.africa (E. Ali).

https://doi.org/10.1016/j.esd.2024.101545
Received 18 May 2024; Received in revised form 27 July 2024; Accepted 31 August 2024

communities. Although these interventions have increased the adoption of LPG, biomass-based fuels remain the primary means of cooking for >75 % of Ghanaians (Karakara et al., 2019). To sustain community adoption of cleaner and safer cooking fuels, it is important to understand the socio-economic, cultural, and geographic drivers of household cooking fuel choices to tailor policy interventions appropriately. Accordingly, several studies have been conducted to explore the drivers of household energy choices in Ghana and SSA. Most of these studies identified income, education, and gender as key determinants of households' choices of cooking fuels (Amoah, 2019; Karakara et al., 2019; Rahul et al., 2016). However, the literature is faint on the drivers of household energy choices in mining communities.

Mining activities have varied impacts on the social, economic and environmental well-being of host communities (Erdiaw-Kwasie et al., 2014; European Parliament, 2022). Thus, it is plausible to posit that the proximity of households to mining communities may influence their energy choices, and their ability or willingness to adopt clean energy technologies beyond the widely researched factors. Understanding the nuanced array of factors that inform domestic cooking fuel choices, including in mining catchment communities, is essential for policy interventions to promote sustainable and inclusive energy transition.

The objectives of this study are therefore set as follows: (1) to determine whether the widely cited drivers of household cooking fuel choices such as household size and income levels are true for mining host communities; (2) to determine if the proximity of a household to a mine site affects their choice of cooking fuel choices; and (3) to make practical policy proposals for reforms to promote clean energy use in Ghana and similar contexts.

Theoretical and empirical literature review

Earlier attempts at explaining the drivers of cooking fuel choices among households were hinged on traditional consumer behaviour theory, which proposes that, as rational economic agents, households will abandon their traditional fuels and adopt more convenient, less-polluting fuel choices as their standards of living improve (Ado & Darazo, 2016; Arowolo et al., 2018). As such, the economic status of a household had been perceived as the only determinant of a household's propensity to switch to cleaner cooking fuels. This hypothesis is known as the energy ladder theory (Gyamfi et al., 2020). As depicted in Fig. 1, the energy ladder theory assumes a scenario whereby households climbed an energy ladder as they completely replaced primitive fuels with transition fuels and subsequently switched to advanced fuels as their standards of living improved (Safari et al., 2022).

However, an increasing body of literature has shown that cleaner fuels do not always serve as perfect replacement for traditional fuels irrespective of a household's standard of living. This contrary school of thought observes that households tend to use multiple fuel sources for cooking instead of completely switching fuel choices irrespective of their income levels (Perros, Allison, Tomei, & Parikh, 2022; Price et al., 2021; Yadav et al., 2020). This observation is referred to as the energy stacking model. Masera et al. (2000), one of the most cited critics of the energy ladder models, has for instance, shown that households do not switch between fuels as they become more affluent but rather tend to use multiple fuel sources. Their study demonstrated an array of factors that inform a household's choice of cooking fuels amidst scarce resources and supply uncertainty. Some of these driving factors include (a) economics of fuel, stove type and access conditions to fuels; (b) technical characteristics of cookstoves and cooking practices; (c) cultural preferences; and (d) health impacts. Furthermore, Tucho et al. (2022) found that households continued to use Firewood alongside electricity due to the unreliability of electricity supply in Ethiopia.

In line with the energy stack model, monetary factors do not completely determine if a household transitions to cleaner cooking fuel choices (Goswami et al., 2023). The foregoing introduces non-monetary factors such as fuel accessibility (Oyeniran & Isola, 2024) and household size (Amoah, 2019) as equally important determinants of whether a household transitions to or includes cleaner cooking fuels in their fuel

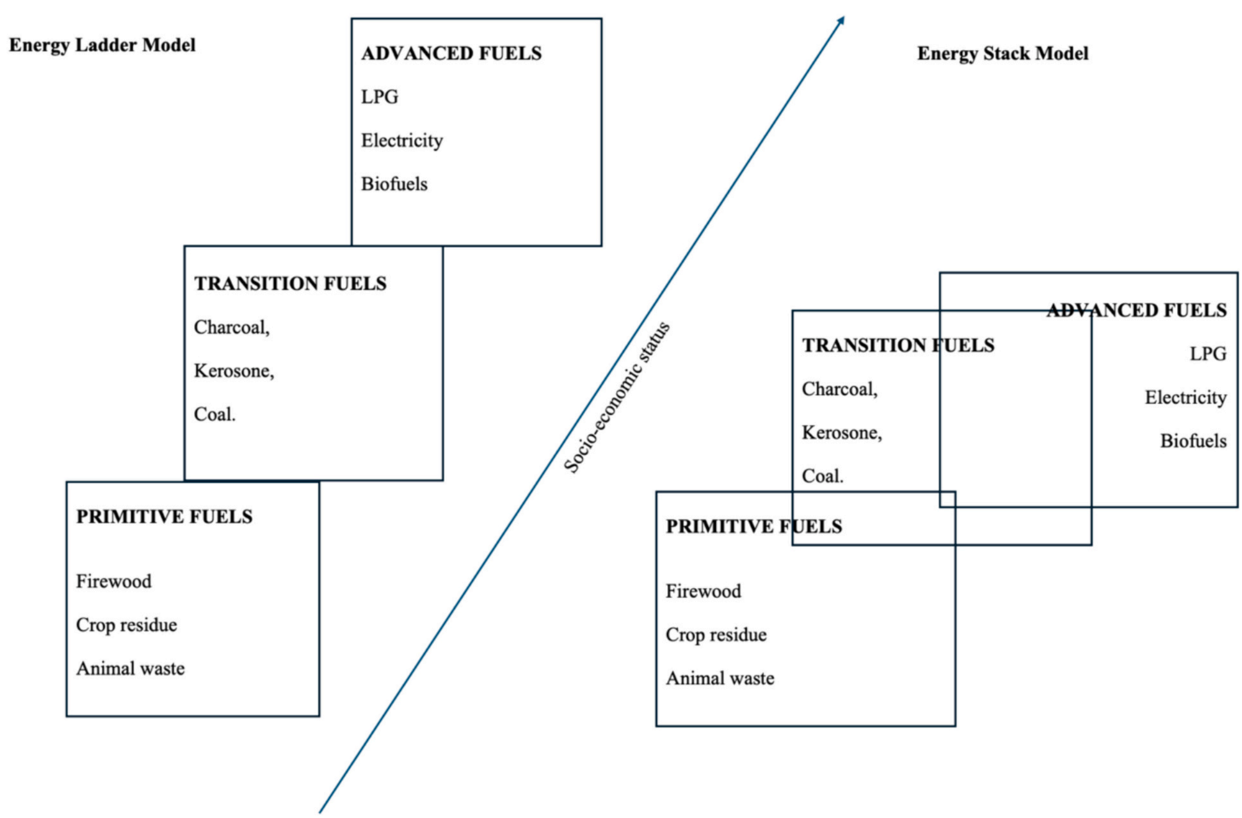

Fig. 1. Energy ladder versus energy stack models (based on Schlag & Zuzarte, 2008).

options.

Notwithstanding contentions between the energy ladder and energy stacking models, there is general consensus even in recent literature on the strong correlation between a household's choice of cooking fuel and their income status as well as the educational level of household heads (Bofah et al., 2022; Danlami et al., 2018; Debebe et al., 2023; Mperejekumana et al., 2021 and Yonas et al., 2015). Cleaner cooking fuels are often expensive, making them more accessible to wealthier households (Nshimiyimana et al., 2024). Ang'u Cohen et al. (2023) found a strong correlation between remittance receipts and the propensity of households to adopt modern forms of energy. The highly educated household heads are able to engage in higher income ventures and therefore more likely to choose cleaner cooking fuels such as LPG or electricity over polluting fuels such as wood and charcoal for cooking (Cohen et al., 2023; Dongzala & Adams, 2022).

Despite the expansive literature on the various factors influencing household cooking fuel choices in rural and urban settings, there is a dearth of research on the specific context of mining host communities. While mining contributes significantly to export earnings and government revenues in mineral-rich economies (Yeboah et al., 2022), the socio-economic and environmental impact of mining on host communities are well documented. For instance, mining has been associated with depleting forest covers (Okyere et al., 2021) and declining standards of living of mining host residents (Mwakesi et al., 2020). The existence of mining activities in a community therefore predisposes or exposes residents to varied socio-economic, environmental and cultural dynamics that might inform the propensity of a household to choose cleaner cooking fuels as their main source of cooking.

In a novel attempt, this study investigates the effect of the proximity of a household to a mine site on their choice of cooking fuel among other widely cited factors such as household size and income index.

Materials and method

Study area and sampling

The study was conducted in the Ahafo Region of Ghana. The study focused on catchment communities within a 20 km radius of the Newmont Ghana Ahafo mine site. This approach of surveying communities in close vicinity to mining operations takes precedence from the methodology of Dikgwatlhe and Mulenga (2023) whose study on the perceptions of mining impact on households only focused on towns and settlements in the vicinity of the targeted mining areas. Furthermore, twenty (20) km is considered the widest impact radius of mining activities (Brugger et al., 2021).

The Asutifi North district specifically hosts the Newmont-Ahafo mine. Google Earth Pro was used to identify the circumference around the mining site and the catchment communities for household sampling. Based on the population density, ρ, (people per square kilometre) and average household size, S, of the Asutifi North district which are 78.4 people per squared kilometre and 3.6 people per household respectively (GSS, 2021), the number of households within the 20 km radius of the mine site, H_t, was calculated using the formulae shown in Eqs. (1) and (2).

$$H_t = \frac{P}{S} \tag{1}$$

$$P = 1254.64 \times \rho \tag{2}$$

where 1254.64 represents the Google Earth coverage area in square kilometers of catchment communities within a 20 km radius of the Ahafo mine site, and P is the total number of people within 20 km radius of the mine site.

So $P = 1254.64\ km^2 \times \left(78.4/km^2\right)$, as given by Eq. (2).

Therefore, the total population, P, within a 20 km radius of the Newmont Ahafo mine site is about 98,363.776, and H_t *equals* 27,323.27, as given by Eq. (2) and Eq. (1) respectively. An estimated household sample size was then calculated for a 95 % confidence interval, and 5 % error margin for each mining catchment area as illustrated in Eq. (3). A prevalence of 50 % (0.5) was assumed based on recommendations from previous studies (Wassie et al., 2021).

$$N = \frac{\left(\frac{Z_a}{2}\right)^2 \times p(1-p)}{e^2} \tag{3}$$

where:

N = the desired sample size.; p = 0.5 is the assumed population proportion expected to use some form of cooking fuel; e = 5 % is the margin of error; $(Z_a/2) = 1.96$ is the critical value for the hypothesis test at 95 % confidence interval (5 % significance level). Therefore, N equals 384.16, as given by Eq. (3). This sample size was increased by 10 % to account for any non-responses. Accordingly, at least 426 households were surveyed, which falls within the sample size range used in previous studies with similar objectives (see Ado & Darazo, 2016).

Household survey approach

A total of 14 villages, towns and settlements were identified to fall within the 20 km radius of the Newmont Ahafo Mine site. These settlements were clustered based on their proximities into households within 5 km, 10 km, 15 km and 20 km radii of the mine site respectively. Within a 5 km radius, one (1) community was identified: Ntorosoro. Six (6) communities were found within a 10 km radius of the mine site, namely Kenyasi number 1, Kenyasi number 2, Akyerensua, Hwidiem, Wamahinso, and Gyedu. Within a 15 km radius of the mine, three (3) communities were identified: Manfo, Dwenase, and Maabang. Finally, four (4) communities fell within the terminal 20 km radius of the mine site, thus Atroni, Nkaseim, Pobiso and Nkrafokrom. The total number of surveys was distributed proportionally to the population of the towns, villages and settlements. Households were then sampled in each community according to a random walk procedure. Enumerators identified a random Geographic Positioning Systems (GPS) point within each village or community and walked in opposite directions of the cardinal points; North, South, East and West, selecting and surveying every 3rd house (or cluster of houses belonging to the same family). In larger villages, enumerators selected every 5th or 8th household, aiming to cover every length and breadth of the village until the sample size for that village is realized. The study area and surveyed catchment communities are illustrated in Fig. 2.

The target respondent for each household was the household head. Household heads were asked, "What type of fuel does your household mainly use for cooking." Respondents chose one option among "Electricity", "LPG", "kerosene", "Charcoal", "Timber", "Crop residue", "other", "Don't Know" and "Rather not say". Enumerators then validated responses by physically inspecting where the cooking is usually done. The Kobo collect tool was used to administer the survey and automatically record survey responses.

Estimation of household income level and status

Household's possession of assets (cars, TV, etc.) and the education level of household heads were used as proxies for the economic status (income index) of the respondent households. This is because it was impracticable to ascertain the income earnings of households due to the unformalized nature of the occupations of most households in the study area and the erratic nature of their income flows. In such situations, Cabrera et al. (2018) recommended the use of multiple indicators. Indeed, the use of single variables such as income earnings of households as a measure of Socio Economic-Status (SES) is subject to self-reporting information bias (Cabrera et al., 2018). Yet there is no single measure

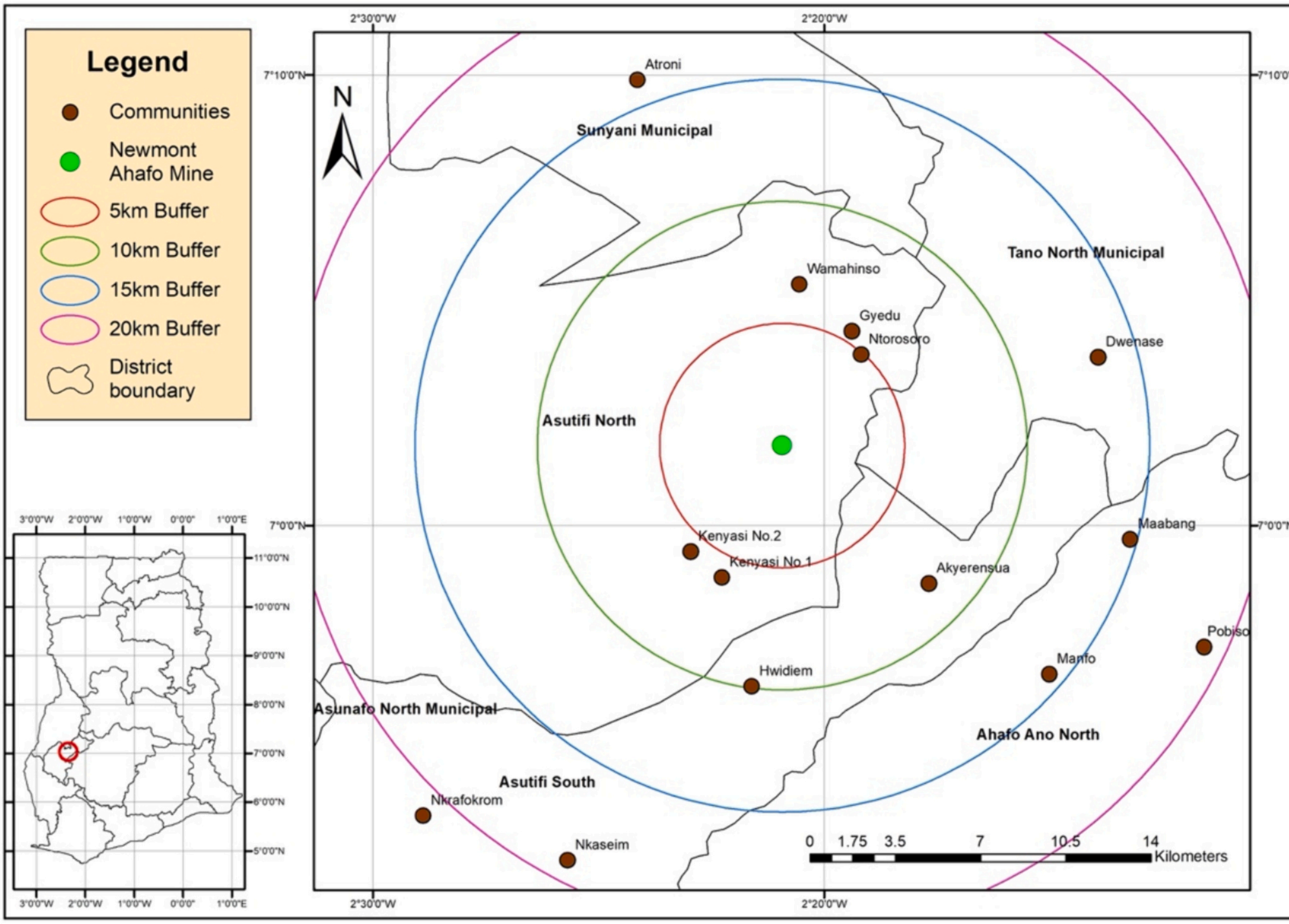

Fig. 2. A map of the study area.

that best reflects SES (Galobardes et al., 2006). As a result, a weighted combination of education and income is increasingly being used as a proxy for gauging the subjective socio-economic status of individuals (Galobardes et al., 2006; Lindberg, Chen, Olsen, & Abelson, 2022).

In fact, the impact of education on household income levels has been widely researched. The income levels of households generally increase in direct proportion to the education level of the household head, with an additional year of education reportedly associated with a 4 % increase in households' income. (Vu, 2020). Similarly, Bilenkisi et al. (2015) showed that households' risk of poverty decreased as the level of education of the household head increased. A strong consensus therefore emerges in the literature on the positive correlation between the educational level of a household head and the household's income status (Pham et al., 2024).

Given the demonstrated strong collinearity between educational level and income status of households, level of education was ascribed a weight of 50 % (0.5) in the income index. This weight is in consonance with the findings of Lindberg, Chen, Olsen, & Abelson (2022) which reported that education had the highest weight on the socio-economic position of households. The proxy income index variables and their respective weights used in this study are shown in Tables 1 and 2.

This study suggests a maximum achievable income index of 0.7, which is then multiplied by 10 to minimize scaling issues. Accordingly, a household with the maximum level of education (university) and possessing a car, TV, computer, refrigerator, and satellite will have an income index of 7.0. For instance, consider a household with a tertiary (university education) who also possesses a car, computer, refrigerator, satellite and a television. Tertiary (university) education carries a weight of 0.4 (Table 1), and education carries an index weight of 50 % (Table 2). Thus, the effective income index for tertiary education is 0.2 (50 % of 0.4). The total income index for such a household becomes 0.2 + 0.25.0.1 + 0.06 + 0.05 + 0.04, summing up to 0.7 and scaled up to 7.

Subsequently, an income status class is computed as a function of the income index threshold which bins households into low-income, middle-income, and high-income brackets. We classify households with an

Table 1
Weights of education levels.

Education level	Weight
Primary	0.03
JHS	0.07
Secondary	0.10
Vocational training diploma	0.2
Technical Diploma	0.2
Tertiary (university)	0.4

Table 2
Weights of income index proxy variables.

Index proxy variable	Weight
Education	0.5
Car	0.25
Computer	0.1
Refrigerator	0.06
Satellite	0.05
TV	0.04

income index between 0 and 2 as low income, an index >2 but <5 as middle income and an income index >5 as high income.

Results and discussions

Data and descriptive statistics

Modal analysis of the 426 households surveyed (summary in Table 3) revealed that most households surveyed lived within 10 km of the mine i.e., a total of 157 households. The prevalent energy choice was charcoal with a total of 172 observations. As well, the highest level of education of many households surveyed was the secondary level of education. Most importantly, a household size of 2 was greatly observed among the respondents. It is worthy of note that the distribution of household size is exponential, stemming from a greater number of respondents residing in smaller-sized households and fewer respondents residing in larger families. About 379 respondents reported not owning any cars, 336 respondents owned TVs, and 370 households reportedly did not own any computers, and 221 respondents owned a fridge.

Chi-square test and multinomial logit regression modelling

The extent to which household energy choice is informed by the combination of Proximity to the mine, Income Index, and Household Size was first assessed using a Chi-squared test, and subsequently a Multinomial Logit Regression model. The predictor variable is nominal and categorical with 6 categories ('Charcoal', 'Crop residue/manure', 'Electricity', 'Firewood', 'LPG', and 'Kerosene'). The nominality of the predictor variable makes it a classification problem for this analysis. Another advantage is that the data is not ordered which makes drawing inferences using chi-square and multinomial logistic regression appropriate.

Chi-square test of independence

A chi-square test of independence (at alpha = 0.05) was conducted to assess whether proximity to the mine, income status, and household size together influence household energy choice. This test helps identify a relationship between the variables and the chosen energy source, but it doesn't reveal the individual impact of each factor. The test produced a statistic of 135.315017191022 (degrees of freedom: 72) and a *p*-value of 9.274171805691725e-06 (highly significant). Since the *p*-value is much lower than our chosen significance level (alpha = 0.05), we fail to reject the null hypothesis. These results strongly suggest that a combined effect of proximity to the mine, income status, and household size likely influences the energy choices of households in mining communities.

Multinomial logistic regression using MLOGIT

The relationship between household characteristics and energy choices was assessed using a Multinomial Logit (MNL) model. The modal energy choice (charcoal) was used as a reference fuel in the MNL model. This model offers a significant advantage over the chi-square test by providing insights into the individual and combined effects of proximity to the mine, income status, and household size on the likelihood of choosing specific energy sources.

This analysis thus reveals not only whether these variables collectively influence energy choices (similar to the chi-square test) but also how each variable specifically affects the likelihood of choosing different energy sources (e.g., LPG, firewood, etc.). The model returned the test statistics presented in Table 4.

The results show a Likelihood Ratio test (LRT) p-value of 1.48e-31. In statistical terms, this indicates a very high level of significance (p-value <0.05). This finding strongly suggests that the combined effect of these independent variables is highly unlikely to be due to chance, and they play a significant role in predicting household energy choice. A detailed analysis of the effects of the various factors on household energy choices (Table 5) is presented in the subsequent chapters.

Income effect

The results (Table 5) show that household income increases, there's a clear trend towards a cleaner energy source like LPG, while traditional options such as crop residue/manure and firewood become less popular. This pattern is backed by strong statistical evidence, indicating a significant positive correlation between income level and the likelihood of selecting LPG as an energy source (coefficient = 0.5034, z-statistic = 6.399, p-value <0.001). The odds ratio of 1.65 (anti-log of the log odds ratio of 0.5034) indicates that any unit increase in the household income index results in a 65 % higher chance of the household choosing LPG over charcoal. However, the income effect on electricity (coefficient = −0.4013, z-statistic = −1.112, *p*-value = 0.266) and kerosene (coefficient = −0.6163, z-statistic = −1.345, p-value = 0.179) remains uncertain, with statistically insignificant p-values for the chosen confidence interval of 95 %.

The statistical insignificance of the effect of income on electricity usage even among high-income earners might be explained by the unreliability electricity supply in Ghana and most part of sub-Saharan Africa. While Rubinstein et al. (2022) found that higher-income earners in Cameroon were twice as likely to use electricity than lower-income earners, their findings agree that frequent power outages and unstable power supply dissuaded electricity usage for cooking purposes. However, the effect of income on incentivizing a transition away from polluting fuels such as wood and crop residues as reported in this study is generally in consonance with the postulation by Arowolo et al. (2018) and Ado and Darazo (2016) who linked the drivers of cooking fuel choices to the traditional consumer behaviour theory which relies absolutely on income levels. This is true in the context of this result as far as the selection of LPG over charcoal is concerned.

Policy interventions aiming to promote the use of LPG and dissuade the use of Firewood would therefore have to focus on uplifting

Table 3
Modal analysis of categorical variables.

	Mode	Number of observations
Predictor variables		
Proximity	10 km	157
Education level	Secondary	254
Household size	2	123
Possession of car	No	379
Possession of TV	YES	336
Possession of satellite	YES	238
Possession of computer	NO	370
Possession of refrigerator	YES	221
Response variable		
Household energy choice	Charcoal	172

Table 4
MLOGIT regression results.

Dep. variable	Household energy choice
Model	MNLogit
Method	MLE
Date	Thu, 28 Mar 2024
Time	20:21:30
Converged	TRUE
Covariance Type	nonrobust
No. Observations	426
Df Residuals	412
Df Model	10
Pseudo R-squ.	0.1561
Log-Likelihood	−463.06
LL-Null	−548.72
LLR p-value	1.48e-31

Table 5
Full summary statistics of MLOGIT inference test.

	coef	std err	z	P > |z|	[0.025	0.975]
Household energy choice = Crop residue						
Proximity	−0.0174	0.032	−0.546	0.585	−0.080	0.045
Household size	−0.3803	0.176	−2.163	0.031	−0.725	−0.036
Income index	−1.6299	0.503	−3.243	0.001	−2.615	−0.645
Household energy choice = Electricity						
Proximity	−0.0382	0.055	−0.695	0.487	−0.146	0.070
Household size	−1.041	0.430	−2.423	0.015	−1.883	−0.199
Income index	−0.4013	0.361	−1.112	0.266	−1.109	0.306
Household energy choice = Firewood						
Proximity	0.0061	0.014	0.428	0.669	−0.022	0.034
Household size	0.0885	0.049	1.809	0.071	−0.007	0.184
Income index	−0.6342	0.122	−5.188	0.000	−0.874	−0.395
Household energy choice = LPG						
Proximity	−0.0478	0.019	−2.559	0.01	−0.084	−0.011
Household size	−0.3072	0.082	−3.744	0.00	−0.468	−0.146
Income index	0.5034	0.079	6.399	0.00	0.349	0.658
Household energy choice = Kerosene						
Proximity	−0.1775	0.07	−2.524	0.012	−0.315	−0.040
Household size	−0.2909	0.247	−1.176	0.239	−0.776	0.194
Income index	−0.6163	0.458	−1.345	0.179	−1.515	0.282

household income levels as opposed to sensitization and education on the negative impacts of biomass fuels. It is therefore plausible to prioritise economic interventions over awareness campaigns in the bid for mining communities to transition to clean cooking fuels.

Proximity effect

An analysis of the effect of proximity on household energy choices is shown in Table 5. For crop residue/manure and electricity, proximity does not exhibit significant influence (coefficients = −0.0174, −0.0382 respectively, with non-significant *p*-values) as shown in Table 5. Similarly, households closer to the mine do not demonstrate a statistically significant inclination towards choosing firewood (coefficient = 0.0061, z-statistic = 0.428, p-value = 0.669). On the other hand, proximity to the mine negatively affects LPG usage (coefficient = −0.0478, z-statistic = −2.559, *p*-value <0.01), suggesting a preference for LPG among households farther from the mine. Specifically, every kilometre farther away from the mine site results in a 4.7 % (log odds ratio of −0.0478) chance of the household choosing LPG over charcoal. Conversely, households closer to the mine site are less likely to choose LPG over charcoal. Similarly, kerosene usage is negatively impacted by proximity (coefficient = −0.1775, z-statistic = −2.524, *p*-value <0.05), indicating that households farther from the mine are [16 %] more likely to opt for kerosene over charcoal.

The results show that proximity to the mine site is indeed, a driving factor in the propensity of a household to adopt LPG or kerosene usage, even though proximity does not affect biomass (Firewood or crop residue/manure) usage. This finding may be explained in terms of the general remoteness of mining operations (Cole & Broadhurst, 2020) which affects the ability of households in close proximity to mine operations to access LPG, thus suggesting a higher accessibility for these fuels as a community is located farther away from the mine. Unlike biomass which is locally available, petroleum products such as kerosene and LPG require transport infrastructure to make them accessible to remote communities, where mining operations mostly happen. Clean cooking policies with the objective of promoting LPG usage in leu of charcoal or Firewood in mining communities must therefore address accessibility barriers.

Household size effect

A study of household size's effect on energy choices reveals varied correlations across different fuel sources. For crop residue/manure, household size demonstrates a statistically significant correlation (coefficient = −0.3803, z-statistic = −2.163, *p*-value = 0.031), suggesting that larger households are less likely to use crop residues as their main source of cooking fuel. This might be explained in terms of the low energy density of crop residues (Havrysh et al., 2021), making them unsuitable for the cooking needs of larger families. However, larger households are [64 %] less likely to choose electricity (coefficient = −1.0410, z-statistic = −2.423, p-value <0.05) over charcoal. Conversely, larger households are [9 %] more likely to choose firewood over charcoal (coefficient = 0.0885, z-statistic = 1.809, p-value = 0.071). Also, smaller households are [26 %] more likely to choose LPG over charcoal (coefficient = −0.3072, z-statistic = −3.744, p-value <0.001). A household's decision to choose kerosene is not affected by the size of the household (coefficient = −0.2909, z-statistic = −1.176, p-value = 0.239).

This result reveals that larger households would prefer firewood as cooking fuel as opposed to cleaner options like electricity and LPG. It is worth noting the cultural undertone to the choice of firewood for larger households in Ghana due to its suitability for large-scale cooking. Culturally, large households prepare food on large-scale basis and distribute to household members as opposed to individual household members preparing food separately. This therefore requires the use of larger and heavier utensils which can be supported better by the three-stone stoves fueled by firewood. The result therefore indicates that [larger] households in mining host communities are no different in this regard and would relegate options such as LPG and electricity for firewood. This is in line with the findings of Amoah (2019) and Masera et al. (2000) who accounted for factors such as cultural preferences and technicalities of cooking practice as influencers of the choice of fuel for cooking. The results highlight policy implications for clean cooking interventions with respect to the cooking practice of large household sizes. Such interventions should therefore prioritise innovative cooking stove technologies that can support the large and heavy nature of utensils typically used in large households.

Relative importance of predictor variables

Analysis using decision tree classifiers and random forests confirmed significant interactions between household characteristics (income index, household size, proximity to mine) and their choice of energy source. A feature importance analysis of the random forest model

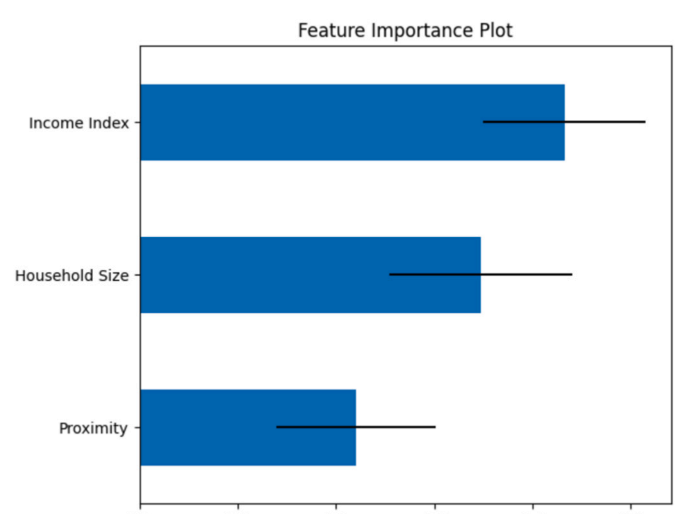

Fig. 3. Feature importance plot.

(Fig. 3) revealed the relative influence of these variables as follows: income index has the strongest impact (importance: 0.432602) on energy choice, followed by household size (importance: 0.347218) and proximity to mine (importance: 0.220180). These findings suggest that income plays the most crucial role in determining household energy choices.

Conclusions and policy recommendation

The foregoing analysis revealed the collective and individual influence of income, household size and proximity of households to mine operations on cooking fuel choices. The feature importance analysis adds more insight to the interrelation between these determinants in terms of their relative contributions to the choice. For the data employed in this study, the income level of households emerged as the most important determinant while proximity to mine emerged as the least important. While literature is widely published on the impact of income levels and household sizes on the choice of cooking fuel, this study introduced the perspective of proximity to a mine site to understanding the dynamics of mining activities in host communities. The findings hence reveal the importance of proximity to the mine as a driver of household cooking fuel choices (especially LPG and other fossil-based fuels that require infrastructure networks).

The study confirms earlier research on the positive correlation between household income and their propensity to adopt cleaner fuels, specifically LPG. This study further confirms earlier studies to the effect that larger households are less likely to choose electricity and less likely to choose LPG over charcoal for cooking, but are more likely to choose Firewood over charcoal. This can be explained in terms of the unsuitability of electric stoves for cooking for large families, and the higher costs of electricity and LPG compared to Firewood. In a novel attempt, this study reveals that the proximity of households to the mine site significantly affects the choice of two cooking fuel sources: Kerosene and LPG. It is observed that households closer to mine sites are less likely to use LPG and less likely to use kerosene. It is material to note that the only statistically significant predictor of a household's decision to use kerosene is the Proximity of the household to the mine site. Neither Income nor Household size easily predicts a household's usage of kerosene with 95 % confidence. A possible cause for this is limited access of mining host communities to petroleum products such as LPG and kerosene, due to the remote nature of mining sites.

Based on the foregoing conclusions, the study recommends that the government should subsidize the cost of LPG for mining communities and also improve the accessibility of such communities to LPG. This can be done by exploring innovative approaches such as an LPG Pay-As-You-Go[1] model in mining and other rural communities. Under the PAYG model, subscribed households are given free, smart and pre-filled LPG cylinders. The households are then able to buy (through a simple USSD code) the smallest amount of LPG to meet their current cooking needs, thus relieving them of the cost burden often associated with bulk purchases of LPG. The PAYG model would also help address any possible challenge of limited access of host mining communities to LPG infrastructure in the short term since the PAYG LPG service providers would be able to track the cooking needs of subscribers and refill empty cylinders en masse. In the long term, however, the government should incentivize the private sector to establish LPG filling stations in rural areas, especially mining host communities to improve access to cleaner cooking fuel for all.

[1] Modern Energy Cooking Services (2021). MECS Behaviour Change Project Report (public version). Retrieved from: https://mecs.org.uk/wp-content/uploads/2021/04/Understanding-Pay-As-You-Go-LPG-Customer-Behaviour.pdf.

Limitations of the study

A limitation of this study is the Independence of Irrelevant Alternatives (IIA) assumption inherent in Multinomial Logit Models. This assumption is to the effect that the odds of a household choosing between any two fuel choices over the base fuel is unaffected by the presence of other alternatives. This may not completely reflect the real-world decision-making process where the introduction or removal of an alternative can influence the relative attractiveness of the other choices. However, this limitation is significantly mitigated by the fact that this study explored a nearly exhaustive list of cooking fuel options currently prevalent in Ghana. This notwithstanding, future studies should explore households' response to emerging clean cooking fuel options such as ethanol. Furthermore, the scope of this study did not include variations in cooking fuel preferences across different gender groups. Given the gender dynamics in mining host communities, it would be interesting to investigate whether the prevailing literature on gendered cooking fuel preferences holds true in mining catchment communities.

Nomenclature

Symbols

H_t	Number of households within the 20 km radius of the mine site
km^2	Squared kilometers
$Z_a/2$	Critical value for the hypothesis test at 95 % confidence interval
e	Margin of error
N	Desired sample size
p	Assumed population proportion
P	Total population of people within 20 km radius of mine site
ρ	Population density

List of abbreviations

ACEP	Africa Centre for Energy Policy
GHG	Greenhouse Gases
IIA	Independence of Irrelevant Alternatives
LPG	Liquefied Petroleum Gas
LRT	Likelihood Ratio Test
MNL	Multinomial Logit
OECD	Organisation for Economic Co-operation and Development
PAYG	Pay-As-You-Go
SES	Socio Economic Status
SSA	Sub-Saharan Africa
UENR	University of Energy and Natural Resources
WHO	World Health Organisation

CRediT authorship contribution statement

Eliasu Ali: Writing – review & editing, Writing – original draft, Validation, Project administration, Methodology, Formal analysis, Data curation, Conceptualization. **Kodzo Yaotse:** Writing – review & editing, Project administration, Funding acquisition, Conceptualization. **Eric Osei-Bonsu Obeng:** Writing – review & editing, Writing – original draft, Visualization, Methodology, Formal analysis, Data curation, Conceptualization. **Samuel Gyamfi:** Validation, Supervision. **Mohammed Saani Osman:** Writing – review & editing, Data curation. **Theophilus Adoko:** Validation, Conceptualization. **Satyanarayana Narra:** Writing – review & editing, Validation, Supervision.

Declaration of competing interest

Verbal consent was sought from community members prior to conducting the surveys. The researchers declare no competing interest in the conduct of this study.

Acknowledgement

The researchers express profound gratitude to the Africa Centre for Energy Policy (ACEP) for providing funding to assess the local impact of mining in host communities in Ghana. Special gratitude also goes to the ETH NADEL Global Cooperation and Sustainable Development for their role in designing the household survey instrument used for this study. Final appreciation is also extended to residents of the communities and households for their cooperation and enthused responses during the survey.

References

Ado, A., & Darazo, I. R. (2016). Determinants of fuels stacking behaviour among households in Bauchi Metropolis. *The Business and Management Review, 7*(3), 84–97.

Amoah, S. T. (2019). Determinants of household's choice of cooking energy in a global south city. *Energy and Buildings, 196*(2019), 103–111.

Arowolo, A. O., Ibrahim, S. B., Sanusi, M. M., Ayinde, A. F., & Sheleru, K. M. (2018). Households' cooking energy preferences and determinants of transition to nonbiomass fuels in rural Nigeria. *Journal of Sustainable Development in Africa, 20*(1), 1520–5509.

Beek, N. V., Vindel, E., Heun, M. K., & Brockway, P. E. (2020). Quantifying the environmental impacts of cookstove transitions: A societal exergy analysis based model of energy consumption and forest stocks in Honduras. *Energies, 13*, 3206.

Bensch, G., Jeuland, M., & Peters, J. (2021). Efficient biomass cooking in Africa for climate change mitigation and development. *One Earth, 4*, 879–890.

Bilenkisi, F., Gungor, M. S., & Tapsin, G. (2015). The impact of household heads' education levels on the poverty risk: The evidence from Turkey. *Educational Sciences: Theory & Practice, 15*(2), 337–348.

Bofah, R. O., Appiah-Konadu, P., & Ngwu, F. N. (2022). Transition to cleaner cooking energy in Ghana. *Clean Energy, 6*(3), 446.

Brugger, F., Bezzola, S., & Fischer, F. (2021). *Resource impact dashboard: Theory and methodology*. ETH Zurich University.

Cabrera, J. C., Karl, S. R., Rodriguez, M. C., & Chavez, C. (2018). *Investigating socioeconomic status proxies: Is one proxy enough? American educational research association*. New York: University of Minnesota Digital Conservancy.

Cohen, A., John, M. N., Alexander, M. M., & Henry, M. M. (2023). Determinants of the sustained use of household clean fuels and technologies: Lessons from Vihiga county, Kenya. *Energy Reports, 9*, 1990–2001.

Cole, M. J., & Broadhurst, J. L. (2020). Mapping and classification of mining host communities: A case study of South Africa. *The Extractive Industries and Society, 7*, 954–959.

Danlami, A. H., Applanaidu, S. D., & Islam, R. (2018). An analysis of household cooking fuel choice: A case of Bauchi State, Nigeria. *International Journal of Energy Sector Management, 12*(2), 265–283.

Debebe, B., Senbeta, F., Diriba, D., Teferi, E., & Teketay, D. (2023). Determinants of household energy choice for domestic chores: Evidence from the Semien Mountains National Park and Adjacent Districts, Northwest Ethiopia. *Cleaner Energy Systems, 4*, Article 100063.

Dikgwatlhe, P., & Mulenga, F. (2023). Perceptions of local communities regarding the impacts of mining on employment and economic activities in South Africa. *Resources Policy, 80*, Article 103138.

Dongzala, A., & Adams, A.-M. (2022). Determinants of urban household choice of cooking fuel in Ghana: Do socioeconomic and demographic factors matter? *Energy, 256*, Article 124613.

Erdiaw-Kwasie, M. O., Dinye, R. D., & Mabunyewah, M. (2014). mpacts of mining on the natural environment and wellbeing of mining-fringe communities in Prestea, Ghana. *Greener Journal of Social Sciences, 4*(3), 108–122.

European Parliament. (2022). *Social and environmental impacts of mining activities in the EU*.

Galobardes, B., Shaw, M., Lawlor, D. A., Lynch, J. W., & Smith, G. D. (2006). Indicators of socioeconomic position (part 1). *Journal of Epidemiology and Community Health*, 95–101.

Goswami, A., Bandyopadhyay, K. R., Singh, P., & Gurtu, A. (2023). Rural energy transition for cooking in India—Revisiting the drivers. *Sustainability, 15*(9), 7635.

GSS. (2021). *Ghana population and housing census general report*. Accra: Ghana Statistical Services.

Gyamfi, K. S., Gaura, E., Brussey, J., Trindade, A. B., & Verba, N. (2020). Understanding household fuel choice behaviour in the Amazonas State, Brazil: Effects of validation and feature selection. *Energies, 13*(15), 1–21.

Havrysh, V., Kalinichenko, A., Brzozowska, A., & Stebila, J. (2021). Agricultural residue management for sustainable power generation: The Poland case study. *Applied Sciences, 11*(13), 5907.

IEA. (2022). SDG 7: Data and projections. Retrieved from https://www.iea.org/reports/sdg7-data-and-projections/access-to-clean-cooking.

Karakara, A. A.-W., Dasmani, I., & Bechenrieder, G. (2019). An econometric analysis of domestic fuel consumption in Ghana: Implications for poverty reduction. *Cogent Social Sciences, 5*, Article 1697499.

Kumar, P., Singh, A., Arora, T., Singh, S., & Singh, R. (2023). Critical review on emerging health effects associated with the indoor air quality and its sustainable management. *The Science of the Total Environment, 872*(6), Article 162163.

Lindberg, M. H., Chen, G., Olsen, J. A., & Abelson, B. (2022). Combining education and income into a socioeconomic position score for use in studies of health inequalities. *BMC Journal, 22*. Article 969.

Masera, O. R., Saatkamp, B. D., & Kammen, D. M. (2000). From linear fuel switching to multiple cooking strategies: A critique and alternative to the energy ladder model. *World Development, 28*(12), 2083–2103.

Mperejekumana, P., Li, H., Wu, R., Lu, J., Tursunov, O., Elshareef, H., … Dong, R. (2021). Determinants of household energy choice for cooking in Northern Sudan: A multinomial logit estimation. *International Journal of Environmental Research and Public Health, 18*(21), 1–14.

Mwakesi, I., Wahome, R., & Ichang'i, D. (2020). Mining impact on communities' livelihoods: A case study of Taita Taveta County, Kenya. *AIMS Environmental Science, 7*(3), 286–301.

Nshimiyimana, J. P., Mukeshimana, M. C., & Nshimyimana, E. (2024). Tracking the progress towards adopting LPG as a clean cooking fuel in Rwanda: User's perspective. *Energy for Sustainable Development, 80*, Article 101441.

Ohimain, E. I. (2012). The benefits and potential impacts of household cooking fuel substitution with bio-ethanol produced from cassava feedstock in Nigeria. *Energy for Sustainable Development, 16*(3), 352–362.

Okyere, M., Aitey, J. Z., & Ajabuin, B. (2021). Large scale mining in Ghana: A review of the implications on the host communities. *Journal of Degraded and Mining Lands Management, 9*(1), Article 2502-2458.

Oyeniran, I. W., & Isola, W. A. (2024). Patterns and determinants of household cooking fuel choice in Nigeria. *Clean Energy, 8*(2), 144–155.

Perros, T., Allison, A. L., Tomei, J., & Parikh, P. (2022). Behavioural factors that drive stacking with tradditional cooking fuel using the COM-B model. *Nature Energy, 7*, 886–898.

Pham, T. T., Lang, N. D., Ho, C. M., & Vo, D. H. (2024). Educational attainment, household income and wealth accumulation in Vietnam. *Social Indicators Research, 172*, 635–671.

Price, M., Barnard-Tallier, M., & Troncoso, K. (2021). Stacked: In their favour? The complexities of fuel stacking and cooking transitions in Cambodia, Myanmar, and Zambia. *Energies, 14*(15), 4457.

Quinn, A. K., Bruce, N., Puzzolo, E., Dickinson, K., Sturke, R., Jack, D. W., … Rosenthal, J. P. (2018). An analysis of efforts to scale up clean household energy for cooking around the world. *Energy for Sustainable Development, 46*, 1–10.

Rahul, D. B., Behera, B., & Ali, A. (2016). Patterns and determinants of household use of fuels for cooking: Empirical evidence from sub-Saharan Africa. *Energy, 117*(117), 93–104.

Rubinstein, F., Ngahane, B. H., Nilsson, M., Esong, M. B., Betang, E., Goura, A. P., … Puzzolo, E. (2022). Adoption of electricity for clean cooking in Cameroon: A mixed-methods field evaluation of current cooking practices and scale-up potential. *Energy for Sustainable Development, 71*, 118–131.

Safari, J. G., Mwongerezi, J. K., & Hyandye, C. B. (2022). Patterns and predictors of household fuel choices in Maswa District, Tanzania. *Cogent Social Sciences, 8*(1), 1–13.

Schlag, N., & Zuzarte, F. (2008). *Market barriers to clean cooking fuels in Sub-Saharan Africa: A review of literature*. Stockholm: Stockholm Environment Institute.

Tucho, G. T., Deti, M., Dadi, D., & Teshome, T. (2022). *Urban households' biomass energy fuel stacking and its implications for sustainable development goal seven: The case of Jimma Town* (p. 6). Global Challenges: Ethiopia.

Vu, H. V. (2020). The impact of education on household income in rural Vietnam. *International Journal of Financial Studies, 8*(1), 11.

Wassie, Y. T., Rannestad, M. M., & Adaramola, M. S. (2021). Determinants of household energy choices in rural sub-Saharan Africa: An example from southern Ethiopia. *Energy, 221*.

Yadav, P., Davies, P. J., & Asumadu-Sarkodie, S. (2020). Fuel choice and tradition: Why fuel stacking and the energy ladder are out of step? *Solar Energy, 214*, 491–501.

Yeboah, S., Nyarkoh, J., & Bright. (2022). *The impact of mining on the ghanaian economy: A comprehensive review (1992–2020). Munich personal RePEc archive*.

Yonas, A., D, B. A., Gunnar, K., & Alemu, M. (2015). Modeling household cooking fuel choice: A panel multinomial logit approach. In *Working papers in economics* (p. 632).