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Multiple fuel use in low-income communities: socio-economic determinants and impacts on household air pollution and respiratory health in South Africa

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A R T I C L E I N F O

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A B S T R A C T

Domestic fuel use contributes significantly to household air pollution levels and to the disease burden in low-income households in South Africa. The link between residential fuel stacking and switching, and respiratory health, mediated by household air pollution, remains underexplored, posing challenges to transition to cleaner fuels. This study identified socio-economic determinants of fuel use patterns in two low-income communities of KwaZamokuhle and eMzinoni in South Africa. It also examined the impacts of these patterns on household air pollution levels and respiratory health outcomes. Over half of households relied on dirty fuels across all needs. Average household $PM_{2.5}$ levels exceeded national daily standards (40 μg/m^3). Education level and employment status were significant factors in determining fuel choice, with employed participants less likely to rely on dirty fuels. Town-specific characteristics also influenced household fuel use patterns. In terms of health, 9.5 % of participants had obstructive airways disease and 26.9 % tested positive for inhalant allergens. Heating fuels were strongest predictor of obstructive airways disease (>75 %) whereas cooking fuels were the main predictor of allergen sensitivity (~75 %). The stepwise introduction of cleaner fuels predicted better respiratory health outcomes. The findings of this study suggest that even the partial adoption of cleaner fuels has health benefits and supports the formulation of context-specific mitigation efforts aiming to address negative health effects associated with household air pollution.

1. Introduction

Fuel choice to meet household energy needs is influenced by factors such as access, supply, affordability, culture, household size, safety, knowledge, season and behaviour (Perros et al., 2022; Waleed and Mirza, 2023). These factors affect the combination of fuels used for cooking, heating and lighting. Multiple fuels may be used simultaneously (fuel stacking) or alternatingly (fuel switching) (Akintan et al., 2018; Jewitt et al., 2020). In low-income settings, less efficient but cheaper ‘dirty’ fuels like coal and biomass are preferred over cleaner energy like electricity (Kapsalyamova et al., 2021). Many low-income households choose to use electricity to light their homes and for using electrical appliances, but not to cook or to warm their homes due to affordability (Gould et al., 2022).

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Several conceptual frameworks capture the complex nature of household energy patterns (Elasu et al., 2023; Perros et al., 2022; Waleed and Mirza, 2023). The energy ladder and the energy stacking model have characterized the gradual change from traditional to clean energy sources (Masera et al., 2000; van der Kroon et al., 2013; Waleed and Mirza, 2023). More recent theories highlight the importance of other household-specific factors such as geographic location, income, employment level, gender and personal preferences and the role these play in the energy transition, influencing the variability of the household fuel mix (Gould et al., 2022; Jewitt et al., 2020; Waleed and Mirza, 2023). In rural or low-income settings, it is common that a household will use liquid petroleum gas (LPG) at the beginning of the month for cooking, then switch to more affordable wood when the LPG has run out, or to simultaneously use coal to heat while also using electricity to light and power appliances like a fridge (Gould and Urpelainen, 2018; Pauw et al., 2022a). In India, many households keep their traditional biomass cookstoves as a complement to their 'cleaner' stove, and though 80 % of rural Indian households have a gas connection, more than half additionally used a polluting fuel (Shankar et al., 2020).

Dirty fuels used at a household level may elevate household air pollution (HAP) levels (Du et al., 2018). HAP exposure studies focus on the 'main' fuels (the primary energy source used in a household for a specific activity) used for cooking or heating (Sustainable Energy Africa, 2017). When people use a mix of fuels to meet their energy needs this can affect HAP exposure. Using wood as a main fuel and using a cleaner fuel (like LPG) as an additional fuel for cooking has been associated with fine particulate matter ($PM_{2.5}$) and black carbon concentrations half as high when compared to using only wood as a fuel for cooking (Shupler et al., 2020).

The use of polluting fuels in households has been associated with adverse health effects such as respiratory diseases, and ischemic heart disease (Mortimer et al., 2022; WHO, 2019). In South Africa, HAP from cooking with traditional and dirty fuels, including wood, was responsible for an estimated 5590 deaths (Health Effects Institute, 2024). Households that continue to use traditional, dirty fuels alongside clean ones reduce the health benefits of a clean energy transition (Azam, 2023). For instance, households in India that made a complete transition to LPG were found to have a reduced probability of self-reports of coughing or breathing issues, whilst households that transitioned to a stack of clean and dirty fuels showed no health improvements (Azam, 2023). In many households, it is difficult to make the complete switch from dirty to clean fuels (Perros et al., 2023). Participants in this study found it hard to switch to clean fuels due to affordability as long boiling foods take more energy to cook.

Although 89 % of households in South Africa are connected to the national electricity grid, the use of solid and liquid fuels is common (StatsSA, 2022). In 2013, the South African Department of Energy identified that many low-income households use multiple fuels, with even electrified households using wood, paraffin, candles and generators over and above electricity (Republic of South Africa, 2013; Sustainable Energy Africa, 2017). In South Africa, fuel switching or stacking occurs for many reasons such as the exhaustion of subsidies for free basic electricity, the depletion of grant funds, or the need to cook meals with longer preparation times (Kasangana and Masekameni, 2019; Kimemia and Annegarn, 2016; Makonese et al., 2016; Manyatsha et al., 2022; Musango, 2014; Pauw et al., 2022b). Factors like unreliable or hazardous electricity supply and the inadequacy of certain cooking methods for preparing large meals during special events also contribute to this practice (Kasangana and Masekameni, 2019; Kimemia and Annegarn, 2016; Makonese et al., 2016; Manyatsha et al., 2022; Musango, 2014; Pauw et al., 2022b).

Few studies in South Africa have identified determinants of fuel combinations used in low-income residential settings and how these combinations potentially influence HAP and health. This study aimed to investigate socio-economic determinants of fuel stacking habits, HAP and health in two low-income communities in South Africa. The objectives were 1) to identify socio-economic determinants of using different 'main' and 'additional' fuel combinations for cooking, heating and lighting in the low-income communities; 2) to determine the association between household $PM_{2.5}$ concentrations across the fuel combinations in the study sites; and 3) to quantify the associations between combinations of heating, cooking and lighting fuel used and measured respiratory health outcomes, namely obstructive airways disease and allergen sensitivity.

2. Materials and methods

2.1. Study area and population

The towns of KwaZamokuhle and eMzinoni (Fig. 1) commonly use coal for cooking and heating in households (Pauw et al., 2022b). The towns were part of a study to quantify the health impacts of HAP-targeted interventions [28], but it was halted after the baseline data collection due to COVID-19. Nonetheless, our study used the cross-sectional data from a subset of randomly selected households and assessed the health impacts of using dirty fuels. Research ethics clearance was granted by the <blinded for peer review>.

2.2. Sample characteristics

Overall, 908 participants (452 from KwaZamokuhle and 456 from eMzinoni) took part in a household survey (Table 1). A total of 113 household $PM_{2.5}$ measurements were analyzed (67 from KwaZamokuhle and 46 from eMzinoni). Across both communities, a total of 432 lung function tests and 260 allergen sensitivity tests were used for analysis for this study.

2.3. Survey

Participants consisted of females (>18 years old), more likely to cook in a household, and living in permanent residential structures (formal housing) with access to municipal services. The survey consisted of questions about demographics and socio-economic status, cooking, heating and lighting (Supplementary material).

2.4. Household air quality

Between July 2019–February 2020, household $PM_{2.5}$ measurements were conducted using battery-operated Airmetrics MiniVol samplers and TSI DustTrak monitors. These were each calibrated according to manufacturers' specifications: for airmetrics, please see https://www.airmetrics.com/and for TSI, https://tsi.com/. Briefly, The AirMetrics MiniVol sampler is calibrated primarily to ensure that the flow rate at the particulate matter (PM) inlet corresponds to the manufacturer's specification of 5 L/min at ambient temperature and pressure. Calibration involves an annual adjustment of the flowmeter using a certified transfer standard (e.g., laminar flow element), creating a calibration curve between the indicated and true flow. Prior to deployment, a project-specific flow set-point is calculated, correcting for local temperature and pressure, and verified by a single-point audit with a calibrated device. Routine checks include leak testing with a dummy filter and confirming that actual flow is within ±10 % of the target rate. The flowmeter must also be recalibrated following component replacement or at least once per year, ensuring traceable accuracy for regulatory or research-grade sampling.

The TSI DustTrak series of monitors (II and DRX) require both zero and span calibrations to ensure accurate real-time aerosol measurements. Zero calibration is performed before each use by attaching the manufacturer-supplied zero filter, which sets the baseline signal. Flow calibration, factory-set at 3.0 L/min total (≈2.0 L/min sample + 1.0 L/min sheath), is verified using an external flowmeter and adjusted in the instrument menu to maintain ±5 % accuracy. To account for aerosol-

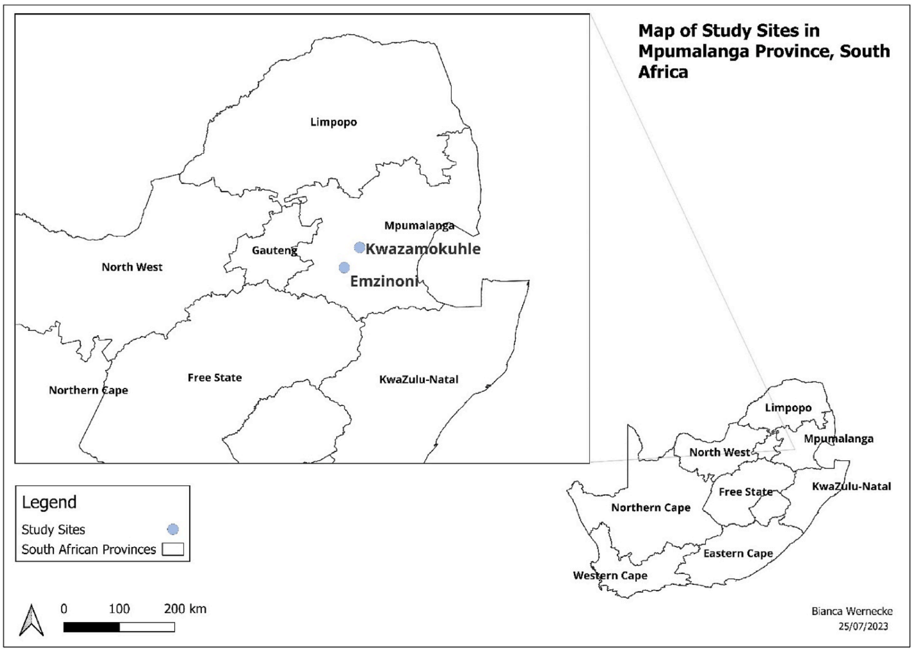

Fig. 1. Location of KwaZamokuhle and eMzinoni in Mpumalanga Province, South Africa.

Table 1
Demographics and socio-economic characteristics of participants in KwaZamokuhle and eMzinoni.

Characteristics	n (%)
Age	N = 908
18–29 years	203 (22)
30–59 years	497 (54)
60+ years	208 (22)
Education	N = 908
Currently in primary or high school	18 (2)
Finished primary school or high school	441 (48)
Studying towards a diploma/degree	9 (1)
Completed tertiary education	32 (3)
Other	408 (44)
Income (ZAR)[a]	N = 471
<760	41 (8)
760–1058	30 (6)
1059–1558	42 (8)
1559 - 2000	161 (34)
2001–5000	130 (27)
5001–10 000	31 (6)
10 001–20 000	27 (5)
20 001–50 000	9 (1)
Employment	N = 908
Unemployed	760 (83)
Employed	260 (28)
Household member number	N = 908
1–2	127 (13)
3–4	297 (32)
5–6	269 (29)
7–8	139 (15)
9–10	58 (6)
>10	18 (1)
Town	N = 908
eMzinoni	456 (50)
KwaZamokuhle	452 (49)

[a] (Statistics South Africa, 2023).

specific optical properties, the DustTrak allows the application of a photometric calibration factor (PCF), derived by co-locating the instrument with a reference gravimetric method and adjusting readings accordingly; restoring PCF to 1.0 reverts to the factory setting based on Arizona road dust. Advanced models (DRX) also permit a size correction factor to refine particle size distribution measurements. These procedures, undertaken routinely, ensure that DustTrak measurements remain comparable with reference methods while reflecting site-specific aerosol characteristics.

2.5. Health assessments

Pulmonary technologists conducted lung function tests on consenting participants using the Easy One Spirometry device (NDD Medizintachnik AG) (Miller et al., 2005). Forced vital capacity (FVC) and per second forced expiratory volume (FEV1) were used to derive FEV1/FVC ratios to identify obstructive airway disease (FEV1/FVC ratio <0.7) (Gold, 2023). The blood IgE test, carried on consenting participants (positive total IgE antibody levels ≥ 0.35 kU/L) (Popescu and Vieru, 2018; Sompornrattanaphan et al., 2020), represented the development of allergies but did not necessarily represent clinical symptoms of an allergic reaction (Sompornrattanaphan et al., 2020).

2.6. Statistical analysis

An assessment was made of the frequency of use of main and several additional fuel types listed by the participants for cooking, heating and lighting. Electricity and LPG were classified as clean fuels. Paraffin, wood and coal were classified as dirty fuels (Stoner et al., 2021). Candles were considered dirty fuel.

Four progressively dirty fuel combination categories were created: 1) clean main fuel + clean secondary fuel; 2) clean main fuel + dirty additional fuel; 3) dirty main fuel + clean additional fuel and 4) dirty main fuel + dirty additional fuel (Stoner et al., 2021).

Chi-squared tests were conducted to explore associations between fuel use and age, education level, income, employment status, household member number and town (Chen et al., 2023; Owusu-Amankwah et al., 2023; Sithole et al., 2022). To assess the strength of relationships, the Cramer's V test was performed. Multinomial regression analyses were run using the same variables to better understand the intricacies of the relationships between these variables. Crude and adjusted relative risk ratios with 95 % confidence intervals (CI) were calculated.

Boxplots and descriptive statistics illustrating median and quartile percentile values of daily household $PM_{2.5}$ concentrations (μg/m^3) were drawn up per fuel combination for cooking, heating and lighting. All statistical analyses were conducted in STATA 18 (Statacorp, 2023).

Generalized boosted regression models (GBM) were run to assess which fuel use activity was more influential in predicting the likelihood of obstructive airways disease and allergen sensitivity (Afsaneh et al., 2022; Natekin and Knoll, 2013). Then importance scores are assigned to each predictor variable based on the contribution to the model's predictive accuracy (Natekin and Knoll, 2013). Variable importance measures assessed which features were most influential and were calculated using H2O's GBM R Package (Fryda et al., 2023; R Core Team, 2023). Partial dependence plots (PDPs) were used to visualize the relationship between the fuel combinations for cooking and heating and the predicted outcomes of obstructive airways disease and allergen sensitivity. From this, the fuel combinations that had the highest predictive ability of the considered health outcomes (i.e., obstructive airways disease and allergen sensitivity) were identified.

3. Results

3.1. Main and additional fuels for cooking, heating and lighting

Overall, electricity, coal, wood and candles were most commonly used by households (Table 2). Electricity was the preferred main fuel for cooking, whilst coal was the most frequently used additional fuel. Coal was used frequently as a main and additional fuel for heating. Electricity was frequently used as a main fuel for lighting and candles were the most frequently used additional fuel.

The most frequently reported additional cooking fuels, in order, were coal, coal and

wood, electricity and wood, and electricity. For heating, the most used fuels were coal

and wood, coal, electricity, and coal and electricity. Candles were the main additional

fuel for lighting, followed by electricity and candles combined.

3.2. Fuel use combinations

Over half of the households used exclusively dirty fuel combinations for heating and about a third used them for cooking, despite all households having access to electricity (Fig. 2). Less than 4 % of households used exclusively clean fuels for cooking, heating and lighting. Most households combined clean main fuels with dirty fuels for cooking and lighting.

3.3. Household $PM_{2.5}$ concentrations

Average daily $PM_{2.5}$ concentrations were generally high and exceeded daily $PM_{2.5}$ South African National Ambient Air Quality Standards

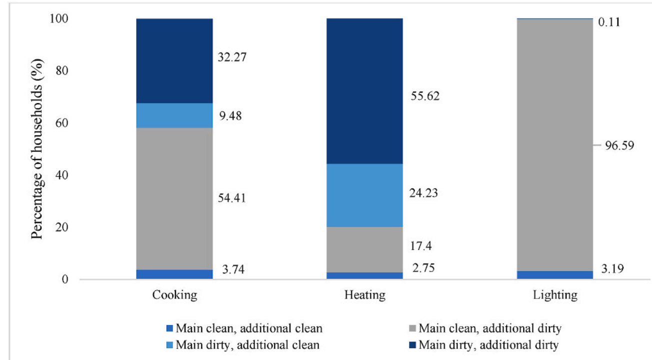

Fig. 2. Fuel use combinations used for cooking, heating and lighting in the sample population.

(40 μg/m^3) (Republic of South Africa, 2012). Table 3 shows the mean and median indoor daily average PM2.5 concentrations in relation to fuel combinations used for cooking, heating and lighting in the study sample.

There were no differences in household $PM_{2.5}$ concentrations between the different combinations of dirty fuels used ($p > 0.05$) (Supplementary Table S1). Although, the highest $PM_{2.5}$ concentrations occurred where dirty fuels were used for cooking and heating, whereas households that used clean main and additional fuels for cooking had lower $PM_{2.5}$ levels (3). The inter-quartile and standard deviations

Table 3
Mean (±standard deviation) and median (interquartile range) indoor daily average $PM_{2.5}$ concentrations (μg/m3) in relation to fuel combinations used for cooking, heating and lighting in the study sample.

	Main clean, additional clean fuels	Main clean, additional dirty fuels	Main dirty, additional clean fuels	Main dirty, additional dirty fuels
Cooking	N = 3 Ave 192 Std Dev 119 Med 149 IQR 226	N = 53 Ave 177 Std Dev 175 Med 105 IQR 145	N = 13 Ave 173 Std Dev 195 Med 105 IQR 137	N = 44 Ave 221 Std Dev 200 Med 186 IQR 203
Heating	N = 4 Ave 152 Std Dev 72 Med 167 IQR 102	N = 17 Ave 168 Std Dev 152 Med 102 IQR 204	N = 22 Ave 131 Std Dev 146 Med 97 IQR 70	N = 70 Ave 223 Std Dev 203 Med 172 IQR 195
Lighting	N = 3 Ave 142 Std Dev 71 Med 149 IQR 142	N = 110 Ave 196 Std Dev 187 Med 123 IQR 185	–	–

N = Sample size; Ave = Mean; Std Dev = standard deviation; Med = median; IQR = inter quartile range.

Table 2
Overview of main and additional fuels for cooking, heating and lighting (N = 908).

Fuel	Cooking		Heating		Lighting	
N = 908	**Main n (%)**	**Additional n (%)**	**Main n (%)**	**Additional n (%)**	**Main n (%)**	**Additional n (%)**
Electricity	521 (57)	360 (40)	168 (19)	269 (30)	904 (99)	74 (8)
LPG	7 (0.8)	17 (2)	10 (1)	17 (2)	2 (0.2)	1 (0.1)
Paraffin	1 (0.1)	1 (0.1)	0 (0)	0 (0)	0 (0)	22 (2)
Wood	11 (1)	350 (39)	20 (2)	343 (38)	0 (0)	0 (0)
Coal	368 (41)	762 (84)	703 (77)	620 (68)	0 (0)	0 (0)
Candle	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	868 (96)
Solar	0 (0)	0 (0)	0 (0)	0 (0)	0 (0)	26 (3)

Note: Totals do not always add up to n = 908 and 100 %, as participants could select more than one additional fuel. Categories "fireplaces", "blankets", "petrol generator", "other" and "none" were mentioned by 1 % or fewer of the participants and are not listed in this table.

demonstrated high variability in the data (see Supplementary Table S1).

3.4. Fuel use determinants

In order of significance, the variables town, income, education and employment status were significantly associated with the fuel combinations for cooking (Supplementary Table S2). Education level and town were significantly associated with the fuel combinations for heating. For lighting, only the variable 'town' was moderately associated with the fuel combinations.

The 'employment status 'and 'town' in which the households were located were most likely to influence fuel combinations choice for cooking, heating and lighting (Table 4). Employed participants had a lower likelihood of using fuel combinations with an 'additional dirty' element for cooking. Participants in the town of KwaZamokuhle were more likely to use exclusively 'dirty' fuels for cooking and heating, and also more likely to use a cleaner fuel combination for lighting, compared to eMzinoni.

The adjusted models also showed the importance of the variables 'employment status' and 'town' in determining the fuel combination households use for cooking and heating (Table 5). Participants who were employed were less likely to use fuel combinations for cooking with a 'dirty' fuel than those who were unemployed. Employed participants were less likely to use main clean and additional dirty fuels for heating than to use exclusively clean fuels. The likelihood of using exclusively 'dirty' fuel combinations in KwaZamokuhle was higher for cooking but not consistently significant for heating when compared to eMzinoni.

3.5. Fuel combinations and respiratory health outcomes

There were 9.5 % of participants with obstructive airways disease and 26.9 % tested positive for inhalant allergens. The GBM model showed heating fuels were the strongest predictor of obstructive airways, accounting for over 75 % (Fig. 3). Lighting fuels contributed just over one-fifth of the influence, while cooking fuels had the least influence. In contrast, cooking fuels were the main predictor of allergen sensitivity, contributing ~75 %, with heating fuels accounting for ~25 %.

Table 4
Significant crude relative risk ratio (RRR) estimates and 95 % confidence intervals (95 % CI) of fuel combinations and socio-economic determinants.

Variable	Main clean, additional clean	Main clean, additional dirty	Main dirty, additional clean	Main dirty, additional dirty
Cooking RRR (95 % CI)				
Employment status Employed *(Reference = unemployed)*	Baseline category	0.42 (0.19–0.90)	0.30 (0.12–0.79)	0.36 (0.16–0.79)
Town KwaZamokuhle *(Reference = eMzinoni)*	Baseline category	Not significant	Not significant	8.30 (3.87–17.82)
Heating RRR (95 % CI)				
Employment status Employed *(Reference = unemployed)*	Baseline category	0.38 (0.14–0.98)	Not significant	Not significant
Town KwaZamokuhle *(Reference = eMzinoni)*	Baseline category	0.29 (0.09–0.59)	Not significant	4.87 (2.10–11.29)
Lighting RRR (95 % CI)				
Employment status Employed *(Reference = unemployed)*	Baseline category	0.42 (0.19–0.94)	Not significant	Not significant
Town KwaZamokuhle *(Reference = eMzinoni)*	Baseline category	3.24 (1.37–7.66)	Not significant	Not significant

Table 5
Significant adjusted relative risk ratio (RRR) estimates and 95 % confidence intervals (95 % CI) of fuel combinations and socio-economic determinants.

Cooking fuel combination	RRR (95 % CI)	Heating fuel combination	RRR (95 % CI)
Main clean, additional clean Base outcome	NA	**Main clean, additional clean** Base outcome	NA
Main clean, additional dirty	*0.20 (0.53–0.79)*	**Main clean, additional dirty**	*0.21 (0.05–0.90)*
Employment status *Employed*	*Not significant*	Employment status *Employed*	*0.24 (0.06–0.90)*
Town *KwaZamokuhle*		Town *KwaZamokuhle*	
Main dirty, additional clean	*0.20 (0.4–0.93)*	**Main dirty, additional clean**	*0.22 (0.52–0.92)*
Employment status *Employed*		Employment status *Employed*	
Main dirty, additional dirty	*0.16 (0.04–0.63)*	**Main dirty, additional dirty**	*0.26 (0.07–0.99)*
Employment status *Employed*	*4.82 (1.50–15.45)*	Employment status *Employed*	*Not significant*
Town *KwaZamokuhle*		Town *KwaZamokuhle*	

*Baseline for Town = eMzinoni; Employment = unemployed.

Partial dependence plots revealed that dirtier heating fuels increased the predicted risk of obstructive airways disease (Fig. 4). However, cooking fuels showed little distinction in impact. For allergen sensitivity, dirtier cooking and heating fuels decreased predicted impacts, as the fuel combination got dirtier (Fig. 5). The exception was the main dirty and additional dirty fuel combination for cooking, which had the highest predicted impact.

4. Discussion

Many South African households stack and switch the fuels they use for cooking, heating and lighting (Gelo et al., 2023; Manyatsha et al., 2022; Musango, 2014; Pauw et al., 2022a). The use of multiple fuels to meet cooking energy needs has been well documented (Adams et al., 2023; Perros et al., 2023; Shupler et al., 2020). Fewer studies have looked into the stacking and switching behaviour for heating and lighting, and even fewer have considered all three energy needs.

Previous studies have shown that using clean main and additional fuels for cooking has been associated with a reduction in household

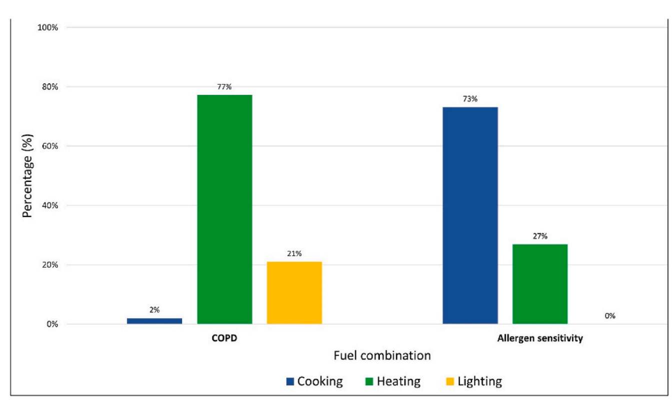

Fig. 3. Relative importance of fuel combination for cooking, heating and lighting in predicting COPD and allergen sensitivity in residents of the study communities.

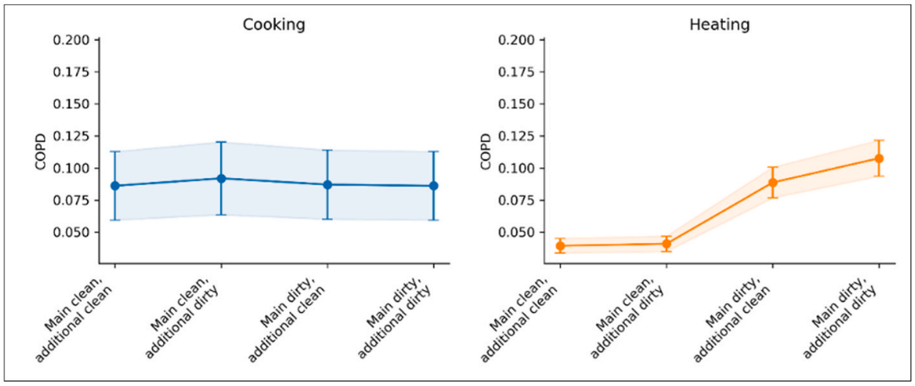

Fig. 4. Partial dependence plots of the relationship between fuel use combinations for cooking and heating and the prevalence of COPD. The y-axis plots the mean response.

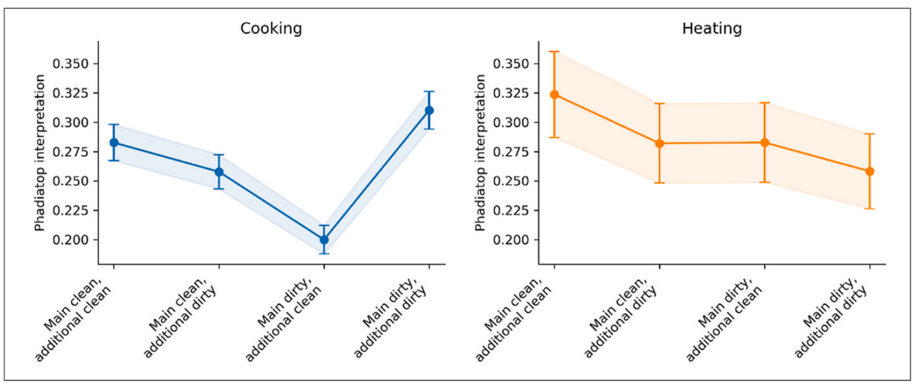

Fig. 5. Partial dependence plots of the relationship between fuel use combinations for cooking, heating and lighting and the prevalence or risk of allergen sensitivity (Phadiatop interpretation). The y-axis plots the mean response. The Phadiatop interpretation shows positive results (i.e., >0) therefore all of these values are positive for allergic sensitivity.

$PM_{2.5}$ concentrations (Shupler et al., 2020). The use of clean fuel combinations in this study was minimal (<4 % of households). However, when a clean fuel was included into the fuel combination, it appeared to be associated with a reduction in household $PM_{2.5}$ concentrations. It is evident that fuel combinations play a significant role in household $PM_{2.5}$ concentrations. These findings suggest that, regardless of the specific fuel combination used for cooking, heating, or lighting, household $PM_{2.5}$ concentrations were consistently high and showed considerable variability. This variability may indicate the influence of other indoor air pollution sources, such as emissions from neighbouring houses, coal-fired power stations, and local industries, highlighting the complex interplay of factors affecting air quality.

The town of residence provides insights into regional variations and cultural preferences and key insights might lead to benefits from interventions. Uniform interventions may not be easily reproducible in multiple places, even if socio-economic characteristics and fuel availability are similar. There are often diverse cultures and customs in different towns that drive behaviour. It is well documented that people prefer to conform to social norms and act on the advice of people they trust rather than unknown 'experts' (Frederiks et al., 2015), which can result in what the neighbors are doing having an overriding influence on practices like residential fuel use.

Employment, education, and income are modifiable determinants, offering opportunities for targeted interventions such as policies or educational campaigns to influence fuel use behaviour. The identification of employment status as a key determinant was not unexpected as related socio-economic factors such as nature of occupation, level of education and financial status have been shown to have a positive impact on the use of cleaner fuels (Adeyemi and Adereleye, 2016; Mperejekumana et al., 2021). Employed participants were less likely to use dirty fuel combinations for cooking. It is speculated that employment status may influence fuel use patterns beyond income levels. Spending less time at home may limit the need for cooking and heating, which could reduce the use of dirty fuels, whereas households with members present for longer periods may rely more heavily on these fuels. Working away from home reduces time spent indoors, potentially motivating a shift towards cleaner fuels. Concerns over smoke-related odors may drive employed individuals to prefer cleaner fuel options due to social stigma.

Between 20 and 30 % of the South African population is affected by respiratory allergies which corresponds to the findings in our study (27 %) (Mbugi and Chilongola, 2010). While HAP has been linked to obstructive airways disease (Mortimer et al., 2022), it is interesting to find in this study that the importance of fuels used for heating is much higher than the importance of fuels used for cooking and lighting for this respiratory illness. Additionally, in this study, coal was more frequently used for heating (77 %) than for cooking (41 %) and this could potentially be because households in these communities make use of coal stoves to heat their homes for longer periods of time, burning coal and wood which contribute to HAP. Obstructive airways disease in particular has been linked to chronic HAP exposure, and less to acute exposure to smoke pollutants (Ortiz-Quintero et al., 2022; Torres-Duque et al., 2021). On the contrary, studies in rural villages in India, where there is a hotter climate, showed that dirty fuels are used more often for cooking and wood in traditional cookstoves showed a higher risk to respiratory health in women (Indu et al., 2024).

The acute exposure to $PM_{2.5}$ has been linked to increases in the number of hospital visits for IgE-mediated allergy, especially for the sensitization to specific inhalant allergens (Hou et al., 2021). A study in Bangladesh showed that replacing biomass fuels with liquefied petroleum gas reduced IgE levels, lymphocyte proliferation and recovery towards T and B cell immune balance (Raqib et al., 2023). Cooking usually takes place over shorter periods of time, when compared to heating, and frequently includes high and acute HAP exposure episodes for household members. The link between exclusively clean cooking fuels and allergen sensitivity warrants further investigation but may be related to the influence of other pollution sources, including ambient sources infiltrating the indoor environment.

4.1. Study limitations

This cross-sectional data were originally tailored to objectives from another study. Whilst the sample size allowed for greater understanding of fuel use, a questionnaire specifically designed to unpack multiple fuel use would have been more suitable. Despite this, our findings remain valuable as the first study of its kind in the area. A study tracking the changes in fuel use patterns over time would further enhance these insights.

Though the fuel combinations created for this study represent aggregated indicators, grouping fuels in this manner enabled more straightforward comparisons between households. Future studies should unpack the different fuel types separately. Additionally, these combinations do not distinguish between 'stacking' and 'switching' practices.

Interpretation of the GBM model output should consider the limitations of the dataset, potential biases, and the complexity of other real-world factors impacting obstructive airways disease and allergen sensitivity. Analyzing self-reported and social behaviour data adds complexity to a study due to inherent biases in personal reporting and the dynamic, intricate nature of social interactions. Due to logistical and financial reasons, the sample sizes for the measured health outcomes were smaller than the sample for the questionnaire.

5. Conclusions

Our findings suggest reduced household $PM_{2.5}$ concentrations with stepwise increased introduction of cleaner fuels into the fuel mix. Additionally, it was found that the dirtier the fuel mix, the greater the impact on respiratory health. This warrants further research into the putative health benefits of cleaner fuels and just energy transitions in low-income settings. Stacking and switching with cleaner fuels, even in combination with dirty fuels may lead to meaningful health improvements in a sustainable way. It is unlikely that households will stop stacking into the near future and focusing on interventions that address and manage the introduction of more clean fuels into the existing mix could represent a valuable and strategic approach.

Beyond enhancing people's motivation to shift to cleaner fuels, improvement in opportunity and better availability, accessibility, or affordability may be more effective in encouraging their adoption (Perros et al., 2022). Our study suggests the importance of considering employment, education, income and town dynamics when developing strategies to guide fuel use behaviors.

Despite electrification, dirty fuels still contribute to the energy mix in KwaZamokuhle and eMzinoni. Prevalence of obstructive airways disease and allergen sensitivity was similar to national prevalence suggesting a substantial contribution to the disease burden of these towns. There was a potential influence of cleaner fuel mixes on reduced HAP levels and consequent reduced respiratory health outcomes, even in combination with dirtier fuels. Fuel stacking and switching practices are likely to continue into the future in South African and among low- and middle-income countries with similar contexts. Targeted interventions that strategically introduce cleaner energy sources into existing household fuel stacking and switching practices could positively impact HAP levels and health.

CRediT authorship contribution statement

Bianca Wernecke: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Caradee Y. Wright:** Writing – review & editing, Writing – original draft, Supervision, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Kristy Langerman:** Writing – review & editing, Supervision. **Angela Mathee:** Writing – review & editing, Funding acquisition, Conceptualization. **Nada Abdelatif:** Writing – review & editing, Writing – original draft, Formal analysis. **Marcus A. Howard:** Writing – review & editing, Data curation. **Nkosana Jafta:** Writing – review & editing, Writing – original draft, Methodology, Formal analysis, Data curation. **Christiaan Pauw:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Data curation, Conceptualization. **Shumani Phaswana:** Writing – review & editing, Formal analysis, Data curation. **Kareshma Asharam:** Writing – review & editing, Formal analysis, Data curation. **Ishen Seocharan:** Writing – review & editing, Data curation. **Hendrik Smith:** Writing – review & editing, Methodology, Data curation. **Rajen N. Naidoo:** Writing – review & editing, Writing – original draft, Funding acquisition, Formal analysis, Conceptualization.

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Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.apr.2025.102815.

Data availability

The monitoring data are available upon request from the corresponding author. The health data are available for reuse with a data sharing agreement.

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