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Cooking energy sources and the lived experience of health: Evidence from Sub-Saharan Africa

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A B S T R A C T

Background: Despite global commitments under Sustainable Development Goal 7, almost one billion people in Sub-Saharan Africa still rely on polluting cooking fuels. Although biomedical research has established the health risks of household air pollution, less is known about how cooking energy sources relate to adults' everyday experiences of health and safety across countries.

Methods: Using harmonised survey data from 10,637 adults in Kenya, Nigeria, South Africa and Uganda from the gEneSys survey, conducted 2024-2025, this study compares self-rated health, perceived harm and chronic illness across eight primary cooking energy sources. Multivariate regression models used multiple imputation and adjusted for socioeconomic, demographic, health-related and contextual factors.

Results: Cooking sources did not form a simple health hierarchy. Solar-based electricity was associated with the most favourable self-rated health and perceived safety, although this group was small and potentially selective. Direct comparisons among other modern sources revealed only a few outcome-specific differences and no consistent ranking. Traditional and open-fire cooking sources showed the clearest disadvantages in perceived harm and more moderate differences in self-rated health, but no consistent pattern for chronic illness. These associations remained visible after adjustment.

Conclusions: Cooking source was most clearly associated with lived health experience rather than reported chronic illness. Clean-cooking research and monitoring should therefore complement exposure and morbidity indicators with measures of self-rated health and perceived safety. Policies should address not only fuel replacement, but also affordability, reliability, safety and the social conditions under which energy is used.

1. Global goals and local realities in clean cooking

Around the world, the way households cook has profound implications for public health, environmental sustainability and social equity. Under Sustainable Development Goal 7 (SDG 7), governments have pledged to ensure access to affordable, reliable, sustainable and modern energy for all, with modern cooking solutions recognised as a core component of that agenda [1]. Yet in practice, clean cooking remains one of the most persistent energy access challenges of our time. The International Energy Agency (IEA) estimates that more than 960 million people in Sub-Saharan Africa (SSA) still rely on polluting fuels such as firewood, charcoal, crop residues and kerosene, while fewer than one in five households in many countries have access to a clean alternative [2,3]. Without accelerated progress, the region will account for the overwhelming majority of people still cooking with traditional fuels by 2030.

The consequences of these energy inequalities extend far beyond convenience or energy efficiency. Indoor air pollution from polluting fuels is among the leading environmental risk factors for disease and premature death, contributing to respiratory infections, cardiovascular illness, chronic obstructive pulmonary disease and low birth weight [4,5]. The problem disproportionately affects women and children, who spend more time near the cooking area, but also exposes entire households and communities to harmful levels of smoke and particulates. Despite decades of intervention programmes, the transition to clean cooking has remained slow. Progress has been constrained by affordability barriers, unreliable or absent electricity infrastructure, and the limited alignment of clean-cooking interventions with locally embedded cooking practices and everyday household needs [6].

While the distinction between “clean” and “polluting” fuels is well established, important gradations within the clean category are now gaining attention. Cooking with electricity is emission-free at the point of use, but its accessibility depends on grid reliability and affordability. Gas stoves are often promoted as a transitional solution; however, they

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emit nitrogen dioxide (NO_2) and other pollutants indoors, which can reach concentrations exceeding outdoor air quality standards [7,8]. Conversely, solar-based systems and induction cookers eliminate combustion emissions entirely at the point of use but remain limited by cost and availability. Even among electricity users, reliance on diesel or petrol generators can introduce additional exhaust exposure, creating a paradox of "dirty electricity" in contexts of unreliable grids. These distinctions suggest that technical classifications of cooking fuels do not automatically translate into uniform experiences of health, safety, or well-being in everyday household life.

This is conceptually important because many clean-cooking metrics classify fuels by the stove or fuel used at the point of cooking, while everyday health experience may also depend on the wider energy pathway through which cooking becomes possible. Grid electricity, generator-based electricity and solar-based electricity can all support electric cooking, but they differ substantially in reliability, background emissions, affordability and exposure context. Distinguishing these pathways therefore helps address a core gap in clean-cooking research, namely whether technically modern sources are experienced as similarly safe and health-enhancing, or whether infrastructural conditions such as grid unreliability and generator dependence complicate the expected clean-cooking gradient.

Much of the existing evidence on cooking energy and health focuses on children or on measured pollutant exposure rather than on adults' own health experiences. Clinical and exposure-based studies show that cleaner fuels reduce particulate matter ($PM_{2.5}$) and carbon monoxide concentrations [9–11], yet these designs rarely capture how individuals *perceive* or *feel* the difference. We define this lived health experience through both perception-based indicators, such as adult self-rated health (SRH) and perceived harm associated with household energy use, as well as through a chronic illness indicator to offer complementary perspectives on this issue: they capture different degrees of proximity to everyday experience, from situated risk appraisal to general health evaluation and long-term health constraints. Moreover, perceptions of risk influence energy behaviour itself. Households that view smoke as dangerous are more likely to adopt cleaner cooking solutions [12,13].

However, large, harmonised datasets that combine information on self-rated health, perceived harm and cooking energy sources across multiple African countries remain extremely rare. Surveys such as the DHS or MICS record energy types but typically omit adult health assessments [14]. In contrast, randomised trials capture health outcomes but at limited scales and in selected settings. As a result, policymakers lack comparative, cross-country evidence on how different energy sources relate to adults' perceived health and safety. This gap is especially relevant because energy-related health inequalities may become visible in lived experience before they appear in diagnosed morbidity statistics [15,16].

This study addresses that gap using harmonised data from the gEnesys survey, conducted in Kenya, Nigeria, South Africa and Uganda. The analysis compares health outcomes across eight types of cooking energy—grid electricity, generator-based electricity, gas (piped gas, LPG, or biogas), traditional fossil or biomass stoves, three-stone or open fires, thermal solar cookers, a residual "else" category, and solar-based electricity. The latter serves as the analytical reference category because it combines electric cooking at the point of use with a reported solar energy source and therefore represents the lowest expected household-and-system combustion exposure in the dataset. By combining self-rated health, perceived harm, and the prevalence of chronic illness, the study provides one of the first harmonised cross-country analyses of how everyday cooking energy sources are associated with different dimensions of adult health experience in Sub-Saharan Africa.

Here, lived experience of health is understood as health as it is experienced and evaluated in everyday life, rather than defined solely by diagnosed disease. We operationalise this perspective through three complementary indicators rather than a single scale: self-rated health as an overall evaluation of bodily and psychological well-being, perceived harm as an everyday appraisal of risk and safety, and chronic illness as a less experience-near indicator of a reported long-term health constraint. In doing so, the study goes beyond predefined technical classifications of clean cooking and incorporates how households themselves experience health and risk in daily life. Beyond quantifying the problem, it seeks to understand which energy sources are associated with more favourable self-rated health, lower perceived harm, and lower reported chronic illness, thereby contributing to the design of fair and feasible pathways toward universal clean cooking under SDG 7.

2. Health and cooking energy: the evidence base

Cooking energy represents one of the most direct intersections between energy systems and public health. The health consequences of different cooking fuels follow a well-established exposure gradient, especially when comparing solid or polluting fuels with cleaner alternatives. Traditional biomass fuels such as wood, charcoal, crop residues and dung generate dense smoke containing fine particulate matter ($PM_{2.5}$), carbon monoxide (CO), and other toxins. Long-term exposure to such pollutants increases the risk of respiratory infections, cardiovascular disease, and adverse pregnancy outcomes [4,9,17,18]. The World Health Organization thus classifies electricity, LPG, natural gas, biogas, alcohol and solar as *clean*, whereas biomass, coal and kerosene are *polluting* [5].

2.1. Health risks of polluting cooking fuels

The association between solid fuel use and respiratory disease is among the most consistent findings in environmental health research. Meta-analyses confirm elevated risks of childhood pneumonia and chronic obstructive pulmonary disease (COPD) among those exposed to biomass smoke [19,20]. For example, the Prospective Urban and Rural Epidemiology (PURE) study across eleven countries found higher adult mortality and cardiorespiratory morbidity among users of solid fuels [9].

Evidence also links household air pollution to adverse pregnancy outcomes. Reviews by Amegah et al. [18] and Luo et al. [21] associate exposure to polluting fuels with low birth weight and preterm birth. Yet even large randomised controlled trials such as the Household Air Pollution Intervention Network (HAPIN), which supplied LPG stoves in Guatemala, India, Peru and Rwanda, have shown mixed results. While the trial achieved major reductions in $PM_{2.5}$ and CO exposures, it did not find statistically significant improvements in infant pneumonia or birthweight [10,11]. This discrepancy underscores the difficulty of demonstrating causal biomedical effects over short time frames, even when exposure reductions are substantial. It also suggests that different health indicators may respond at different speeds and through different mechanisms to changes in household energy use.

Household air pollution contributes not only to respiratory but also to cardiometabolic risks. Fine particulates increase blood pressure and vascular inflammation [22], while biomass smoke has been linked to cataract formation [23]. Emerging studies suggest links between household air pollution, maternal mental health and child neurodevelopment, highlighting that the full health burden extends beyond the respiratory system.

2.2. Gradations within clean energy

Recent work has refined the understanding of what counts as *clean cooking*. While gas and LPG are often treated as clean transitional fuels, indoor exposure studies show that gas stoves can raise nitrogen dioxide (NO_2) levels to, or beyond, recommended limits [7,8]. By contrast, electric or induction cooking produces no burner-side emissions. Experimental cooking tests have shown substantially lower indoor NO_2 concentrations when cooking with induction rather than gas. These findings suggest a hierarchy of relative risk:

electricity < gas/LPG < biomass.

However, this technically plausible hierarchy should not be assumed to appear uniformly across health outcomes or everyday contexts, as perceived safety, self-rated health and diagnosed illness may reflect different combinations of exposure, infrastructure, affordability, housing conditions and prior health status.

A further nuance concerns generator-based electricity, which remains common in Nigeria and parts of East Africa. Studies show that portable petrol and diesel generators can elevate indoor concentrations of CO, $PM_{2.5}$ and volatile organic compounds, occasionally leading to carbon monoxide poisoning. In these cases, electricity is "clean" at the stove but "polluting" through background emissions, underscoring that the health implications of cooking energy depend not only on fuel type but also on generation source and ventilation.

2.3. From exposure to lived health experience

The biomedical literature establishes that polluting fuels can create substantial exposure risks, but it does not fully explain how these risks are experienced, evaluated, and reported in everyday life. This distinction is central for social-scientific energy research, and considering both sides enables a more in-depth insight into lived health experience. Energy-related burdens may become visible as perceived discomfort, concern, or reduced well-being before they appear in diagnosed morbidity. To capture this experience, we focus on two perception-based indicators with self-rated health and perceived harm, enabling an assessment of how people evaluate their own health and risks. Beyond this, including chronic illness nevertheless provides an important contrast to the more experience-near indicators, because it allows us to examine whether associations with cooking energy extend beyond perception and self-evaluation to reported long-term health constraints. For this reason, the present study treats perceived harm, self-rated health and chronic illness as complementary indicators rather than interchangeable measures of a single health outcome.

We therefore do not expect the three outcomes to respond equally to current cooking source. Perceived harm is likely to be closest to everyday exposure, because smoke, odour, heat, unstable flames, fuel handling and generator exhaust are directly perceptible. Self-rated health may capture a broader assessment of well-being and early symptoms, but it also reflects socioeconomic position, mental health and general living conditions. Chronic illness is likely to be the least immediately responsive to current cooking source, because it depends on cumulative exposure histories, long latency periods for many cardiorespiratory conditions, survival and selection processes, and access to healthcare and diagnosis. A weak or inconsistent association between current cooking source and chronic illness would therefore not necessarily imply the absence of health-relevant energy burdens; rather, it may indicate that self-reported chronic illness is a more cumulative and less immediately responsive outcome.

Most clean-cooking research to date has centred on children or on clinical and exposure-based endpoints. While this work has been crucial for establishing the biomedical risks of polluting fuels, it captures only part of how energy-related health inequalities manifest in everyday life. A growing body of research therefore highlights the importance of self-rated health and perceived harm among adults as complementary indicators that reflect how health and risk are experienced and evaluated in daily contexts.

Importantly, self-rated health is not merely a subjective opinion. A substantial body of longitudinal evidence demonstrates that self-rated health is a strong and independent predictor of subsequent mortality and morbidity across diverse populations. Early reviews already showed remarkably consistent associations between poor self-rated health and elevated mortality risk, even after controlling for diagnosed disease and socioeconomic characteristics [24]. Subsequent reviews and longitudinal studies confirm that self-rated health is associated not only with mortality but also with functional decline and broader health trajectories [15,16].

The predictive validity of self-rated health is commonly interpreted as reflecting an integrative assessment process, in which individuals combine information about symptoms, functional limitations, mental well-being, fatigue, and early or unmeasured health changes that may not yet be clinically diagnosed. Conceptual work by Jylhä [25] formalises this understanding, arguing that self-rated health synthesises multiple dimensions of bodily and psychological experience into a single evaluative judgement.

Consistent with this perspective, empirical studies have demonstrated systematic associations between self-rated health and various biological health markers. For example, Dowd and Zajacova [26] found that poorer self-rated health was generally associated with less favourable profiles across metabolic, cardiovascular, inflammatory, and organ-function biomarkers, suggesting that self-rated health may reflect underlying physiological risk in addition to diagnosed conditions.

Empirical evidence from energy-related contexts supports the relevance of self-rated health for clean cooking research. For example, Nduka and Jimoh [13] found that the use of clean cooking energy in Nigeria may be linked to higher self-rated health and was positively associated with women's reported happiness, life satisfaction, and overall wellbeing, and correlated with reduced mental health problems compared with reliance on more polluting fuels.

Similarly, longitudinal panel data from China indicate that transitions from solid fuels to cleaner cooking options are associated with improvements in women's self-rated and others-rated health, although no significant association was found with independence in daily activities [27]. These findings align with the broader literature in suggesting that self-rated health is sensitive to everyday environmental exposures and living conditions shaped by household energy use.

Perceived harm provides a complementary perspective by capturing how individuals appraise health risks associated with their cooking environment. Studies from Ethiopia show that a majority of pregnant women in rural Ethiopia reported high levels of health risk perception regarding household air pollution from biomass smoke, and nearly three-quarters perceived benefits associated with using improved stoves [28].

Risk and harm perceptions are not only evaluative outcomes but also key behavioural mechanisms: a substantial literature in health psychology demonstrates that perceived risk influences preventive behaviour, technology adoption, and protective practices [29,30]. In the context of clean cooking, such perceptions may influence protective practices and adoption decisions, while also reflecting existing exposure conditions [28,30]. In this context, perceived harm is especially important because it is likely to be closer to everyday cooking experience than chronic illness. Smoke, odour, eye irritation, heat, fire risk, fuel handling, and generator exhaust are directly perceptible features of household energy use. Perceived harm may therefore capture an immediate experiential layer of energy-related health inequality that is not necessarily visible in clinical or diagnostic indicators.

Despite their demonstrated relevance, self-rated health and perceived harm remain underutilised in large-scale, cross-national energy research. Major survey programmes such as the Demographic and Health Surveys (DHS) and Multiple Indicator Cluster Surveys (MICS) typically record cooking fuel use but omit adult self-rated health and perceived-harm measures [14]. As a result, existing data infrastructures prevent integrated analyses that link everyday energy choices to both lived health experience and longer-term health constraints across countries.

2.4. Knowledge gaps

From this body of research, four main gaps emerge. First, despite strong biomedical and epidemiological evidence linking polluting fuels to disease, limited attention has been paid to adult health perceptions and to how individuals experience and evaluate health in everyday life. Second, the lack of harmonised, multi-country data in Sub-Saharan Africa constrains comparative analysis, as most existing surveys do not jointly capture information on cooking fuels, adult self-rated health, and perceived harm in a consistent manner. Third, variation within ostensibly clean energy sources remains underexplored. Electricity derived from different sources, such as grid electricity, solar power, or generators, may entail distinct health implications, yet these differences are rarely examined empirically. Fourth, it remains unclear whether cooking energy is more strongly associated with immediate experiential indicators, such as perceived harm, than with broader self-rated health or with chronic illness as a more institutionally mediated health indicator.

Addressing these gaps is crucial for policy under SDG 7. Rather than relying on a single health outcome, this study combines self-rated health, perceived harm, and the prevalence of chronic illness to capture complementary aspects of how everyday energy choices relate to health. This multidimensional outcome perspective makes it possible to assess energy-related health inequalities across different levels of lived experience, examining whether technically cleaner cooking options are also associated with more favourable everyday health evaluations, lower perceived harm, and fewer reported long-term health constraints.

3. Data and methods

3.1. Data collection and sample

Data were drawn from the *gEneSys Survey*, a cross-national component of the gEneSys project examining social impacts of energy systems. The survey was conducted by Fraunhofer IAO in collaboration with Ipsos between October 2024 and January 2025 across ten countries, including Kenya, Nigeria, South Africa, and Uganda. Participants were recruited through quota-based sampling from Ipsos' online panel infrastructure, with quotas set for age and gender. Each country contributed between 2535 and 3001 adult respondents (aged 18–75), yielding an initial sample of approximately 11,536 individuals.

While this quota-based online panel sampling strategy allows for a broad spectrum of households to be included, it does not come without limitations: online panels may underrepresent less digitally connected, lower-income, rural and less formally educated populations, including groups with higher dependence on biomass fuels. In addition, representativeness is difficult to establish where the population statistics used for quota setting are themselves relatively broad or uncertain, as was particularly the case for Uganda. The dataset is therefore best suited for comparative and multivariate analyses of associations within the surveyed population, rather than for estimating nationally representative prevalence rates of cooking energy use or health outcomes.

This limitation is particularly relevant for interpreting biomass and open-fire cooking. In nationally representative Sub-Saharan African samples, biomass dependence is often concentrated among rural, lower-income and less formally educated households. In the present online-panel sample, however, respondents reporting traditional fossil/biomass stoves or three-stone/open-fire cooking as their primary cooking source represent a more specific subgroup. Additional descriptive checks show that these respondents account for 18.6% of the analytic sample (n = 1979), but 54.1% live in urban environments and 54.3% have high education. Biomass/open-fire users in this dataset should therefore not be interpreted as representative of the full rural biomass-dependent population in Sub-Saharan Africa. Rather, they capture biomass reliance within a digitally connected, relatively urban and comparatively highly educated survey population. This may attenuate contrasts between biomass and other cooking-source groups and reinforces that the analysis estimates associations within the surveyed population rather than nationally representative biomass-related health inequalities.

The standardised questionnaire captured household energy use, cooking practices, health outcomes, and perceived environmental risks and was administered through an online survey. All non-response, invalid, and user-missing codes in the variables used for analysis were harmonised to a common missing-value indicator (NA) before imputation, and key outcome and covariate variables were range-checked against their valid response categories. The analytic sample was defined prior to imputation. Starting from the Sub-Saharan African regional sample, we restricted the data to respondents with observed and valid information on their primary cooking source, resulting in an analytic pool of N = 10,637. Cooking source was therefore not imputed. Remaining item non-response in the health outcomes and covariates used for the multivariate models was addressed through multiple imputation.

Missing data were examined systematically prior to analysis. Variable-level summaries and visual inspections indicated non-random patterns of missingness. Binary indicators of missingness were regressed on observed covariates, supplemented by bivariate diagnostics. Because missingness in variables used for the health-outcome analyses was associated with observed socioeconomic and contextual variables, the Missing Completely At Random (MCAR) assumption was rejected. Under the standard assumption that, conditional on observed covariates, missingness does not depend on unobserved values, the data were treated as Missing At Random (MAR) [31,32].

Based on this assumption, missing data on outcomes and covariates were handled using multiple imputation by chained equations [33]. Twenty imputed datasets were generated. Imputation methods were specified according to variable type: predictive mean matching was used for continuous variables, logistic regression for binary variables, polytomous logistic regression for nominal factors, and proportional odds models for ordered variables, following established recommendations [34]. The ordinal outcomes were treated as ordered factors before imputation, chronic illness was treated as a binary factor, and variables without missing values were not imputed. All analyses were pooled across imputations using Rubin's rules [35]. The use of 20 imputations follows recent guidance recommending larger numbers of imputations when the fraction of missing information may be non-negligible [34,36].

3.2. Measures

Three indicators of adult health served as dependent variables: self-rated general health, perceived absence of harm or risk associated with household energy use, and the presence of a self-reported chronic illness. Self-rated health was measured on a five-point Likert scale ranging from *very poor* (1) to *very good* (5), while perceived harm was assessed on a seven-point scale from *very harmful* (1) to *not harmful at all* (7). Higher values therefore indicate greater perceived safety, or equivalently lower perceived harm. Chronic illness was recorded as a binary variable (0 = no, 1 = yes). Descriptive statistics for all variables, including means, standard deviations and sample proportions, are displayed in Tables 1 and 2. As described above, these three health outcomes capture complementary but conceptually distinct dimensions of health. The indicators are therefore analysed separately rather than combined into a single health scale.

Bivariate correlations between the three health outcomes underscore their related but distinct nature. Chronic illness is clearly associated with self-rated health (Spearman's $\rho = -0.30$, $p < .001$), indicating that respondents reporting a chronic condition tend to evaluate their overall health less favourably. The association between self-rated health and perceived safety is small and positive ($\rho = 0.17$, $p < .001$), suggesting partial overlap between general health evaluations and risk perceptions without redundancy. By contrast, chronic illness shows only a very weak association with perceived safety ($\rho = -0.05$, $p < .001$). Taken together, these patterns suggest that, while the three outcomes are statistically related, they capture distinct dimensions of health, thereby justifying their separate consideration in the multivariate analyses that follow.

The primary predictor, cooking energy source, was categorised into eight groups following the World Health Organization's household

Table 1
Descriptive statistics of cooking source and health outcomes. All results were calculated using the raw, pre-imputation data.

Variable		Self-rated health (1: very poor – 5: very good)	Perceived safety (1: very harmful – 7: not harmful at all)	Chronic illness (0: no – 1: yes)	N
		M (SD)	M (SD)	n %	
Cooking source	1 Grid electricity	4.24 (0.724)	5.98 (1.53)	18.2% (0.386)	1802
	2 Generator	4.42 (0.728)	5.87 (1.70)	14.2% (0.349)	576
	3 Gas (piped/biogas/LPG)	4.32 (0.686)	5.81 (1.67)	14.2% (0.349)	5286
	4 Traditional fossil/bio stove	4.17 (0.731)	4.81 (2.26)	18.4% (0.388)	945
	5 Three-stone/open fire	4.22 (0.718)	4.81 (2.33)	15.1% (0.358)	1034
	6 Thermal solar cooker	4.41 (0.683)	5.81 (1.58)	13.1% (0.339)	110
	7 Else	4.09 (0.741)	5.07 (2.24)	23.0% (0.421)	433
	8 Solar-based electricity (reference)	4.49 (0.685)	6.17 (1.44)	15.0% (0.357)	451
					10,637

energy classification framework [37]: grid electricity, generator-based electricity, gas, including LPG, biogas, or piped gas, traditional fossil or biomass stoves, three-stone or open fires, thermal solar cookers, other or unspecified sources, and solar-based electricity, which serves as the reference category. Solar-based electricity was chosen as the analytical reference category because it combines electric cooking at the point of use with a reported solar energy source. It therefore represents the category with the lowest expected household-and-system combustion exposure in the dataset, while providing a larger and more stable reference group than thermal solar cooking. This choice does not imply that solar users represent an experimentally comparable group. Access to solar-based electricity may itself be socially selective and associated with household resources, infrastructure, technology preferences or local energy systems. The reference group is also relatively small (n = 451; about 4% of the analytic sample) and unevenly distributed across countries: Kenya n = 45 (1.6%), Nigeria n = 144 (5.1%), Uganda n = 38 (1.6%) and South Africa n = 224 (8.7%). We therefore use solar-based electricity as a substantively meaningful comparison point, but interpret all contrasts against this category cautiously.

To account for potential confounding and part of the social selectivity in access to different cooking sources, the models controlled for age in years, gender, education level, perceived income sufficiency, urban–rural environment, dwelling type, household composition, diagnosed mental health problems, care responsibilities, and country. These variables capture key socioeconomic, demographic and contextual dimensions that might influence both household energy choice and health outcomes. However, residual selection by unobserved factors such as local infrastructure quality, electricity reliability, asset ownership, or technology preferences cannot be ruled out. The reference category is therefore used for comparative modelling rather than as evidence of a causal technology effect.

3.3. Analytic strategy

First, descriptive statistics were used to summarise the distribution of cooking sources and to report mean values for the three health outcomes, alongside the key social and demographic controls (see Tables 1 and 2). These figures provide an overview of the sample composition and highlight baseline differences across energy groups.

Second, logistic regression and ordered logit models were conducted to estimate the adjusted associations between cooking source and health outcomes while accounting for socioeconomic and contextual factors. Logistic regression was applied to the binary chronic-illness outcome. Ordered logit models were applied to self-rated health and perceived safety.

Tests of the proportional-odds assumption indicated some global deviations, particularly for perceived safety. To assess whether these violations affected the focal comparisons, we conducted Brant diagnostics across the 20 imputed datasets and distinguished between global tests, focal cooking-source contrasts and control variables. In the adjusted ordered-logit models, the focal cooking-source contrasts did not show evidence of proportional-odds violations: 0 of 140 cooking-source tests were significant at $p < .05$ for self-rated health, and 0 of 140 were significant at $p < .05$ for perceived safety. By contrast, some global and covariate-level diagnostics indicated deviations, especially for perceived safety. Fully adjusted partial proportional-odds specifications did not yield stable variance estimates for all outcomes. We therefore retained pooled ordered-logit models as the main specification for the two ordinal outcomes. The resulting odds ratios are interpreted as average cumulative associations across outcome thresholds rather than as threshold-specific effects (see Annex Table 4).

Each outcome was modelled twice: first using cooking source as the only predictor, and then with the full set of socioeconomic, demographic, health-related and contextual covariates. The cooking-source-only models describe the unadjusted associations, whereas the adjusted models assess whether these associations persist after accounting for observed differences between energy-user groups. For the binary logistic models for chronic illness, country-clustered robust standard errors were computed within each imputed dataset and pooled using Rubin's rules. For the ordered logit models for self-rated health and perceived safety, standard errors were calculated using conventional pooled variance estimates from multiple imputation. Country was included as a covariate in the adjusted ordinal models, but these models should not be interpreted as providing fully cluster-adjusted country-level inference. Regression coefficients are reported as odds ratios (Exp (B)) with 95% confidence intervals.

4. Results: associations between cooking energy sources and health outcomes

The analyses examined how different cooking energy sources are associated with three health outcomes—self-rated health, perceived harm, and chronic illness—first without and then with adjustment for the socioeconomic, demographic, health-related, and contextual controls described in the methods section.

4.1. Descriptive overview

The analytic pool of N = 10,637 adults from the four Sub-Saharan African study countries included respondents with heterogeneous socioeconomic and household characteristics (see Annex, Table 2), but should not be interpreted as nationally representative. Mean age was 32 years, 46.5% of respondents were female, and about two-thirds had tertiary education. The sample also varied across housing conditions, household structures and living environments. Based on a binarised version of the original seven-point urban–rural scale, 72.3% of valid responses referred to urban environments and 27.7% to rural environments. Respondents lived in a wide range of dwelling types, including separate houses (20.8%) and apartments (37.1%), as well as compound houses (20.0%) and improvised or unfinished structures (over 3% combined). Household compositions varied similarly, with respondents living alone (16.3%), with partners and children (36.5%), extended family (22.6%), or in shared housing arrangements.

Across the pooled sample, households relied on a wide range of cooking energy sources (Table 1). Gas and LPG were the most common clean fuels, followed by grid electricity, while three-stone and open-fire cooking remained widespread. Cooking based on solar electricity, used by about 4% of respondents (n = 451), served as the analytical reference category. Annex Table 5 reports the distribution of cooking sources by country. Solar-based electricity was present in all four countries but unevenly distributed, ranging from 38 respondents in Uganda and 45 in Kenya to 224 in South Africa. Because this group is relatively small and potentially selective, descriptive differences and regression contrasts involving solar-based electricity should be interpreted cautiously.

Self-rated health varied across energy types, but the descriptive

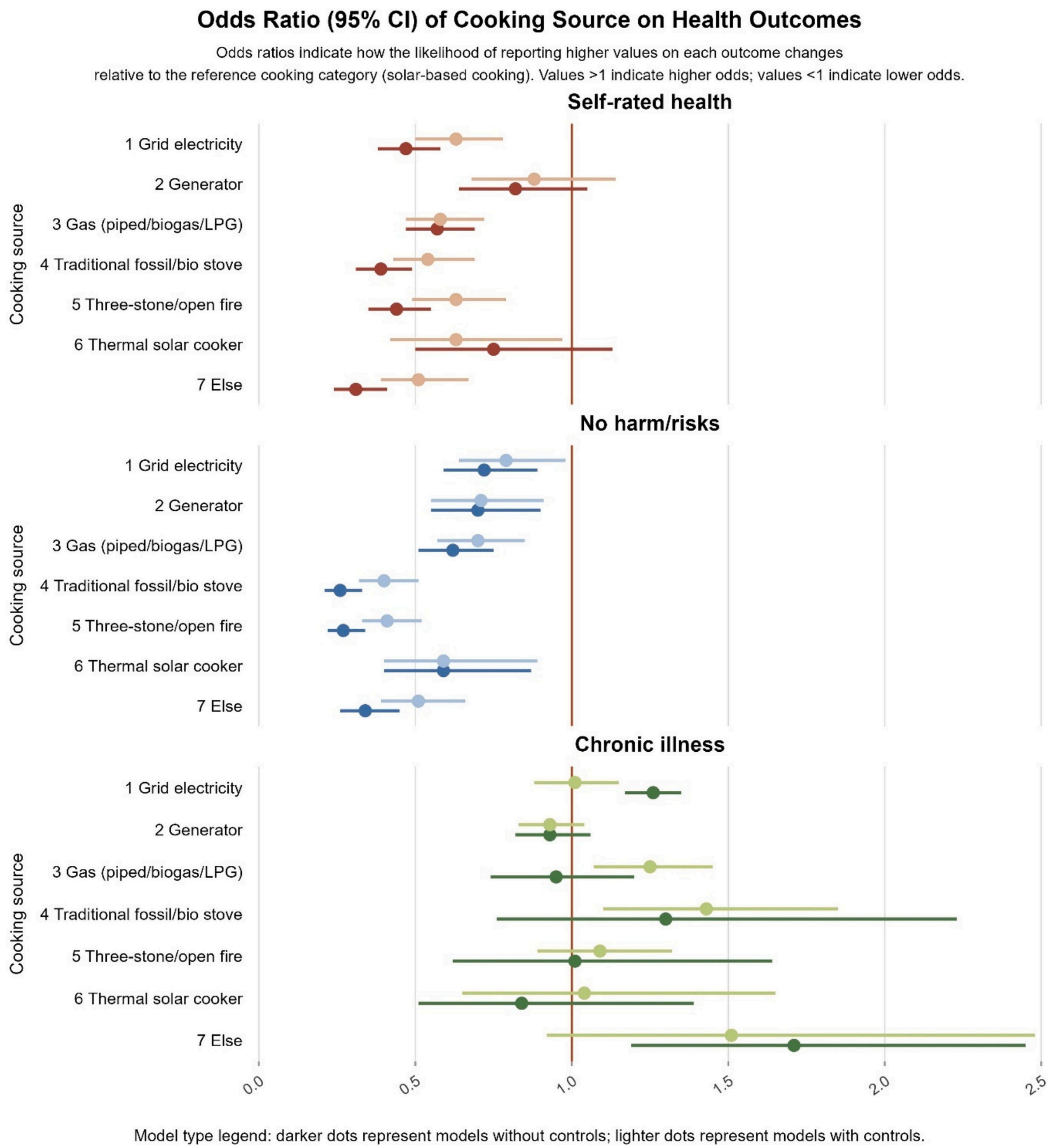

Fig. 1. Odds ratios for the associations between cooking source and health outcomes. Solar-based electricity (Category 8) is the reference category. Self-rated health and perceived safety are estimated using pooled ordered logit models; chronic illness is estimated using binary logistic regression with country-clustered robust standard errors. Estimates are shown for cooking-source-only models and fully adjusted models. N = 10,637.

pattern did not form a simple linear hierarchy. Respondents using solar-based electricity reported the highest mean self-rated health (M = 4.49, SD = 0.69), followed by generator-based electricity and thermal solar cookers. Gas users reported moderately lower scores, while users of traditional biomass stoves and open fires showed lower self-rated health levels. However, the differences in mean self-rated health were generally modest, and descriptive comparisons alone do not account for socio-economic or contextual differences between energy users.

Perceived safety followed a clearer pattern: solar-based electricity was rated as least harmful (M = 6.17, SD = 1.44), with grid electricity and generators close behind. Traditional stoves and three-stone fires received the lowest safety evaluations, indicating substantial perceived health risks. This descriptive contrast was more pronounced than the corresponding differences in self-rated health.

Chronic illness prevalence showed a less consistent descriptive pattern, ranging from 13% among thermal-solar users to roughly 18% among biomass users. Grid electricity also showed a prevalence of about 18%, while the residual "else" category showed the highest prevalence. These descriptive differences are consistent with the interpretation that chronic illness may be shaped by factors beyond current cooking source, including selection into energy types, prior exposure histories, and access to diagnosis.

4.2. Patterns of the regression analysis with and without controls

Fig. 1 displays the odds ratios for the three health outcomes by cooking source. The estimates are shown relative to the reference category (solar-based electricity). Because the adjusted models account for observed socioeconomic, demographic, health-related and contextual differences between energy-user groups, the interpretation focuses primarily on these specifications. The cooking-source-only models are reported to show how the associations change after covariate adjustment. All regression estimates are reported in Table 3 (see Annex) and are used to assess the robustness and covariate sensitivity of the findings.

If an odds ratio has a confidence interval that crosses the value of 1, this indicates that the estimated association for that cooking source is not statistically distinguishable from the reference category at conventional levels. The figure illustrates how the three health outcomes vary across cooking sources. Overall, the results show that solar-based electricity is associated with the most favourable self-rated health and perceived safety, whereas differences among many other cooking sources are small or statistically uncertain and do not form a clear hierarchy. The strongest and most consistent cooking-source differences appear for perceived harm, while chronic illness shows the least differentiated pattern. This pattern should be interpreted as comparative association rather than evidence of a causal technology effect.

4.2.1. How does self-rated health vary across cooking sources?

In the adjusted model for self-rated health, respondents using solar-based electricity form the reference category and show the highest self-rated health in the descriptive and adjusted comparisons. Most alternative cooking sources exhibit lower odds of reporting good self-rated health, with odds ratios clustering between approximately 0.51 and 0.63. Generator use (OR = 0.88, 95% CI 0.68–1.14) is the only cooking-source category that does not differ statistically from solar-based electricity in the adjusted self-rated health model. Thermal solar cookers also show lower odds of more favourable self-rated health (OR = 0.63, 95% CI 0.42–0.97), although this estimate should be interpreted cautiously given the very small group size. Grid electricity, gas, traditional biomass stoves, three-stone fires, and the residual "else" category show significantly lower odds of more favourable self-rated health relative to the reference.

The corresponding unadjusted model yields a highly similar pattern, suggesting that the observed associations are not fully explained by the socioeconomic and contextual covariates included in the model. Adjustment attenuates some estimates but does not eliminate the lower odds observed for most non-solar cooking sources.

Overall, the results indicate that solar-based electricity is associated with higher self-rated health than most other cooking sources, but the pattern beyond that is diffuse. Direct pairwise comparisons show more favourable self-rated health for generator electricity than for grid electricity and gas, but no consistent ranking across all modern cooking sources. While solar-based electricity stands out descriptively and in the adjusted model, the differences among the remaining cooking sources do not form a clear or graded hierarchy. Thus, as an indicator of lived experience of health, self-rated health appears primarily sensitive to the contrast between solar-based electricity and most other cooking sources, while offering limited systematic differentiation among the remaining technologies.

4.2.2. How is cooking energy associated with perceived safety?

In the adjusted model for perceived safety, a clearer and more consistent pattern emerges across cooking energy sources. Solar-based electricity, used as the reference category, is associated with the most favourable evaluation. A cluster of modern energy sources, including grid electricity (OR = 0.79, 95% CI 0.64–0.98), generator use (OR = 0.71, 95% CI 0.55–0.91), gas (OR = 0.70, 95% CI 0.57–0.85), and thermal solar cookers (OR = 0.59, 95% CI 0.40–0.89), shows lower odds of perceiving household energy use as free from harm or risks than the solar-based electricity group, but the magnitude of these associations is broadly similar.

By contrast, biomass-based cooking stands out more clearly even after adjustment. Users of traditional fossil/biomass stoves (OR = 0.40, 95% CI 0.32–0.51) and three-stone or open fires (OR = 0.41, 95% CI 0.33–0.52) report substantially lower odds of perceiving household energy use as free from harm or risks than the solar-based electricity reference group. These estimates represent the largest departures from the reference category across the three outcomes.

Comparisons with the cooking-source-only models show a broadly similar ordering of cooking sources for perceived harm. This pattern suggests that the perceived-harm differences are not fully accounted for by the included socioeconomic and contextual covariates. A plausible interpretation is that perceived harm is closer to everyday sensory experience than the other outcomes. Smoke exposure, unstable flames, heat, odour, fuel handling, and perceived danger are directly perceptible features of biomass-based cooking and may therefore be more immediately reflected in risk appraisals. Within the framework of lived experience of health, perceived harm emerges as the most differentiated outcome, closely tied to everyday sensory exposure and practical risk awareness.

4.2.3. Post-hoc comparisons among modern cooking sources

Post-hoc pairwise contrasts among the four modern cooking sources revealed only a small number of outcome-specific differences. For self-rated health, generator electricity was associated with higher odds than grid electricity and gas. For perceived safety, grid electricity was associated with higher odds than gas. All remaining pairwise contrasts were non-significant. Thus, the contrasts do not support a consistent hierarchy among modern cooking sources across the two ordinal outcomes (Annex Table 6).

4.2.4. How does cooking energy relate to chronic illness?

In the adjusted model for chronic illness, a limited number of cooking sources differ statistically from solar-based electricity, and no coherent or graded hierarchy emerges across technologies. Gas use (OR = 1.25, 95% CI 1.07–1.45) and traditional fossil/biomass stoves (OR = 1.43, 95% CI 1.10–1.85) are associated with a significantly higher likelihood of reporting a chronic illness. The remaining cooking sources, including grid electricity (OR = 1.01, 95% CI 0.88–1.15), generator use (OR = 0.93, 95% CI 0.83–1.04), three-stone or open fires (OR = 1.09, 95% CI 0.89–1.32), thermal solar cookers (OR = 1.04, 95% CI 0.65–1.65), and the residual "else" category (OR = 1.51, 95% CI

0.92–2.48), do not differ significantly from solar-based electricity once socioeconomic and demographic factors are taken into account.

The pattern of point estimates is non-monotonic, and the magnitude and statistical significance of several associations change after covariate adjustment. The findings therefore do not support a stable gradient of chronic illness across cooking technologies. Moreover, comparisons with the unadjusted models show that the magnitude and significance of these associations are sensitive to covariate adjustment, underscoring the strong role of socioeconomic and contextual factors in shaping chronic morbidity.

Overall, chronic illness emerges as a less differentiated and more indirect association in relation to current cooking source in this setting. In contrast to perceived harm, where biomass-based cooking shows pronounced differences, associations with chronic illness are smaller, less stable, and contingent on model specification. This pattern suggests that chronic illness reflects a more cumulative and institutionally mediated dimension of health, shaped by long-term exposure histories, healthcare access, and life-course conditions, rather than the lived experience of everyday cooking practices alone.

4.3. Robustness and interaction tests

Further robustness and diagnostic checks were conducted to assess the stability of the main associations. Proportional-odds diagnostics indicated some global deviations, particularly for safety. However, Brant diagnostics across the 20 imputed datasets showed that these deviations were not concentrated in the focal cooking-source contrasts once covariates were included. In the adjusted models, none of the focal cooking-source tests indicated a violation at $p < .05$ for self-rated health (0/140 tests) or perceived safety (0/140 tests). Deviations were instead more visible in global diagnostics and in some control variables. Additional checks did not indicate major multicollinearity or influential-case patterns that would invalidate the substantive interpretation. These checks support the stability of the reported associations, while limitations related to sampling, imputation and standard-error estimation remain relevant for interpreting statistical precision.

To assess whether the results were affected by the specific role of generator-based electricity, all models were re-estimated excluding this category. Generator-based electricity combines electric cooking at the point of use with potentially polluting forms of electricity generation and could therefore blur distinctions between clean and polluting energy pathways. Excluding this category did not materially alter the findings.

Furthermore, interaction terms between gender and cooking source were tested to examine whether associations differed by gender, given women's theoretically plausible greater exposure to cooking smoke. Exploratory interaction models suggested some gender-specific differences in the association between cooking source and chronic illness, particularly for grid electricity, gas and open fire. In these categories, female participants showed a higher likelihood of reporting chronic illness than male users. However, these patterns were not the focus of the present study and should be interpreted cautiously, as the models were not designed to explain mechanisms of gendered exposure, diagnosis, or vulnerability. We therefore treat these interaction results as exploratory and as a motivation for future research rather than as a central finding.

4.4. Summary of key findings

The results of this study suggest that energy-related health inequalities are most evident in how people experience and perceive health risks associated with everyday cooking practices. Self-rated health and perceived harm differentiate more clearly and consistently across cooking energy sources than chronic illness, highlighting perceived harm as the dimension in which energy-related differences become most visible.

Across the models, solar-based electricity is associated with the most favourable self-rated health and perceived safety. However, the ranking of cooking sources beyond this reference category is diffuse. For both self-rated health and chronic illness, most modern cooking sources cluster closely together. Direct pairwise contrasts reveal several outcome-specific differences among modern cooking sources, but these differences do not form a consistent hierarchy across the two ordinal outcomes. Given the small and potentially selective solar-based electricity group, this pattern should be interpreted as a comparative association rather than as a causal technology effect.

Biomass-based cooking stands out primarily in terms of perceived harm rather than as a uniformly adverse option across all health outcomes. Users of traditional biomass stoves and three-stone fires report markedly higher levels of perceived harm, which is consistent with the direct perceptibility of smoke exposure, unstable flames, heat, odour and fire risk. By contrast, their disadvantages in self-rated health are more moderate, and associations with chronic illness are smaller, less consistent and more sensitive to covariate adjustment.

Socioeconomic and contextual factors account for part of the variation, but their influence differs by outcome. Adjusting for income, education and living conditions changes the results most clearly for chronic illness, where several odds ratios shift direction or lose significance. For self-rated health and perceived harm, the adjusted models more closely resemble the unadjusted ones, suggesting that the observed associations are not fully explained by the included covariates. Cooking energy therefore remains a meaningful correlate, particularly for perceived harm, where the disadvantages of biomass remain large after adjustment.

Taken together, the results show that cooking energy is most clearly associated with perceived harm, less consistently with self-rated health, and only weakly with chronic illness. This outcome-specific pattern motivates the broader interpretation developed in the conclusion.

5. Conclusions: lived health experience and the social case for clean cooking

This study provides one of the first harmonised cross-country analyses of how different cooking energy sources are associated with adult health and perceived well-being in Sub-Saharan Africa. Its central contribution lies in moving beyond exposure-based or purely biomedical outcomes and instead analysing health as it is lived and evaluated in relation to everyday energy use. The findings only partially support the hypothesised hierarchy of relative risk, in which electricity is expected to perform more favourably than gas or LPG, and gas or LPG more favourably than biomass. Instead, the results point to outcome-specific patterns: solar-based electricity is associated with more favourable self-reported outcomes, while biomass-based cooking stands out most clearly in perceived harm.

Although several direct differences emerge among modern cooking sources, they are outcome-specific and do not produce a consistent hierarchy across health indicators. People's evaluations of their own health and their perceptions of harm align partly with the broad divide between biomass and cleaner sources, the pattern is not a simple technological hierarchy. This suggests that cooking energy is connected to health not only through exposure, but also through how people experience safety, control, discomfort and risk in daily life.

The results also highlight the role of broader structural conditions. Reported mental health problems, income sufficiency, education and country context all show meaningful associations with the health outcomes, indicating that associations between cooking energy and health are embedded in wider socioeconomic and infrastructural conditions. Even after adjustment, however, cooking energy remains most clearly associated with perceived harm: biomass users continue to report distinctly lower safety evaluations than users of modern fuels. This pattern points to an important role for energy literacy in clean-cooking transitions. Perceived harm reflects everyday awareness of household energy risks, particularly those linked to smoke, heat, unstable flames, fuel handling and generator exhaust. Clean-cooking interventions can build on these experiential forms of knowledge rather than relying solely on technical classifications of clean and polluting fuels. By contrast, chronic illness is less clearly differentiated by current cooking source, suggesting that reported longstanding health problems reflect cumulative exposure histories, healthcare access, and broader life-course conditions rather than everyday cooking practices alone.

5.1. Limitations

Several limitations should be noted. First, the cross-sectional design restricts causal inference, and reverse causation cannot be ruled out. The study therefore does not estimate causal effects of cooking technologies, but analyses associations between cooking energy sources and different dimensions of adult health experience.

Second, the quota-based online panel design limits generalisability. As discussed in the methods section, the sample should not be interpreted as nationally representative of the adult populations of Kenya, Nigeria, South Africa and Uganda. This is particularly relevant because less digitally connected, lower-income, rural and less formally educated groups may be underrepresented and may also be more likely to depend on biomass fuels. Broad or uncertain population statistics for quota setting, especially in Uganda, further limit claims about representativeness. The findings are therefore best understood as comparative associations within the surveyed population rather than as nationally representative prevalence estimates.

Further, the use of solar-based electricity as the analytical reference category requires caution. Solar-based electricity involves no direct combustion emissions at the point of use, but access to it may be socially selective. Although the models adjust for income sufficiency, education, urban–rural environment, dwelling type, household composition, care responsibilities and country, residual selection by unobserved factors such as local infrastructure quality, electricity reliability, asset ownership or technology preferences cannot be ruled out.

Additionally, the analysis relies on respondents' reported primary cooking source and cannot fully capture fuel stacking, historical exposure, secondary fuel use or seasonal changes in cooking practices. This may blur distinctions between categories and attenuate differences between cooking sources. Both health and energy variables are also self-reported, which may introduce recall or desirability bias. At the same time, the self-reported nature of self-rated health and perceived harm is substantively meaningful for this study, because these indicators capture dimensions of health and risk that are often invisible in clinical or exposure-based datasets.

Lastly, the missing-data strategy and standard-error estimation should be considered when interpreting statistical precision. The analyses used 20 imputed datasets, with imputation methods tailored to variable type. Country-clustered robust standard errors were used for the binary chronic-illness models. For the ordered logit models of self-rated health and perceived safety, standard errors were based on conventional pooled variance estimates from multiple imputation. Country was included as a covariate in the adjusted ordinal models, but these models should not be interpreted as providing fully cluster-adjusted country-level inference.

5.2. Policy implications

The findings reinforce the relevance of clean cooking as a public health priority under SDG 7 and as an important enabler of SDG 3 (Good Health and Well-being). A central implication is the need to accelerate the transition away from traditional biomass fuels and to expand access to reliable electricity and solar-electricity-based cooking. Strengthening access to affordable, decentralised electricity and solar solutions, particularly in rural and underserved areas, may support perceived safety and everyday well-being.

At the same time, policy needs to acknowledge the widespread reliance on transitional and mixed-fuel systems. Many households combine multiple cooking sources, including gas and generators, which create specific health and safety risks. Risk-reduction strategies such as improved ventilation standards, clear safety guidance, and community-level information on the safe use of generators can help mitigate accident and pollution risks during transitional phases of the energy transition. In addition, clean-cooking policies should invest in energy literacy around the health and safety implications of everyday cooking practices. Communication should address not only the benefits of cleaner fuels, but also practical risks related to smoke exposure, ventilation, fire safety, generator use, fuel stacking and the safe use of transitional cooking technologies.

The results further highlight the value of integrating perceived health and safety indicators into clean-cooking monitoring and evaluation frameworks. Perceived harm displays large differences between biomass-based and modern cooking sources and appears more sensitive to cooking energy than reported chronic illness. Incorporating experience-based health measures can therefore provide an early, low-cost signal of well-being inequalities that may not yet be visible in morbidity statistics.

Finally, reducing structural barriers to the adoption of clean cooking technologies remains essential. Income sufficiency, living conditions, and country context play a substantial role in shaping both health outcomes and access to cleaner energy options. Policy approaches that lower upfront costs, improve infrastructure reliability and reduce economic constraints for low-income households can support transitions away from biomass-based cooking. Linking clean-cooking initiatives with broader health, housing, and social policies can further help ensure that cleaner energy options are accessible under everyday conditions of use.

5.3. Theoretical and research implications

Future research should adopt longitudinal and mixed-method designs to better trace pathways between energy use, exposure, perception and health. Integrating pollutant monitoring with self-rated health and perceived harm measures would allow for finer calibration of exposure–perception linkages and help explain when technical improvements in cooking energy are also reflected in everyday health experience. Further research should also examine the mental health dimensions of energy poverty, such as stress and insecurity related to fuel affordability, reliability or access, to provide a more complete picture of the psychosocial burden of unclean or unreliable energy.

Rather than assuming a graded relationship between technical cleanliness and health, future work should examine threshold effects, that is, whether health-related improvements plateau once households move beyond biomass dependence. It should also investigate the social mechanisms that sustain or limit these improvements. Understanding how energy access interacts with education, income, housing, gendered care responsibilities and local infrastructure will be crucial for explaining why modern sources may yield similar outcomes once socioeconomic factors are considered.

In summary, the energy sources most favourably evaluated in everyday life are not defined by technical cleanliness alone, but by the social and infrastructural conditions in which they are used. Achieving universal access to clean cooking therefore requires more than replacing one fuel with another. It requires attention to affordability, reliability, housing conditions, safety and the ways in which people experience health and risk in daily life. This broader perspective is central for advancing environmentally sustainable, socially equitable and health-sensitive energy transitions.

CRediT authorship contribution statement

Clemens Striebing: Writing – review & editing, Writing – original draft, Supervision, Project administration, Investigation, Data curation, Conceptualization. **Yuwei Zhou:** Formal analysis. **Marco Cellini:** Writing – review & editing, Methodology. **Mona Bielig:** Writing – review & editing. **Martina Schraudner:** Writing – review & editing, Funding acquisition.

Ethical statement

Prior to commissioning the data collection to Ipsos, the research protocol underwent a formal review by the Data Protection Officer of the Fraunhofer Society. Given the inclusion of potentially sensitive data from both EU and non-EU citizens, the European Commission - acting as the project's funding body - commissioned an independent ethics review. As part of this process, a comprehensive Data Protection Impact Assessment (DPIA) was developed jointly by Fraunhofer IAO and Ipsos. The ethics review concluded positively, approving the survey design and data management procedures.

All participants were existing members of online panels owned by Ipsos or its contractual partners and took part on the basis of informed, voluntary consent. Ipsos ensured that only non-personally identifiable data were transmitted to the research team. No directly identifying information was transmitted to, collected by, or retained by the research team.

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Declaration of competing interest

We declare no competing interests.

Annex A.

Table 2 summarises the distributions of the variables used as controls in the multivariate analyses. Reported statistics are based on the raw data prior to imputation and reflect the available information for each variable.

Table 2
Descriptive statistics of control variables. Continuous variables are reported as means and standard deviations; categorical variables are reported as percentages and frequencies. All results were calculated using the raw, pre-imputation data. Percentages are based on valid responses for the respective variable; therefore, denominators vary because of item non-response.

Variable		M (SD) / %	Range	N
Age		32.09 (9.951)	18–75	10,637
Gender	Women	46.5	–	4942
	Men	53.5	–	5695
				10,637
Income perception		2.41 (0.974)	1–4	10,456
Urban/rural environment		5.28 (1.606)	1–7	10,526
Education level	Low education	5.2	–	549
	Medium education	30.3	–	3224
	High education	64.5	–	6864
				10,637
Dwelling	Separate House (Bungalow)	20.8	–	2182
	Semi-detached house	10.0	–	1045
	Flat / apartment	37.1	–	3882
	Compound house (separate rooms, sharing facilities)	20.0	–	2091
	Huts / Buildings (share compound)	4.1	–	433
	Huts / Buildings (private compound)	2.5	–	267
	Tents	0.4	–	43
	Improvised home (e.g., kiosk, container)	0.8	–	81
	Living quarters attached to office / shop	1.4	–	144
	Uncompleted building	1.3	–	134
	Other, please specify:	1.6	–	172
				10,474
Household composition	Alone	16.3	–	1723
	With Parent(s) / Sibling(s)	22.6	–	2387
	With Partner	12.5	–	1317
	With Partner and children	36.5	–	3857
	With children	6.6	–	701
	With Friends / House-share	4.2	–	441
	Other, please specify:	1.2	–	131
				10,557
Diagnosed mental health problems	Yes	20.2	–	2130
	No	79.8	–	8395
				10,525
Country	Kenya	27.0	–	2874
	Nigeria	26.5	–	2820
	Uganda	22.3	–	2373
	South Africa	24.2	–	2570
				10,637
Care responsibilities	I am currently responsible for taking care of someone in need.	27.2	–	2827
	I have been responsible for taking care of someone in the past.	23.8	–	2480
	I am currently responsible for taking care of someone in need and I have been responsible in the past.	32.7	–	3408
	I have never been responsible for taking care of someone in need.	16.3	–	1695
				10,410

Note. Percentages may not sum to exactly 100.0 because of rounding. For household composition, the displayed percentages sum to 99.9, while the unrounded percentages sum to 100.0.

Table 3 reports the estimated associations from the multivariate models, shown separately for specifications without and with covariate adjustment. Results are presented for all three outcome variables, with coefficients expressed as odds ratios and corresponding uncertainty measures.

Table 3
Full model estimates for the associations between cooking source and health outcomes. Solar-based electricity is the reference category. Odds ratios are shown for models without and with covariate adjustment. N = 10,637.

		How is your health in general?					The energy use in my household does not cause any harm or risks to my health.					Do you have any chronic illness or longstanding health problem?				
Variable		Exp (B)	SE	95% CI		p	Exp (B)	SE	95% CI		p	Exp (B)	SE	95% CI		p
				LL	UL				LL	UL				LL	UL	
No controls																
Cooking source	1 Grid electricity	0.47	0.105	0.38	0.58	<0.001	0.72	0.106	0.59	0.89	0.002	1.26	0.035	1.17	1.35	<0.001
	2 Generator	0.82	0.125	0.64	1.05	0.119	0.70	0.126	0.55	0.90	0.005	0.93	0.067	0.82	1.06	0.298
	3 Gas (piped/ biogas/ LPG)	0.57	0.098	0.47	0.69	<0.001	0.62	0.100	0.51	0.75	<0.001	0.95	0.122	0.74	1.20	0.645
	4 Traditional fossil/bio stove	0.39	0.113	0.31	0.49	<0.001	0.26	0.114	0.21	0.33	<0.001	1.30	0.276	0.76	2.23	0.344
	5 Three-stone/ open fire	0.44	0.112	0.35	0.55	<0.001	0.27	0.114	0.22	0.34	<0.001	1.01	0.247	0.62	1.64	0.967
	6 Thermal solar cooker	0.75	0.207	0.50	1.13	0.173	0.59	0.202	0.40	0.87	0.009	0.84	0.257	0.51	1.39	0.504
	7 Else	0.31	0.132	0.24	0.41	<0.001	0.34	0.133	0.26	0.45	<0.001	1.71	0.184	1.19	2.45	0.004
	8 Solar-based electricity	ref.					ref.					ref.				
With controls																
Cooking source	1 Grid electricity	0.63	0.110	0.50	0.78	<0.001	0.79	0.109	0.64	0.98	0.032	1.01	0.066	0.88	1.15	0.914
	2 Generator	0.88	0.131	0.68	1.14	0.326	0.71	0.128	0.55	0.91	0.007	0.93	0.057	0.83	1.04	0.179
	3 Gas (piped/ biogas/ LPG)	0.58	0.106	0.47	0.72	<0.001	0.70	0.104	0.57	0.85	<0.001	1.25	0.078	1.07	1.45	0.005
	4 Traditional fossil/bio stove	0.54	0.123	0.43	0.69	<0.001	0.40	0.120	0.32	0.51	<0.001	1.43	0.131	1.10	1.85	0.007
	5 Three-stone/ open fire	0.63	0.122	0.49	0.79	<0.001	0.41	0.119	0.33	0.52	<0.001	1.09	0.099	0.89	1.32	0.405
	6 Thermal solar cooker	0.63	0.216	0.42	0.97	0.036	0.59	0.205	0.40	0.89	0.011	1.04	0.237	0.65	1.65	0.873
	7 Else	0.51	0.141	0.39	0.67	<0.001	0.51	0.138	0.39	0.66	<0.001	1.51	0.253	0.92	2.48	0.101
	8 Solar-based electricity	ref.					ref.					ref.				
Gender	Women	0.82	0.040	0.76	0.88	<0.001	1.20	0.039	1.12	1.30	<0.001	1.32	0.086	1.12	1.56	0.001
	Men	ref.					ref.					ref.				
Age		0.98	0.002	0.98	0.99	<0.001	1.00	0.002	1.00	1.01	0.296	1.04	0.010	1.02	1.06	<0.001
Income perception		0.71	0.022	0.68	0.74	<0.001	0.85	0.021	0.82	0.89	<0.001	1.15	0.040	1.06	1.24	<0.001
Urban/rural environment		1.08	0.013	1.05	1.11	<0.001	1.11	0.013	1.09	1.14	<0.001	0.96	0.021	0.92	1.00	0.047
Education level	Low edu	0.83	0.090	0.70	0.99	0.043	1.18	0.090	0.99	1.41	0.070	1.54	0.173	1.10	2.16	0.012
	Medium edu	0.86	0.044	0.79	0.94	<0.001	1.16	0.044	1.07	1.27	<0.001	1.05	0.021	1.01	1.09	0.027
	High edu	ref.				ref.					ref.					
Dwelling	Compound house (separate rooms, sharing facilities)	1.04	0.157	0.77	1.42	0.738	1.12	0.155	0.83	1.52	0.464	1.05	0.319	0.56	1.97	0.869
	Flat / apartment	1.02	0.157	0.75	1.39	0.883	1.07	0.154	0.79	1.44	0.679	0.91	0.329	0.48	1.73	0.767
	Huts / Buildings (private compound)	1.15	0.193	0.79	1.68	0.466	0.95	0.189	0.66	1.38	0.791	1.11	0.417	0.49	2.51	0.808
	Huts / Buildings (share compound)	1.02	0.179	0.72	1.45	0.907	0.86	0.179	0.61	1.23	0.411	1.04	0.278	0.61	1.80	0.875
	Improvised home (e.g., kiosk, container)	0.85	0.266	0.50	1.43	0.541	0.81	0.262	0.49	1.36	0.425	0.97	0.204	0.65	1.46	0.901
	Living quarters attached to office / shop	0.91	0.225	0.59	1.42	0.683	0.90	0.222	0.59	1.40	0.651	1.76	0.499	0.66	4.68	0.258

(continued on next page)

Table 3 (*continued*)

Variable		How is your health in general?					The energy use in my household does not cause any harm or risks to my health.					Do you have any chronic illness or longstanding health problem?				
		Exp (B)	SE	95% CI		p	Exp (B)	SE	95% CI		p	Exp (B)	SE	95% CI		p
				LL	UL				LL	UL				LL	UL	
	Semi-detached house	0.96	0.162	0.70	1.32	0.799	0.94	0.161	0.68	1.29	0.693	1.05	0.360	0.52	2.12	0.899
	Separate House (Bungalow)	1.01	0.157	0.74	1.38	0.939	1.09	0.154	0.81	1.48	0.569	1.04	0.311	0.57	1.91	0.899
	Tents	0.73	0.344	0.37	1.43	0.361	0.72	0.326	0.38	1.37	0.316	2.37	0.515	0.86	6.49	0.094
	Uncompleted building	0.97	0.230	0.62	1.52	0.893	1.19	0.224	0.77	1.84	0.441	1.18	0.407	0.53	2.63	0.678
	Other, please specify:	ref.				ref.					ref.					
Household composition	Alone	1.03	0.182	0.72	1.47	0.881	1.19	0.174	0.85	1.68	0.312	1.13	0.218	0.73	1.73	0.584
	With children	0.94	0.191	0.64	1.36	0.727	1.18	0.183	0.82	1.69	0.369	1.13	0.109	0.91	1.40	0.267
	With Friends / House-share	0.76	0.199	0.51	1.12	0.168	1.14	0.191	0.79	1.66	0.480	0.96	0.261	0.58	1.60	0.872
	With Parent(s) / Sibling(s)	0.78	0.181	0.55	1.11	0.169	1.26	0.172	0.90	1.77	0.177	1.21	0.248	0.74	1.97	0.443
	With Partner	0.96	0.185	0.67	1.38	0.813	1.29	0.176	0.91	1.82	0.147	1.02	0.264	0.61	1.70	0.951
	With Partner and children	1.01	0.179	0.71	1.44	0.941	1.29	0.171	0.92	1.80	0.138	0.87	0.186	0.61	1.26	0.464
	Other, please specify:	ref.				ref.					ref.					
Diagnosed mental health problems	Yes	0.43	0.049	0.39	0.47	<0.001	0.78	0.046	0.71	0.86	<0.001	4.52	0.180	3.18	6.42	<0.001
	No	ref.				ref.					ref.					
Country	Kenya	1.12	0.067	0.98	1.27	0.098	0.88	0.065	0.78	1.00	0.048	0.50	0.043	0.46	0.55	<0.001
	Nigeria	2.18	0.067	1.91	2.48	<0.001	1.15	0.065	1.02	1.31	0.028	0.49	0.035	0.45	0.52	<0.001
	Uganda	0.98	0.070	0.86	1.12	0.780	0.71	0.068	0.62	0.81	<0.001	0.78	0.126	0.61	1.00	0.051
	South Africa	ref.				ref.					ref.					
Care responsibilities	Am currently responsible	1.16	0.062	1.03	1.31	0.018	0.94	0.061	0.83	1.05	0.273	1.00	0.029	0.95	1.06	0.963
	Have been responsible in the past	1.00	0.062	0.88	1.13	0.970	0.86	0.061	0.77	0.970	0.015	1.02	0.042	0.94	1.11	0.641
	Am currently responsible and have been responsible in the past	1.22	0.060	1.08	1.37	<0.001	0.94	0.059	0.84	1.06	0.298	1.11	0.042	1.02	1.20	0.016
	Have never been responsible	ref.				ref.					ref.					

Note. N = 10,637. Values are odds ratios, Exp(B), with standard errors, 95% confidence intervals, and p values. Solar-based electricity is the reference category. Self-rated health and perceived safety were estimated using pooled ordered logit models; chronic illness was estimated using binary logistic regression with country-clustered robust standard errors. The latter should be interpreted cautiously given the small number of country clusters. Adjusted models control for age, gender, income perception, urbanity, education, dwelling type, household composition, diagnosed mental health problems, country, and care responsibilities. Urbanity is modelled metrically. Special missing codes were set to missing. Ordered-logit thresholds/cutpoints are omitted. CI = confidence interval; SE = standard error of the unexponentiated log-odds coefficient; Ref. = reference category (OR = 1).

Table 4
Brant proportional-odds diagnostics by outcome, model specification and term type.

Outcome	Model specification	Term type	No. of tests	No. significant	% significant	Minimum p	Median p
Perceived safety	No controls	Focal cooking-source contrast	140	60	42.9	<0.001	0.164
	No controls	Global test	20	20	100.0	<0.001	<0.001
	With controls	Covariate/control	580	142	24.5	<0.001	0.246
	With controls	Focal cooking-source contrast	140	0	0.0	0.106	0.250
	With controls	Global test	20	20	100.0	<0.001	<0.001
Self-rated health	No controls	Focal cooking-source contrast	140	0	0.0	0.110	0.624
	No controls	Global test	20	0	0.0	0.281	0.311
	With controls	Covariate/control	580	140	24.1	<0.001	0.433
	With controls	Focal cooking-source contrast	140	0	0.0	0.205	0.863
	With controls	Global test	20	8	40.0	<0.001	0.401

Note. Brant diagnostics were conducted separately in each of the 20 imputed datasets. "No. of tests" denotes the total number of tests across the imputed datasets, "No. significant" denotes the number of tests with $p < .05$, and "% significant" denotes the corresponding percentage. Focal cooking-source contrasts are the coefficients for the cooking-source categories relative to the solar-based electricity reference category. Covariate/control refers to the adjustment variables included in the adjusted models. The global test is the omnibus Brant test of the proportional-odds assumption for the complete model. In the adjusted ordered-logit models, none of the focal cooking-source contrasts showed a significant proportional-odds violation at $p < .05$. Significant global tests in these models therefore reflect violations associated with one or more control variables rather than with the focal cooking-source contrasts.

Table 5
Counts of primary cooking sources by country in the pre-imputation analytic sample.

Country	Grid electricity	Generator electricity	Gas (piped/biogas/ LPG)	Traditional fossil/bio stove	Three-stone/ open fire	Thermal solar cooker	Else	Solar-based electricity
Kenya	149	81	2021	189	291	28	70	45
Nigeria	230	132	1966	111	136	49	52	144
Uganda	186	40	725	582	536	13	253	38
South Africa	1237	323	574	63	71	20	58	224

Note. Values are counts from the raw, pre-imputation analytic sample, restricted to respondents in the four Sub-Saharan African countries with valid information on their primary cooking source (N = 10,637). LPG = liquefied petroleum gas. Solar-based electricity served as the analytical reference category in the regression models.

Table 6
Post-hoc pairwise Wald contrasts among modern cooking sources in the adjusted ordered-logit models.

Outcome	Comparison	log (OR)	SE	OR	95% CI, lower	95% CI, upper	p
Self-rated health	Grid electricity vs Generator electricity	−0.341	0.098	0.71	0.59	0.86	<0.001
	Grid electricity vs Gas (piped/biogas/LPG)	0.073	0.062	1.08	0.95	1.22	0.242
	Grid electricity vs Thermal solar cooker	−0.015	0.199	0.99	0.67	1.46	0.941
	Generator electricity vs Gas (piped/biogas/LPG)	0.414	0.094	1.51	1.26	1.82	<0.001
	Generator electricity vs Thermal solar cooker	0.326	0.211	1.39	0.92	2.09	0.122
	Gas (piped/biogas/LPG) vs Thermal solar cooker	−0.088	0.194	0.92	0.63	1.34	0.650
Perceived safety	Grid electricity vs Generator electricity	0.114	0.095	1.12	0.93	1.35	0.233
	Grid electricity vs Gas (piped/biogas/LPG)	0.130	0.061	1.14	1.01	1.28	0.032
	Grid electricity vs Thermal solar cooker	0.289	0.187	1.33	0.92	1.93	0.123
	Generator electricity vs Gas (piped/biogas/LPG)	0.017	0.091	1.02	0.85	1.21	0.854
	Generator electricity vs Thermal solar cooker	0.175	0.199	1.19	0.81	1.76	0.377
	Gas (piped/biogas/LPG) vs Thermal solar cooker	0.159	0.182	1.17	0.82	1.67	0.383

Note. Post-hoc Wald contrasts compare grid electricity, generator electricity, gas, and thermal solar cookers in the adjusted ordered-logit models for self-rated health and perceived safety associated with household energy use. Estimates were pooled across all 20 imputed datasets. log(OR) = log odds ratio; SE = standard error; OR = odds ratio; CI = confidence interval; LPG = liquefied petroleum gas. An OR greater than 1 indicates higher odds of being in a higher outcome category for the first cooking source listed in the comparison relative to the second; an OR below 1 indicates lower odds. The contrasts are reported descriptively to examine whether the modern cooking sources form a consistent hierarchy beyond comparisons with the solar-based electricity reference category.

Data availability

The dataset used in the current study is available via Zenodo at https://doi.org/10.5281/zenodo.19224110. The R script used for the analyses is available from the authors upon reasonable request.

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