



Fuel-based lighting and under-five morbidity in semi-rural Mozambique: A cohort study

Ariadna Curto^{a,b,c,1}, Jovito Nunes^{a,d,1}, Fabián Coloma^{a,b}, Stefan Sieber^{a,b},
 Herminio Cossa^d, Teodimiro Matsena^d, Aura Hunguana^d, Charfudin Sacoor^d,
 Edgar Jamisse^d, António Siteo^d, Quique Bassat^{d,e,f,g,h}, Francisco Saute^d, Cathryn Tonne^{a,b,d,h,*}

^a ISGlobal, Barcelona, Spain

^b Universitat Pompeu Fabra (UPF), Barcelona, Spain

^c Health Research Institute of the Balearic Islands (IdISBa), Palma, Spain

^d Centro de Investigação em Saúde de Manhiça (CISM), Maputo, Mozambique

^e ISGlobal, Hospital Clínic - Universitat de Barcelona, Barcelona, Spain

^f Institutí Catalana de Recerca i Estudis Avançats (ICREA), Barcelona, Spain

^g Pediatric Infectious Diseases Unit, Pediatrics Department, Hospital Sant Joan de Déu, University of Barcelona, Barcelona, Spain

^h CIBER Epidemiología y Salud Pública (CIBERESP), Madrid, Spain

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ABSTRACT

Background: Mozambique has one of the lowest electrification rates in the world, leaving its population dependent on polluting fuels for lighting. Limited epidemiological evidence links fuel-based lighting to child health. We examined associations between polluting lighting sources, particularly kerosene, and under-five morbidity in a semi-rural district in Mozambique.

Methods: We constructed a birth cohort from demographic and hospital-based pediatric morbidity surveillance data. We included children born in Manhiça district between January 1, 2016, and December 31, 2020. The most common lighting source (polluting vs clean) used during follow-up was used as exposure. The outcome was the frequency of all-cause and respiratory-linked hospital visits in any of the seven surveilled health facilities within the district. We used zero-inflated negative binomial regression models to calculate Rate Ratios (RR) adjusted for potential confounders at the child, mother, and household level.

Results: We included 17,815 under-five children (49% female) living in 13,574 households. Nearly a quarter of children (24.7%) lived in households using polluting lighting fuels. During follow-up, there were a total of 69,677 all-cause hospital visits (53% respiratory-linked). Children in households with polluting lighting had a 2% higher rate of all-cause hospital visits (RR: 1.02, 95% CI: 0.98, 1.06) and a 2% lower rate of respiratory-linked hospital visits (RR: 0.98, 95% CI: 0.94, 1.03) compared to those with clean lighting. Results were robust to sensitivity analyses testing alternative inclusion criteria based on the definition of health facility catchment area and duration of follow-up time covered by the surveillance system.

Conclusion: Polluting compared to cleaner lighting sources were not associated with hospital visits among children under five. Intervention-based research is needed to better understand the health impacts of air pollution from fuel-based lighting among children living in areas with limited access to electricity.

1. Introduction

Over 2.3 billion people worldwide rely on polluting liquid and biomass fuels for domestic energy (IEA, 2023). These polluting fuels contribute to household air pollution (HAP), a global environmental threat resulting in an estimated 2.3 million premature deaths per year

(Murray et al., 2020), corresponding to 4% of global deaths. The impact of HAP is more pronounced in sub-Saharan Africa (SSA), where approximately 80% of people live without access to electricity (IEA, 2023) and where nearly one-third of premature deaths attributed to HAP occur (GBD Results, 2019). Children younger than 5 years are particularly affected; nearly half (44%) of the premature deaths attributable to

* Corresponding author. ISGlobal, Universitat Pompeu Fabra, Doctor Aiguader 88, 08003, Barcelona, Spain. cathryn.tonne@isglobal.org

¹ Shared primary authorship.

HAP in SSA occurs in this age group (GBD Results, 2019). Pooled estimates from 35 studies indicate that exposure to HAP is associated with a 25% increase in under-five mortality (Lee et al., 2020). The use of kerosene has been discouraged by the World Health Organization (WHO) since 2014, not only due to the health concerns associated with air pollution, but also because of safety concerns related to the risk of burns, fires, and poisoning (WHO Guidelines for Indoor Air Quality, 2014).

Mozambique is one of the countries with the lowest electrification rates in the world, where 33% of the population had access to electricity in 2019, with large disparities between urban (72%) and rural areas (9%) (Naidoo, Kameshnee & Loots, Christiaan, 2020). While grid electricity, solar power, and electricity from batteries or generators are the primary lighting sources for 46% of the population, 28% of the population still relies on polluting lighting sources, including kerosene lamps. Specifically, it is estimated that in 2019, 17% of rural Mozambican households and 7% of urban households used kerosene lamps (Naidoo, Kameshnee & Loots, Christiaan, 2020). Evidence from a previous study in Mozambique showed that women using kerosene lamps have 80% higher personal exposure to black carbon (BC) compared to women using electricity (Curto et al., 2019). BC has been associated with multiple adverse health effects, notably cardiovascular (Luben et al., 2017; Magalhaes et al., 2018; Wolf et al., 2021) and respiratory (Garshick et al., 2018; Liu et al., 2021) diseases.

A modelling study conducted in Mozambique (Anenberg et al., 2017) estimated that HAP as a result of kerosene-based lighting caused 18,000 premature deaths and 696,000 disability-adjusted life years in 2015. Another study conducted in 12 East African countries, including Mozambique, indicated that 12,723 deaths could have been avoided by replacing kerosene lamps with electricity in 2015 (Ortega et al., 2021). While these health impact assessments provide an indication of the high burden of disease attributable to kerosene-based lighting, epidemiological evidence linking kerosene-based lighting to health remains scarce.

Most of the epidemiological evidence on the health effects of household kerosene usage is focused on kerosene-fuel cookstoves, which has been mainly associated with respiratory-linked morbidity in women and children (Pokhrel et al., 2010; Bates et al., 2013; Kashyap et al., 2020; Arku et al., 2020), low birth weight and neonatal death (Epstein et al., 2013; Amegah et al., 2014), and cardiorespiratory outcomes in adults (Arku et al., 2020). Unlike kerosene-fuel cookstoves, kerosene lamps are used for longer and often placed closer to individuals, increasing personal exposure to air pollutants. Results from an intervention study in rural Uganda (Aiden et al., 2018) found that users of kerosene-based lighting were exposed to lighting-related smoke for over five times longer compared to cooking-related smoke (3.3 h vs 44 min).

Despite this, no prior epidemiological studies have specifically focused on the association between the use of polluting lighting sources and under-five morbidity. This study fills this gap and provides a unique perspective on the health impacts of fuel-based lighting, which may differ significantly from those of cooking-related emissions. Further epidemiological research is needed for a comprehensive understanding of the health effects of fuel-based lighting, especially among young children.

Additionally, the majority of prior epidemiological studies have been conducted in Nepal and India (Bates et al., 2013; Epstein et al., 2013; Kashyap et al., 2020; Pokhrel et al., 2010). However, it is essential to generate evidence specific to SSA, where the number of people without access to electricity has increased by 2.5% since 2010 due to population growth (IEA, 2023). The aim of this study was to examine the associations between the use of polluting lighting sources (kerosene, candles, wood) and under-five morbidity in Manhiça district, southern Mozambique, using a population-based cohort constructed from demographic and morbidity surveillance data.

2. Methods

2.1. Study area

The study population is part of the Manhiça Health and Demographic Surveillance System (HDSS), located in Manhiça district (S-Fig. 1). Manhiça district is located about 80 km north of Maputo City, Mozambique's capital, at latitude 25° 24' South and longitude 32° 48' East. The district is in a plain surrounded by the Incomati River, covers an area of 2380 km² and has 6 administrative subdivisions (or "posts") and 16 localities. The surveillance area encompasses a mixture of rural and peri-urban communities. The Manhiça HDSS was established in 1996 by the Manhiça Health Research Centre (*Centro de Investigação em Saúde de Manhiça*, CISM) and, as of 2022, had registered over 209,000 individuals (13% children under five) as permanent residents distributed in about 48,897 households (Sacoore et al., 2023).

2.2. Study population

The study population includes children born in Manhiça district between January 1, 2016, and December 31, 2020, and registered in the HDSS. The HDSS provides data on all residents of the surveillance area on an annual basis and registers residents of Manhiça born in or living in the district for three or more months (Nhacolo et al., 2021). Most head of children's households are engaged in small businesses, subsistence farming, laborers in sugar cane plantations and sugar refining companies, and other small agriculture companies. Children mainly belong to Xichangana and Xironga ethnic groups (Sacoore et al., 2013).

2.3. Cohort

We used data linkage to construct a closed cohort. Children are given a permanent identification number (ID) through the Manhiça HDSS, which is used to link each child to their household of residence (current and previous). Children were included in the cohort if they met the following four criteria: 1) the birth of the child was recorded in the Manhiça HDSS between January 1, 2016, and December 31, 2020; 2) children had complete data on date of birth, sex, and maternal and household characteristics; 3) lighting source data were available at least once during the follow-up period for any of the households that the child lived during the follow-up period; and 4) they were living in the likely catchment area of any of the 7 health care facilities included in the surveillance system. We defined the catchment area of each health care facility by identifying children for whom a given health facility was the closest facility based on Euclidean distance from the child's household. In main analysis, we excluded 10% of children with the largest distance to a given facility, assuming that they might be more likely to visit other facilities not participating in the surveillance system. Catchment areas around each health care facility are shown in Fig. 1.

A total of 27,858 children were born during the follow-up period in the HDSS database. Of these, 2662 (9.6%) were excluded for the following reasons (S-Fig. 2): 5.6% due to invalid follow-up periods (e.g., the same start and end dates), 2.0% due to missing maternal information or because the mothers' childbearing age was outside the 12-49-year range, 0.6% due to missing household characteristics during the follow-up period or within 2 years before or after the follow-up period, and 1.3% due to unknown source of lighting during the follow-up period or within 2 years before or after the follow-up period (i.e., the head of the household responded "I don't know" when asked for the type of lighting source). From this baseline sample of 25,196 children, 29% were excluded in the main analysis because a child's nearest health facility was not included in the surveillance system or the distance from home to a health facility included in the surveillance was in the farthest 10%. We included 17,815 children in the main analysis (S-Fig. 2), of which 4682 (26%) had no hospital visits records during the follow-up period. Children contributed person-time from birth until exit of the

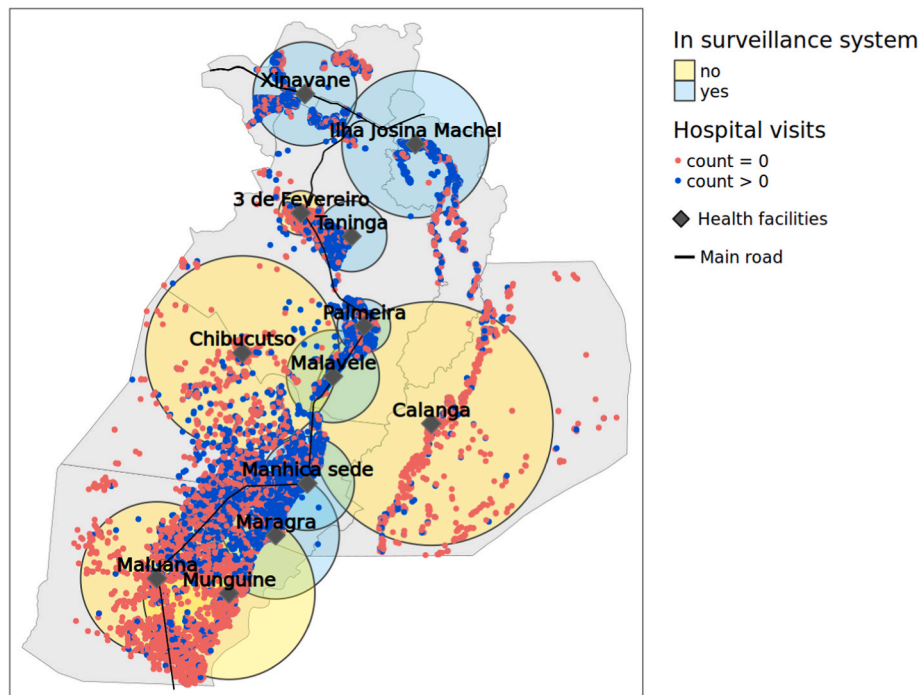


Fig. 1. Buffers representing the catchment area for each health care facility within Manhiça district. Each buffer encompasses 90% of the children for whom the health facility was the nearest facility. Facilities with blue buffers are covered in the surveillance system. Each dot represents a household. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

cohort either through 1) death ($n = 460$); 2) out-migration from the surveillance system ($n = 1598$); or 3) end of follow-up (Dec 31, 2020) ($n = 15,757$) (S-Fig. 2).

2.4. Exposure to polluting lighting sources

Our main exposure was self-reported lighting source. Primary lighting sources in the household were recorded in the HDSS household survey, which is explained elsewhere (Nhacolo et al., 2021). Briefly, the annual household update round includes all households in Manhiça district and is conducted through in-person interviews with the head of the household. Lighting source was defined as polluting if any material or device used for lighting emitted products of incomplete combustion into the air, which included candles, kerosene, and wood. Clean source of lighting was defined as any material or device with zero emission of products of incomplete combustion at point of use, which included battery, electricity, and solar panel (S-Table 1). We assigned the most frequently used primary lighting source reported during the follow-up period, meaning that households that used both electricity and fuel were classified as using electricity if it was the most commonly used source. If household survey data were unavailable during the follow-up period, we used the most recent survey conducted within two years before or after the follow-up. Secondary lighting sources to account for fuel stacking were not available.

2.5. Outcome definition

CISM runs a round-the-clock, pediatric hospital-based morbidity surveillance system, which gathers all pediatric outpatient visits on a daily basis using standardized forms. Although this surveillance does not cover all health facilities across the entire Manhiça district, it includes the two main referral hospitals (Manhiça District Hospital and Xinavane Rural Hospital) along with 5 peripheral health care centers (S-Fig. 1). Since its initiation in 1998, the surveillance system has not always included all these 7 health facilities; Xinavane Rural Hospital was only integrated into the system in January 2019.

We used the pediatric outpatient questionnaire (version OPD5) dataset from the pediatric hospital-based morbidity surveillance system collected from January 1, 2016, to December 31, 2020. We used frequency of hospital visits by all-cause and respiratory-linked causes based on the tenth revision of the International Classification of Diseases (ICD-10) codes. Up to 4 diagnoses are possible per visit. We defined respiratory-linked visits as those where any diagnoses were respiratory-linked (S-Table 2), including both infectious respiratory illnesses (e.g., bronchiolitis, acute [upper or lower] respiratory infection, pneumonia), and non-infectious respiratory diseases (e.g., chronic lower respiratory diseases). To ensure accurate representation of hospital events, visits for the same diagnosis occurring within a 2-day period were counted as the same visit.

2.6. Covariates

We identified potential confounders based on a directed acyclic graph (S-Fig. 3) and by identifying variables that were associated with lighting fuel source and predictors of hospital visits and not caused by lighting source. Our covariates included the following: i) children's age at the end of follow-up (continuous in months); ii) children's sex (binary); iii) year of entry into the cohort or year of birth (categorical); iv) household Socioeconomic position (SEP) (3-level categorical); v) Euclidean (or straight) distance to the nearest 7 healthcare facilities (continuous, in km) and to the nearest major road or National Road number 1 (S-Fig. 1), connecting the south and north of the country (continuous, in km); vi) mother's age at birth of the child (continuous in years); vii) mother's education at birth of the child (3-level categorical), and viii) healthcare facility indicator (7-level categorical). SEP was constructed with a set of variables representing durable household assets (TV, radio, livestock, car, tractor, etc.), the construction materials of the walls and floor of the household, and the characteristics of the cooking and sanitation facilities (kitchen type, water source, etc.) using multiple correspondence analysis (Howe et al., 2012). We used the most frequent value of SEP and household derived variables recorded during the follow-up period or within two years before or after the follow-up.

2.7. Statistical analysis

We used frequencies and percentages to describe the study population and their maternal and household characteristics according to lighting source (polluting vs clean). In the main analysis, we investigated the association between lighting source and hospital visits using a zero-inflated negative binomial (ZI-NB) regression model to account for overdispersion due to the high number of zero counts (i.e. child with no hospital registries during follow-up) (S-Fig. 4). All models included follow-up time (in days) as a logarithmic offset. Results are reported as adjusted Rate Ratios (RR) for all-cause and respiratory-linked hospital visits with 95% confidence intervals (95% CI). We sequentially adjusted for potential confounders: model 1 adjusting for child sex, and following models further adjusting for household SEP (model 2), distance to the nearest healthcare facility and main road (model 3), health facility indicator (model 4), year of birth of the child (model 5), and maternal education and age at birth of the child (model 6, fully-adjusted).

We performed several sensitivity analyses to assess the impact of the definition of the cohort inclusion criteria. First, we assessed alternative definitions of health facility catchment areas (Fig. 1). Expanding the catchment area increases the number of children captured by the surveillance system who visited surveilled facilities, but also raises the risk of including children who had zero hospital visits because they lived too far or attended facilities not part of the surveillance system. We therefore considered catchment areas covering 95% and 100% of the children living closest to one of the 7 health care facilities in the surveillance system. Second, we excluded children whose nearest health care facility was Xinavane Rural Hospital, since it was incorporated later in the surveillance system. Third, we tested sensitivity to the proportion of follow-up time children could spend outside the surveillance area due to temporary out-migration by excluding children whose migration-to-follow-up time ratio was greater than 0.5. Additionally, we performed four sensitivity analyses to ensure the robustness of our findings by 1) removing the potential effect of the COVID-19 pandemic by ending the follow-up time on December 31, 2019, 2) accounting for children living in the same household by adding a random effect for household, 3) excluding the 2335 children who did not exclusively use clean lighting sources during the follow-up, and 4) restricting the analysis to children whose households used polluting cooking fuels or firewood as a specific cooking fuel.

Data management and analyses were done using R, version 4.1.3. The R packages used for these tasks included *dplyr* (Wickham et al., 2023), *tidyr* (Wickham et al., 2024), *lubridate* (Grolemund and Wickham, 2011), *epitools* (Aragon, 2020), and *pscl* (Zeileis et al., 2008).

3. Results

Details of the study population are presented in Table 1. Of the 17,815 children included in the cohort for main analysis, 7629 (42.8%) lived in the same household, including a total of 13,574 households. Most children (66%) lived in households that used electricity as the primary lighting source during follow-up, while nearly a quarter (24.7%) used polluting lighting sources.

The mean age of children at the end of follow-up/censoring was 2.3 years and approximately half were female. The mean maternal age at birth of the child was 25 years. Compared to children living in households using clean lighting sources, children living in households using polluting lighting sources had a higher percentage of mothers with no education (21.8% vs 9.5%) and low household SEP (70.6% vs 14.6%).

Children lived on average 2.4 km from the nearest surveilled health care facility. Manhiça (28%) and Maragra (21%) were the most frequently visited health care facilities by the children included in the cohort. Those using polluting lighting sources were an average of 0.4 km and 0.6 km further away from healthcare facilities and the main road, respectively, compared to those using clean lighting sources. In the cohort definition used in the main analysis, the distance between

Table 1

Characteristics of cohort children included in main analysis (n = 17,815), their mothers, and household environment stratified by primary lighting source.

	Children	Polluting lighting source	Clean lighting source
N	17,815	4405	13,410
Children			
Age at end of follow-up/censoring (years), mean ± SD	2.29 ± 1.45	2.33 ± 1.49	2.28 ± 1.44
Sex, female, n (%)	8873 (49.81)	2190 (49.72)	6683 (49.84)
Duration of follow-up (months), mean ± SD	27.48 ± 17.38	27.99 ± 17.84	27.31 ± 17.23
Number of all-cause hospital visits per child, median ± IQR	2.0 ± 6	2.0 ± 6	2.0 ± 6
Number of respiratory-linked hospital visits per child, median ± IQR	1.0 ± 3	1.0 ± 3	1.0 ± 3
Mother			
Age at birth of the child (years), mean ± SD	25.04 ± 7.09	25.25 ± 7.44	24.97 ± 6.97
Education, n (%)			
No education	2235 (12.55)	960 (21.79)	1275 (9.51)
Primary	15,437 (86.65)	3444 (78.18)	11,993 (89.43)
Secondary	143 (0.8)	1 (0.02)	142 (1.06)
Household			
Socioeconomic position, n (%)			
High	7398 (41.53)	120 (2.72)	7278 (54.27)
Medium	5348 (30.02)	1174 (26.65)	4174 (31.13)
Low	5069 (28.45)	3111 (70.62)	1958 (14.6)
Health facility, n (%)			
Manhiça Sede	4901 (27.51)	723 (16.41)	4178 (31.16)
Xinavane	3267 (18.34)	628 (14.26)	2639 (19.68)
Malavele	946 (5.31)	292 (6.63)	654 (4.88)
Maragra	3683 (20.67)	867 (19.68)	2816 (21)
Ilha Josina Machel	1083 (6.08)	570 (12.94)	513 (3.83)
Taninga	1022 (5.74)	489 (11.1)	533 (3.97)
Palmeira	2913 (16.35)	836 (18.98)	2077 (15.49)
Distance to the nearest health care facility in surveillance (km), mean ± SD	2.38 ± 1.36	2.68 ± 1.49	2.28 ± 1.3
Distance to main road (km), mean ± SD	1.73 ± 1.7	2.20 ± 2.02	1.58 ± 1.56

households and the nearest health facility (from north to south) was 5.3 km for Xinavane, 7.5 km for Ilha Josina Machel, 3.6 km for Taninga, 2.7 km for Palmeira, 4.8 km for Malavele, 4.9 km for Manhiça Sede, and 6.6 km for Maragra.

Main results are presented in Fig. 2 and S-Table 3. A total of 69,677 all-cause child hospital visits were recorded from 2016 to 2020, with half of them (37,339; 53%) being respiratory-linked. Among the respiratory-linked visits, 39% were attributed to bronchitis. Household SEP was the most influential confounding variable in sequential adjustment (+5.3% change in the estimate compared to model 1), followed by surveilled health care facility (−3.9% change in the estimate compared to model 3). In the fully-adjusted model (model 6), the rate of all-cause and respiratory-linked hospital visits among children living in households with polluting lighting sources was 2% higher (RR: 1.02, 95% CI: 0.98, 1.06) and 2% lower (RR: 0.98, 95%CI: 0.94, 1.03), respectively, compared to children living in households using clean lighting.

In sensitivity analyses, results remained unchanged when adjusting

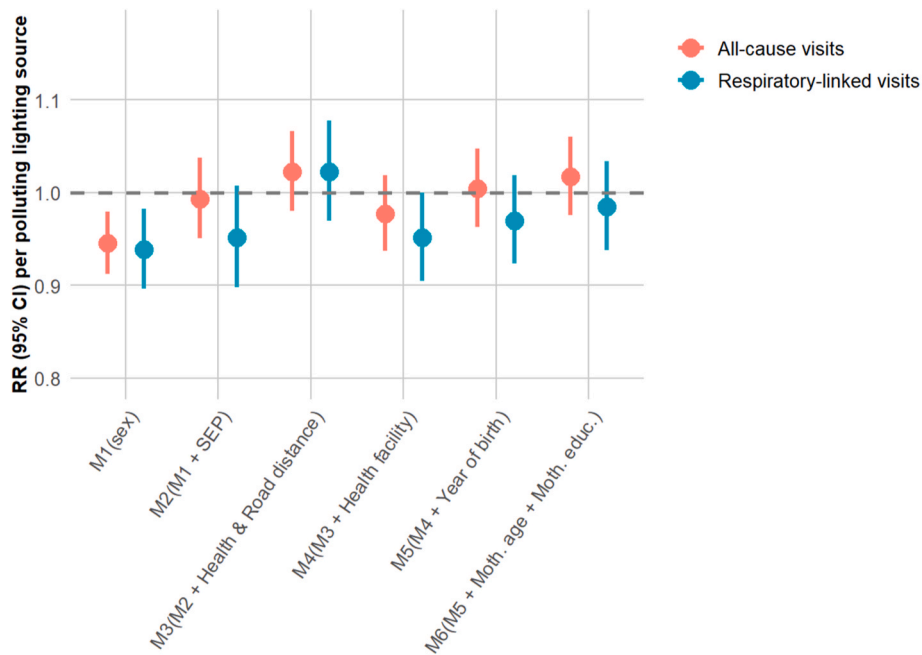


Fig. 2. Relative risks (RR) and 95% Confidence intervals (CI) between self-reported use of polluting lighting sources and all-cause and respiratory-linked hospital visits among children under five in Manhiça district included in main analysis (n = 17,815).

M1- Model 1: child sex.

M2- Model 2: Model 1 + household socioeconomic position (SEP).

M3- Model 3: Model 2 + distance to the nearest healthcare facility + distance to the main road.

M4- Model 4: Model 3 + surveilled healthcare facility indicator.

M5- Model 5: Model 4 + calendar year of birth of the child.

M6- Model 6 (fully-adjusted model): Model 5 + maternal age at birth of the child + maternal education.

the catchment area to include 95% (model S1) and 100% (model S2) of the children in the baseline sample (Fig. 3 and S-Table 4). Excluding the Xinavane health care facility from the main analysis (model S3), which was incorporated into the surveillance system later than the other facilities, also did not affect the results. Lastly, the findings were consistent

when using a more conservative exclusion criteria based on time spent outside the surveillance system (model S4).

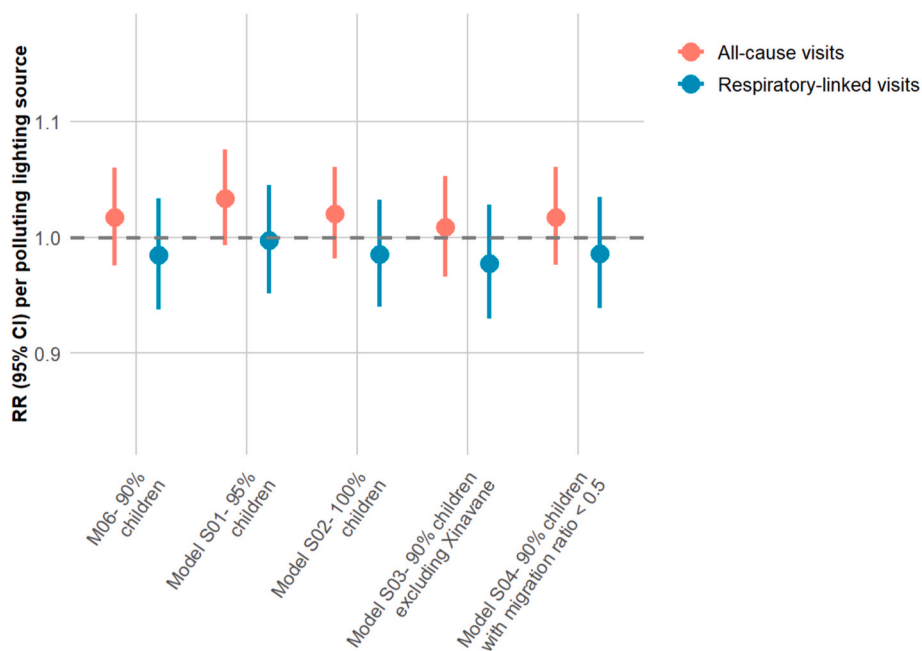


Fig. 3. Relative risks (RR) and 95% Confidence intervals (CI) between the use of polluting lighting sources and all-cause and respiratory-linked hospital visits among children under five in sensitivity analyses.

See S-Table 4 for a full description of the meaning of each model.

4. Discussion

This population-based cohort study of children under 5 years living in Manhiça district resulted in several key findings. First, the use of polluting lighting sources (kerosene, candles, wood) was not associated with child hospital visits. Second, household SEP and the surveilled health facility visited by the children were the most influential confounders in the analysis, as they made the biggest difference in the estimates after adjustment. Third, multiple sensitivity analyses showed that the results were robust, regardless of the catchment area definition and allowing for a more conservative exclusion criteria based on the proportion of time children may have spent outside the surveillance system.

Few epidemiological studies have studied the independent health effects of polluting lighting sources like candles (Soppa et al., 2014; Shehab and Pope, 2019; Loft et al., 2022) and kerosene (Acharya et al., 2015; Lakshmi et al., 2013; Pokhrel et al., 2010). Research on candle exposure primarily comprises experimental studies conducted with healthy volunteers to assess short-term air pollution effects (Shehab and Pope, 2019; Soppa et al., 2014), as well as observational studies conducted in North European countries examining candle use during wintertime (Loft et al., 2022). Most of the research on domestic kerosene exposure has focused on kerosene-based cooking in low- and middle-income countries (LMICs) (Arku et al., 2020; Bates et al., 2013; Epstein et al., 2013; Kashyap et al., 2020), with kerosene not always categorized as a high-polluting fuel (Amegah et al., 2014).

There are only few studies that explored the use of kerosene-based lighting sources on health. Kerosene-based lighting has been previously linked to pulmonary tuberculosis (TB) in women (Pokhrel et al., 2010), acute lower respiratory infections (ALRI) in children under five (Acharya et al., 2015), and stillbirth (Lakshmi et al., 2013). The case-control study conducted by Pokhrel and colleagues involving 375 women from Nepal was the first to conclude that kerosene combustion is a risk factor for TB (Pokhrel et al., 2010). Another case-control study involving 214 children from Nepal observed that the use of kerosene lamps, as opposed to electricity, was associated with an increase of ALRI among children under five (Odds Ratio: 1.4) (Acharya et al., 2015). Additionally, a survey-based study conducted among 188,917 respondents representing all districts in India, found that women using kerosene as the primary source for lighting were at 15% higher risk of delivering a stillbirth than those using liquefied petroleum gas/electricity (Lakshmi et al., 2013). This highlights the scarcity of epidemiological studies aimed at quantifying the effects of fuel-based lighting, especially in SSA countries like Mozambique where access to electricity remains limited in many areas.

We did not find an association between polluting lighting sources, mostly kerosene (80%), and a decrease in hospital visits among children under five. This could be due to factors such as under-ascertainment of cases and residual confounding related to health-seeking behaviors. We found that 26% of the children in the cohort had no records of hospital visits, suggesting that either these children did not get ill during the follow-up (structural zero) or if they did, they did not seek medical attention (under-ascertainment of cases in the passive surveillance system) or they did seek medical attention but the event was not captured by the surveillance system (underreporting of cases). While the structural zeros are the source of the zero inflation and accounted for by the binomial component of the ZI-NB (Blasco-Moreno et al., 2019), the under-ascertainment and underreporting, however, cannot be fully accounted for by the models. To mitigate this, we conducted multiple sensitivity analyses using different catchment area sizes. As the catchment area expands, the number of children who visited a health facility in the surveillance system during follow-up increases, but it also increases the number of children with zero hospital visits; either due to under-ascertainment (not seeking medical attention) or because they sought care at facilities not covered by the surveillance. Several factors may influence the likelihood of sub-Saharan African mothers to seek

medical care for their children, including child age, child order, birth size, and mother's age, socioeconomic status, education, and employment status (Adedokun and Yaya, 2020). In Mozambique, local cultural beliefs and practices also play an important role, such as beliefs in supernatural forces or "magic" and consulting traditional healers, what is locally known as "curandeirismo" (Takeyama et al., 2022). Further research in the area could incorporate the role of "curandeirismo" to better understand how traditional practices and beliefs may affect healthcare-seeking behaviors and reporting accuracy in maternal and child health data. Another possible explanation for the observed null associations is the self-reported exposure data collected through a routine household questionnaire not focused explicitly on household energy use. While relatively easy to collect in a large cohort, this exposure assessment approach is likely to lead to exposure measurement error that could bias associations towards the null.

Although we observed no association between polluting lighting fuel and child morbidity, the high prevalence of exposure together with the broader evidence of health effects of kerosene combustion warrant concern. As part of Sustainable Development Goal 7, access to affordable, clean household energy remains a development priority, particularly in SSA regions with limited electricity infrastructure like Mozambique. Interventions replacing fuel-based lighting have significant potential for reducing health-damaging fine particle exposure. An intervention in Kenya observed a 73% reduction in children's particle exposure after three weeks of using solar lamps (Lam et al., 2018). In contrast to cookstove interventions, such lighting alternatives may prove more feasible and encounter fewer socio-cultural barriers to sustained usage (Curto and Tonne, 2020). Expanding access to household and community-level solar is a promising way to increase access to clean electricity. National-level estimates report 14% of rural households using solar power (Naidoo, Kameshnee & Loots, Christiaan, 2020), which is quite a bit higher than the 5% reported in our study population (S-Table 1). Trends in fuel-based lighting use are uncertain, as they are not as frequently monitored as cooking sources. The use of kerosene for cooking is anticipated to decline across Mozambique and most SSA countries, mirroring trends observed from 1990 to 2010 (Stoner et al., 2021). Although urbanization and household electrification rates are on the rise in Mozambique, the continued rapid population growth may sustain the prevalence of fuel-based lighting, mirroring the trends observed in the country from 2007 to 2017 (Naidoo, Kameshnee & Loots, Christiaan, 2020). Therefore, the promotion of clean lighting sources remains a crucial public health goal. More research is essential to fully understand the health impacts of polluting lighting sources on children's health in low-income settings, and to identify how clean lighting technologies can be scaled in a way that maximizes accessibility, affordability, and health benefits.

To our knowledge, this is the first study quantifying the association between the use of polluting lighting sources and under-five morbidity. A particular strength of our study is the unique population-based cohort we constructed using data from the well-established Manhiça HDSS. This allowed us to construct a large longitudinal database recording all hospital visits over a 5-year follow-up period for each child living within the surveillance area. However, the surveillance system only covers 7 of the 15 health facilities in the district, making it difficult to identify the cohort giving rise to the hospital admissions recorded in the morbidity surveillance (Nhacolo et al., 2021). In the main analysis, we excluded most children who lived nearer to health facilities not included in the surveillance system, and results were similar in sensitivity analyses based on alternative cohort definitions. Multiple additional sensitivity analyses were conducted to address potential influences such as the COVID-19 pandemic, household clustering, the classification of children using clean lighting sources, and the role of polluting cooking fuels. The results remained consistent across all analyses (S-Table 4), further supporting the robustness of our findings.

One limitation of our study is the use of self-reported data collected through household surveys to assess exposure. Not directly measuring

exposure prevented us from deriving an exposure-response function based on continuous exposure measurement data. However, conducting personal or household exposure measurements, as opposed to annual household surveys, poses several challenges: measurements would be of limited duration and sample size due to feasibility constraints especially in a setting with geographically dispersed participants; and higher participant burden. This reliance on self-reported data may have introduced recall bias, as participants may not accurately recall or report their lighting sources over time. Such misclassification of exposure could have led to bias towards the null. Another limitation is that we used the most frequent lighting source reported during the follow-up period or, when not available, the adjacent 2 years to the follow-up period. We assumed that the lighting source remained constant throughout follow-up and years before or after. Our available data could not reliably capture households switching between polluting and clean fuels, leading to potential exposure misclassification and in underestimation of the true effects.

HAP encompasses other sources, such as cooking and heating fuels, which were not considered as co-exposures in our analysis. Although cooking fuels can be a significant HAP source and its exclusion could be considered a potential limitation, we excluded it from analysis because of the lack of variability in cooking fuel use in the study population, where 98% of children lived in households that mostly used polluting sources (firewood, charcoal, kerosene) for cooking (S-Table 1). Our results remained robust after restricting analysis to children only using polluting cooking fuels or firewood.

As an observational cohort study, we cannot rule out the potential for residual confounding, particularly related to health-seeking behaviors. Low household SEP, compared to high SEP (as shown in S-Table 3), and health care facility, both related to health-seeking behavior, were strongly associated with lower frequency of child hospital visits. The distribution of hospital visits across SEP categories shown in S-Table 5 also indicates that higher-SEP households may have better access to or utilization of healthcare services as they have slightly higher number of hospital visits. However, residual confounding may persist due to unmeasured variables such as self-medication or consulting traditional healers (or “curandeiros”) in place of conventional healthcare. The lack of additional individual-level variables, such as gestational age and birthweight, represents a limitation of our study. Other unaccounted for variables, such as household ventilation, may have contributed to our null findings. Although wall material, a proxy for ventilation, was included in our models as part of SEP, more specific variables, such as the type and number of windows, could provide a better assessment of ventilation.

Additionally, many cases of acute respiratory disease are asymptomatic or self-limited and may resolve on their own without contact with the health system or the need for treatment. Consequently, the results in this study likely underestimate the effect of polluting lighting sources on under-five morbidity, attenuating the observed associations. Finally, the cohort is composed of rural and semi-rural populations, which may limit the generalizability of the findings to urban as well as very rural populations, which often differ in terms of environmental exposures, lifestyle factors, and access to healthcare. Additionally, Manhiça, both a province and a district, is one of Mozambique’s southernmost provinces where over half of the districts have electricity access levels above the national average (Naidoo, Kameshnee & Loots, Christiaan, 2020). As a result, the Manhiça district may not fully represent the country’s overall access levels, limiting the external validity of our findings to more rural areas.

5. Conclusion

A substantial proportion of children under five years of age in a semi-rural district in Mozambique live in households using polluting lighting sources, mostly kerosene. However, we did not observe associations between using polluting compared to clean lighting sources and child

hospital visits. Nonetheless, interventions to reduce fuel-based lighting pollution remain crucial to protect health and achieve Sustainable Development Goal 7. Future studies should continue to explore the health impacts of fuel-based lighting, focusing interventions with measured exposure assessment.

CRedit authorship contribution statement

Ariadna Curto: Writing – original draft, Visualization, Validation, Methodology, Investigation, Data curation. **Jovito Nunes:** Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Fabián Coloma:** Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation. **Stefan Sieber:** Writing – review & editing, Validation, Methodology, Investigation. **Herminio Cossa:** Writing – review & editing. **Teodimiro Matsena:** Writing – review & editing, Data curation. **Aura Hunguana:** Writing – review & editing, Data curation. **Charfudin Sacoor:** Writing – review & editing, Project administration, Methodology, Funding acquisition. **Edgar Jamisse:** Writing – review & editing, Data curation. **António Siteo:** Writing – review & editing, Data curation. **Quique Bassat:** Writing – review & editing, Supervision, Funding acquisition. **Francisco Saute:** Writing – review & editing, Supervision, Funding acquisition. **Cathryn Tonne:** Writing – review & editing, Supervision, Resources, Methodology, Funding acquisition, 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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at <https://doi.org/10.1016/j.envres.2025.121199>.

Data availability

The data that has been used is confidential.

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