# A Clustering Approach to Clean Cooking Transition Pathways for low-income Households in Bangalore

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**Abstract**

Improving access to clean cooking is a key part of India's strategy to reduce energy poverty and tackle the health impacts of solid biomass fuel use. Currently policies to promote uptake of clean cooking fuels do not account for local socio-economic and cultural context. However lack of access to clean cooking is a multi-dimensional problem that requires an understanding of both socio-economic macro-scale trends, as well as household and community behaviour at a micro-scale. This study uses data science approaches to integrate quantitative and qualitative data from a survey of low-income households in Bangalore, to identify dominant socio-economic characteristics, behaviours, and decision-making that act as barriers to clean cooking across a community. Key barriers identified include awareness and access to subsidy programmes, safety concerns, as well as weak community networks. Low income households can also be adversely affected by kerosene restrictions intended to promote LPG uptake. The clean cooking transition pathways identified can support targeting of local policy interventions to address barriers to clean cooking faced by different groups of households.

*Keywords:* Cleaning cooking, India, Energy policy, Energy transition, Urban analytics, Clustering

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## 1. Introduction

Continued reliance on solid biomass cooking fuels is a facet of energy poverty in fast growing cities of the Global South that poses significant challenges to development and impacts the health of vulnerable populations (Sadath and Acharya, 2017; Parikh, 2011). Air pollution from biomass fuel combustion in urban areas has been shown to lead to greater health risks from respiratory illness and cancer (Kumar et al., 2020). Policies that promote the uptake of clean cooking are often enacted at the national level and not targeted to the needs of local communities in cities. Indeed, Malakar et al. (2018) explains that policies promoting the uptake of clean fuels can fail if they do not consider the contextual social barriers, and are simply standalone projects to promote 'modern' fuels. This is a multi-dimensional problem and cannot be tackled by top-down economic policies alone. Any top-down effort needs to be aligned and tailored to needs and constraints of local communities and household behaviours (Ravindra et al., 2019; Jenkins et al., 2020). An understanding of plausible transition pathways for energy poor urban households is needed to design effective policies to promote clean fuel uptake (van der Kroon et al., 2013).

Reliance on biomass for cooking is still widespread amongst lower income urban households in India's fast growing cities, including Bangalore. Located in the southern state of Karnataka, Bangalore is one of India's megacities and has become a hub for IT and communications industries. In the second half of the 20th century the city grew rapidly as it became an industrial centre, and attracted migrants from neighbouring towns and districts, almost 30% arriving in search of employment (Government of Karnataka, 1990). Rising land prices pushed the urban poor into squatter settlements with nearly 10% of the population in slums with no access to basic amenities, and heavily dependant on solid biomass fuels (Reddy and Reddy, 1994; Ranganathan, 2018). More recently the expansion of the city has seen a influx of migrant construction labourers. This flow of migrant labourers over time has embedded a spatial inequality amongst many lower-income communities making some of these more susceptible to being

energy poor (Bhan and Jana, 2015).

Government programmes to promote uptake of Liquefied Petroleum Gas (LPG) have focused on reducing cost barriers. For a household transitioning to LPG there are two key costs: that of the connection which includes the first cylinder and stove (between INR 3000-7000, ca. USD 40-95), and the recurring cost of refill cylinders (between INR 700-900, ca. USD 10-12). Through the recent Pradhan Mantri Ujjwala Yojana (PMUY) programme the government bore about half of these connection costs for below poverty line households (Kar et al., 2019). Additionally, households are also entitled to a subsidy of INR 200-300 (ca. USD. 3-4) per refill which is transferred to their bank account, after the upfront subsidy is recovered by the gas companies (Aggarwal et al., 2018). This takes approximately 6 to 10 refills, during which time households pay the higher non-subsidised refill costs.

Recently, studies using predictive quantitative models have investigated socio-economic determinants of adoption of LPG and electricity use in India at a macro-scale. These studies find that while income is a key determinant of clean fuel use (Filippini and Pachauri, 2004; Ekholm et al., 2010), non-income determinants such as piped water access and education (Farsi et al., 2007; Ahmad and Puppim de Oliveira, 2015; Sankhyayan and Dasgupta, 2019; Sharma et al., 2019; Gould et al., 2020), type of employment and land ownership (Sehjpal et al., 2014; Kemmler, 2007), social preferences (Ravindra et al., 2019), and distance from distributors (Sharma et al., 2020) are also decisive. More often than not such quantitative studies focus on rural households. There are also recent studies that have integrated socio-cultural and technical perspectives using Social Practice Theory (SPT) to explore the impact of community or household practices on energy transition (Khalid and Sunikka-Blank, 2017; Bisaga and Parikh, 2018). These tend to be very specific studies of a small number of households (Khosla et al., 2019), and have been mostly focused on middle-class households.

Socio-economic predictive quantitative models using large scale survey data provide insights into broad trends at a macro scale, but these models make generalised assumptions about households being rational consumers with per-

fect knowledge that are simply not true (Chunekar and Sreenivas, 2019). More importantly due to their low resolution at a district or city scale, they offer little insight into decision making and household behaviour at community and household scale. Households will often use more than one fuel, a phenomenon known as fuel stacking, and this behaviour is influenced by factors at a household and community scale. Data on such behaviours and household decision making is needed to understand transitions in residential energy use (Khosla et al., 2019). Higher resolution qualitative data in SPT studies provide insight into behaviours at a micro scale, but they focus on very specific and homogeneous case studies offering little insight into how practices and experience relate to wider socio-economic trends across the wider locality. Higher resolution quantitative and qualitative data at a city and district level is key to understanding household and community differences in clean cooking transition within the decision making context a city-scale.

Developing useful analytical tools to support policies addressing clean cooking transition in fast growing cities in India requires an approach combining qualitative and quantitative data to characterise and identify the different clean cooking transition pathways followed within communities. There is a need to better understand intra-city disparities and trends relating to clean cooking, which may have parallels in access to water and sanitation as detailed by Saroj et al. (2020). Models and analytical tools used in the Global North are not necessarily suitable (Bai et al., 2018), such models often simulate energy use based on parameters on the built environment including area, form, building age, and occupancy or simulate supply scenarios based on different energy technologies (Keirstead et al., 2012). In both cases such models rely on trends, assumptions, and relationships determined from data on cities in the Global North (Reinhart and Cerezo Davila, 2016). The reality in the Global South can be quite different, for example grid availability cannot always be assumed, and climatic differences mean that heating demand is comparatively lower. There is also poor availability of public data on the energy use of India's lowest income groups (Chunekar and Sreenivas, 2019). This is particularly an issue in urban areas which display

greater heterogeneity compared to rural areas, and thus there is a greater need for data to understand differences in energy use amongst these households. An added challenge is that while there is a large body of literature exploring purely qualitative or purely quantitative approaches to understanding clean cooking transitions, there are few attempts to meaningfully integrate these approaches.

In this paper we address this using data science methods, in particular clustering methods. Previous studies such as those by Yu et al. (2011b,a) and do Carmo and Christensen (2016) have made use of clustering methods to distinguish building occupant energy use profiles. Clustering has also proved valuable for identifying energy user profiles for electricity using smart meter data (Wei et al., 2018; Kwac et al., 2014). In other applications clustering has been used to tailor policy recommendations such as a study by Qin et al. (2019) investigating differences in drivers of carbon dioxide emissions between cities. In an Indian context a study by (Neto-Bradley et al., 2020) showed how clustering approaches could identify different types of residential gas adopter using socio-economic data, and a two stage clustering approach has been recently used to characterise residential gas use in the UK (Yuan and Choudhary, 2020).

We build on these approaches by using clustering analysis to integrate quantitative survey and qualitative interview data to identify dominant socio-economic characteristics and behaviours that act as barriers to clean cooking across a community of households within a uniform range of income. We use Bangalore as a case study to define the different clean cooking transition pathways followed by low-income households. Households surveyed represent low socio-economic backgrounds, with per capita incomes below the median income for Bangalore and mostly in the bottom quartile of incomes with a mean of 4458 INR/pp/per month (ca. USD 60). The design and features of our survey and interviews provide a unique in-depth insight into the energy practices, behaviours, and circumstances of individual households. The results show that some groups of low income households will be more at risk of failing to transition to clean cooking and face barriers of access. The variations are due to their socio-economic status, community infrastructure, and energy related behaviours, and these fea-

tures can be used to infer different transition pathways. Characterising these pathways can inform the design of tailored policy interventions to promote clean cooking transition amongst low-income households.

## 2. Methodology

As aforementioned, we developed an integrated approach to our data collection and analysis which draws strength from both quantitative survey data and qualitative household interviews to identify and characterise residential clean cooking transition pathways amongst low income households. An initial quantitative analysis is used to identify key household typologies that are selected for the in-depth interviews to gain information on practices and decision making contexts of households. The interview data is coded and categorised using a network analysis, and combined with the quantitative survey data to characterise distinct transition pathways of low-income household typologies.

### *2.1. Survey Design*

This survey was designed to gather information on socio-economic characteristics of households, fuel use, appliance ownership, decision making and energy related practices. Our survey aims to identify energy use trends and behaviours, directly addressing many of the limitations of existing nationally representative datasets such as the National Sample Surveys (NSS), Indian Human Development Survey (IHDS), and census data. In particular the survey delivers three key benefits with respect to existing national surveys:

- Resolution: By selecting specific districts and wards within cities, and surveying a statistically significant number of households in each, there will be sufficient resolution to draw comparisons between these different neighbourhoods.

- Detailed Energy Use Breakdown: Detailed questioning on energy use will enable collection of data on the patterns of energy use, the services driving these, and reasons for fuel stacking by households.

- Non-income phenomena: By asking a wide range of questions on routines, lifestyle and socio-cultural characteristics alongside the energy use and socio-economic questions, phenomena such as aspirations, time of use profiles, and convenience can be investigated.

The survey instrument was pre-tested on a small group of respondents to single out questions that were difficult to understand or were likely to be interpreted in a manner other than intended. Cognitive pre-testing was used with a sample group of 9 respondents, where respondents "think aloud" while answering questions to allow interviewers to understand how the question is being interpreted and flag problematic questions (DeMaio and Rothgeb, 1996; Krosnick, 1999).

Table 1 summarises the types of variables collected by the 142 questions of the survey instrument. An underlying criteria for the design of the survey instrument was to ensure the potential for compatibility and cross-referencing with the existing IHDS and to a lesser extent other NSSO and census data. To allow for this, a selection of 34 questions characterising the household in terms of household composition, dwelling type, caste, religion, expenditure, and education were taken from the IHDS-II (2011) survey (sections 1-4 in Table 1).

Table 1: Summary of survey data types and sections

| Section | Description of variables |
|---|---|
| 1 | Socio-cultural indicators e.g. Caste, Migration, Dwelling Type |
| 2 | Demographic indicators e.g. Age, No. of People in Household |
| 3 | Economic indicators e.g. Occupation, Income Freq., Expenditure |
| 4 | Education indicators e.g. Literacy, Years of schooling |
| 5 | Appliance Ownership e.g. Electrical appliances and cooking equipment |
| 6 | Fuel Use e.g. Fuel use magnitude, source, and availability |
| 7 | Energy Use Practices: e.g. Fuel use by activity, factors influencing decisions, time of use, acces factors. |

*2.2. Survey Sample*

Appropriate sample selection requires balancing logistical and political practicalities of conducting surveys in targeted city wards against the characteristics of the desired dataset. The method we employ to analyse household energy use is resource and data intensive, and there is a trade-off between spatial coverage and resolution (Ghiassi and Mahdavi, 2017). Since a high resolution is crucial to test and demonstrate our method, we limit this study to a sample of energy poor wards from the city of Bangalore in the southern state of Karnataka. Bangalore is a city of nearly 10 million people and features a diverse range of slums and low income households which exhibit different migration trends, living conditions, livelihoods and practices, however there is limited scholarship on these households making Bangalore a well suited city for our study (Krishna et al., 2014).

The ward level census data available for Bangalore does not contain income information, but from previous analysis of IHDS data ranges of appliance ownership, home ownership, fuel use mix for cooking and lighting, and type of employment for households likely to still be using biomass fuels were identified. Using these ranges, the 2011 census was used to select wards likely to still have significant biomass use or constitute households that have recently transitioned to clean cooking fuels. Seven wards were selected and are shown in Figure 1. These wards are of interest either for their low appliance ownership, low access to finance or home ownership, or high use of alternative cooking fuels which imply that households are at a 'tipping point', having to choose between prevalent options of biomass or a clean alternative (Bhan and Jana, 2015).

Given the mixed nature of the data collected we had to ensure the sample size was sufficiently large for both quantitative and qualitative variables. Guidance on qualitative survey sample sizes varies; following the approach of Fugard and Potts (2015) and assuming that we are interested in identifying key trends with a prevalence of 20% or more, a sample size of 20-30 household per ward is sufficient. The quantitative basis for survey sample sizing was related to desired accuracy of estimates for key quantities. Specifically, that estimates of propor-

tion of LPG users and mean values of monthly fuel use within a ward should have a +/- 10% error at a 95% confidence interval. Using data from the Indian Human Development Survey for expected proportions and means, a rounded sample size of 60 households per ward was selected, and with seven wards of interest identified this made for a total sample of 420 households (Neto-Bradley et al., 2019).

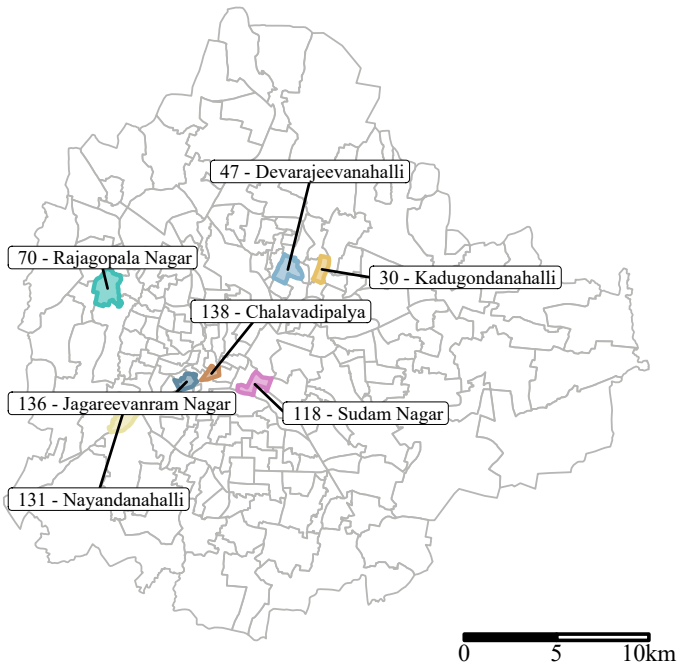



Figure 1: Bangalore city wards selected for survey sample, numbering based on 2011 Bangalore census ward map.

### *2.3. Cluster Analysis*

The data obtained from the survey is clustered to identify distinct groups of households that share common features. Variable selection was carried out to single out relevant variables, and address multi-collinearity in the dataset, which can make it difficult to identify relevant variables and quantify their effect.

Correlation coefficients were used to select variables which had a significant correlation with clean fuel use. A Farrer-Glauber test was used to identify multi-collinearity and where variables had a causal relationship, the less relevant variable was excluded from the dataset. For example, number of members of the household was selected over number of rooms. Due to the complexity of real-world problems, it is not possible to completely exclude multicollinearity, such as the case of Biomass and LPG consumption which while correlated were both key variables.

Agglomerative hierarchical clustering produced the most balanced clustering, with a Gower distance measurement to account for categorical variables in the reduced dataset (Gower, 1966), and using Ward's linkage criterion which selects clusters to merge based on the lowest lack-of-fit sum of squares (Ward, 1963). The silhouette width method was used to determine the optimum number of clusters. All analysis was performed in R using base packages (R Core Team, 2018), as well as the 'dendextend' and 'fpc' packages (Galili, 2015; Hennig, 2018).

### *2.4. Qualitative Interviews*

While the quantitative survey helped us identify the broad socio-economic characteristics of the different type of households, it cannot reveal the lived experiences of accessing clean cooking. To gain a deeper understanding of challenges and the informal methods households employ to meet their daily energy requirements, we conducted follow up qualitative interviews.

Semi-structured interviews with a separate sample of 23 households were conducted in the same seven wards. To safeguard the anonymity of the surveyed households, addresses were not collected and so it was not possible to return to specific households singled out from the survey analysis. Instead, from the seven wards where the survey was conducted a purposive sample informed by the different types of households identified in the preliminary survey analysis were interviewed. Selection of interviewees was targeted to feature a higher proportion of households representing outliers in the survey analysis. The 30 minute

semi-structured interviews allowed flexibility in identifying and discussing issues important to participants. The interviews were conducted in Kannada and Tamil and transcribed in English. Key issues addressed in the interview included household energy consumption preferences and practices, management of finances, social networks and community, and experience of local political networks.

The interviews were coded and analysed using the 'RQDA' package in R (Huang, 2018), which provided a graphical interface for the coding process and facilitated export of datasets to the R environment for analysis alongside the quantitative survey data. The coded interviews were peer-reviewed to eliminate bias of the individual researchers, and coding was then analysed to identify key themes. This coding was used to produce a correlation network, which was clustered using a simple fast-greedy clustering algorithm to identify groups of household with similar narratives of access to clean cooking (Clauset et al., 2004).

### *2.5. Inference of energy transition pathways*

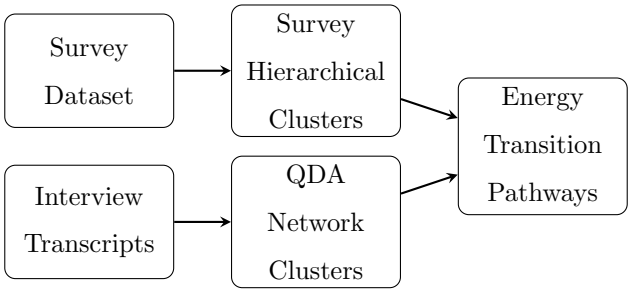



Figure 2: Overview of sources used to produce clusters and pathways

We integrate the interview and survey data in the following manner: Each interviewee is associated with a cluster resulting from their correlation network. In addition, each interviewee is also assigned to one of the survey clusters. This is done using ranked categorical interviewee characteristics extracted from the interviews to form a metadata identifying tag for each interviewee. This quantitative metadata was compared to the survey clusters using a euclidean distance

measure, and interview respondents were attributed to the survey cluster which they were closest to.

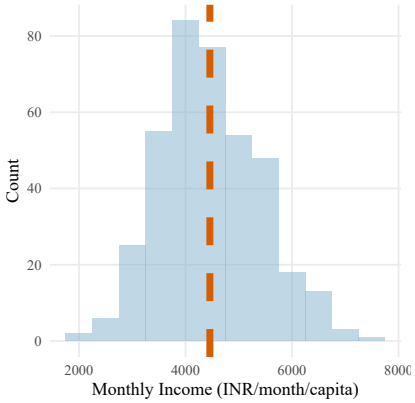
A k-means clustering algorithm was applied to this condensed data to identify groups of households with similar combinations of interview narratives and socio-economic and cultural characteristics. By analysing the mixture of constituent clusters within each group, it becomes possible to infer transition pathways that are specific to the circumstances, concerns, and practices within each group. This method aims to gain information by combining both the quantitative and qualitative data where each provides perspective on different aspects of household energy use, much in the same way that stereo-vision can provide depth perception which each individual image on its own cannot.

## 3. Results and Analysis

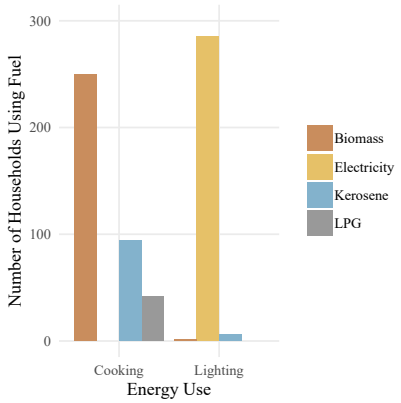
### *3.1. Descriptive Statistics*

Despite the homogeneously low income levels of households surveyed there is a wide range of socio-economic characteristics, appliance ownership, and fuel use as shown in Table 2 and Figures 3. Amongst the households surveyed the majority were either 1st, 2nd, or 3rd generation migrants to Bangalore, and just over 30% migrated to Bangalore in the last 30 years. 96% of households live in slums, with 54% living in notified slums with legal tenancy and 42% in non-notified slums without legal tenancy.

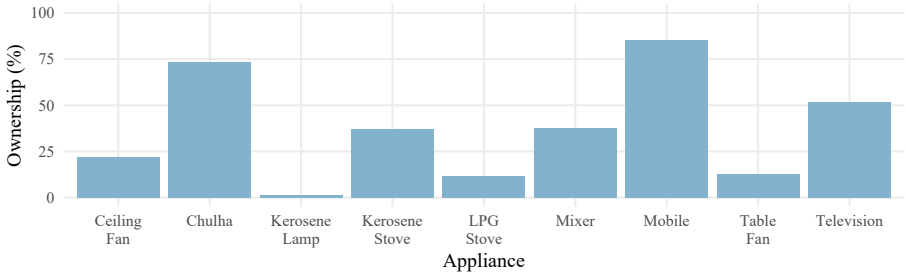
With respect to fuel use, all households use biomass for some of their cooking needs with the majority still being primarily dependant on such fuels. Over 20% use kerosene to meet some portion of their cooking needs and a mere 9% of household primarily use LPG. This is in stark contrast to lighting, where over 65% of households use electric lighting and almost no household uses kerosene or biomass - although over a third of households do not have some form of powered lighting in their homes. This distinction in level of clean fuel use for these two activities is reflected in appliance ownership. The vast majority of household's ownership of electrical powered IT appliances (particularly mobile phones) was



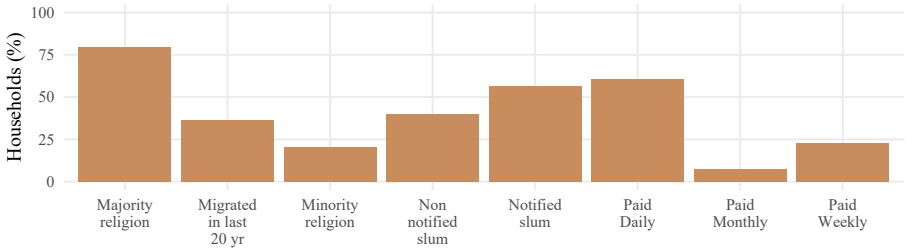

(a) Monthly per capita income distribution



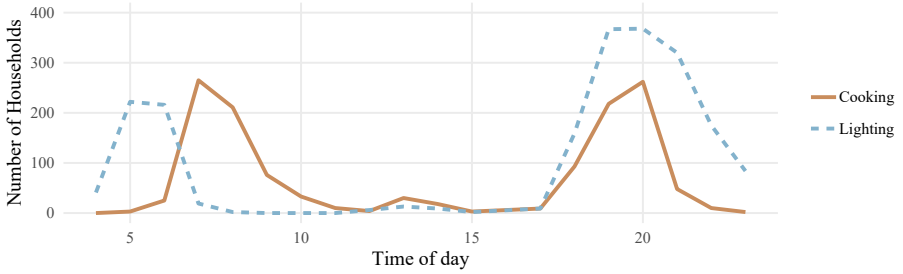

(b) Primary fuel for lighting and cooking




(c) Appliance ownership levels




(d) Socio-economic characteristics of households




(e) Time of use for cooking and lighting

Figure 3: Summary plots of key characteristics, appliance ownership, and energy use of all survey households. Note in 3 (c) a chulha is a traditional type of biomass stove.

Table 2: Descriptive statistics for continuous variables

| Independent variable | Mean | Median | Min. | Max. |
|---|---|---|---|---|
| Income per capita (INR/month) | 4458 | 4400 | 2000 | 7500 |
| Time in Place (years)[a] | 35.29 | 31.00 | 1.00 | 90.00 |
| Electricity Availability (hours/day) | 13.11 | 14.00 | 0.00 | 24.00 |
| Electricity Consumption (kWh/month) | 93.68 | 54.50 | 0.00 | 1977.40 |
| Kerosene Consumption (kWh/month) | 28.01 | 24.79 | 0.00 | 587.00 |
| Cooking appliance ownership[b] | 0.291 | 0.250 | 0.000 | 1.000 |
| IT appliance ownership | 0.685 | 0.500 | 0.000 | 1.000 |
| Hours of Cooking | 3.42 | 4.00 | 1.00 | 7.00 |
| Hours of Lighting | 5.21 | 5.00 | 1.00 | 9.00 |

[a] We followed the IHDS convention of counting years in place up to 90 years. 90 indicates a household has been in place for 90 or more years.

[b] Cooking appliance ownership of 0.000 indicates household uses open fire or 'three stones' stove.

relatively high with 82% of households owning a mobile phone, however fewer households owned a cooling equipment such as fans. For cooking appliances - only 39% of households owned a mixer and 38% owned a kerosene stove.

The time-of-use for cooking and lighting show some similarities in that for both there is a morning and evening peak with little or no daytime use (this fits with residential electricity demand profiles in other studies on India). It is curious to note however that while the evening cooking and lighting peaks coincide, the morning cooking peak lags the lighting peak by about two hours. Given that sunrise in Bangalore is usually within an hour of 6:00am, this explains why the lighting peak dwindles and indicates that households are awake and active for a while before doing any cooking.

*3.2. Survey and Interview Analysis*

Figure 4 shows the dendrogram of the agglomerative clustering in which households are split into five distinct clusters of different sizes, with three large clusters accounting for 76% of households. A further two smaller clusters of similar size account for the remaining 24% of households. While the clusters are not evenly sized they are distinct from one another. Further separation would result in less distinctive clusters, while less separation would result in a larger and more heterogeneous 4th cluster with greater in-cluster variance.

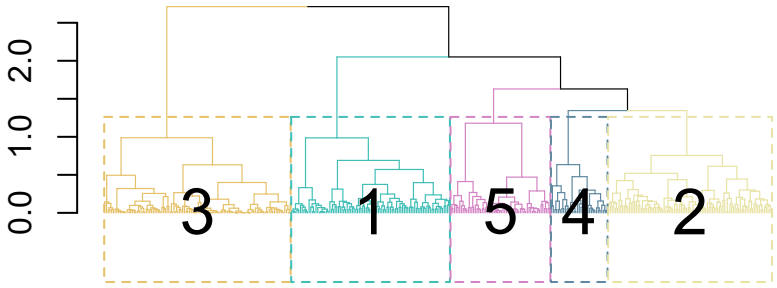



Figure 4: Dendrogram of Agglomerative Clustering Analysis with resulting five clusters identified.

The distinct subsets of households identified through the clustering show features which can be interpreted to identify possible transition behaviours, defined by distinctly different socio-cultural characteristics despite having the same financial means. Variables means for each cluster are shown in Table 3.

Alongside these distinct groups of households identified through the clustering the analysis of the 23 in-depth interviews revealed several key issues common to subsets of households. Survey clusters 3 and 5 were more heavily represented in the interview samples. Seven common issues emerged from the interviews; some of these were corroborated by findings from the survey analysis, while others were not identifiable from the survey data. These seven issues are discussed under the respective headings below.

Table 3: Descriptive statistics of the survey clusters

| Independent variable | 1 | 2 | 3 | 4 | 5 |
|---|---|---|---|---|---|
| No. of Households | 92 | 95 | 108 | 33 | 58 |
| Persons per Household | 3.6 | 3.7 | 3.6 | 4.1 | 3.9 |
| Income per capita (INR/month) | 4413 | 4216 | 4458 | 5188 | 4509 |
| Time in Place (years) | 34.0 | 35.4 | 11.4 | 88.5 | 51.4 |
| Daily Wage Earner (%) | 42.3 | 37.9 | 94.4 | 63.6 | 62.1 |
| Electricity Availability (hours) | 12.4 | 18.8 | 8.9 | 17.8 | 23.2 |
| Electricity Consumption (kWh) | 60.6 | 66.8 | 16.7 | 46.5 | 82.5 |
| Biomass Consumption (kWh) | 431.7 | 275.5 | 257.6 | 105.3 | 86.0 |
| LPG Penetration (%) | 1.1 | 16.9 | 2.8 | 12.1 | 32.8 |
| Kerosene Penetration (%) | 30.4 | 70.5 | 4.6 | 57.6 | 51.7 |
| Appliance ownership (%) | 24.1 | 34.4 | 13.9 | 27.2 | 38.2 |
| Hours of Cooking | 3.9 | 3.7 | 2.6 | 3.9 | 3.3 |
| Hours of Lighting | 6.3 | 5.8 | 3.4 | 7.6 | 4.7 |
| Majority Religion (%) | 82.6 | 92.6 | 99.1 | 45.5 | 37.9 |
| SC/ST[a] (%) | 77.2 | 86.3 | 33.3 | 42.4 | 31.0 |
| OBC[b] (%) | 22.8 | 10.5 | 66.7 | 57.6 | 69.0 |
| Notified Slum (%) | 9.8 | 7.4 | 97.2 | 0.0 | 60.3 |
| HoH[c] Literacy (%) | 41.3 | 49.5 | 38.3 | 18.1 | 50 |
| Awareness of Gov. Programmes (%) | 0.0 | 1.1 | 82.4 | 0.0 | 89.7 |
| Beneficiary of Financial Support (%) | 7.6 | 17.9 | 0.0 | 3.0 | 22.4 |

[a] Scheduled Caste/Scheduled Tribe

[b] Other Backward Castes

[c] Head of Households

#### *3.2.1. LPG access*

More than half the interviewed households were using LPG as their primary cooking fuel, although only two benefited from an upfront cost subsidy. Across all clusters the majority of households were not aware of government support

and subsidies available to them. Only the households in clusters 3 and 5 had any significant awareness of such support, with over 80% aware of government subsidies in these clusters. Clusters 3 and 5 also have a greater proportion of households paid daily or weekly, living in non-notified slums, and in the case of cluster 3 they are also recent migrant arrivals to the city. Cluster 5 constitutes households that have received the highest level of financial support (22.4%) and LPG penetration of 32.8%.

Frequency of payment is an important factor in household energy decision making. Many low-income households are paid on a day-to-day basis which restricts cash flow, limiting purchasing power, as well as resulting in lower income security. Households in cluster 3 who are largely migrant labourers on daily wages have the lowest LPG penetration rates, 2.8% as shown in table 3, despite the high level of awareness of government subsidies generally available. The informal nature of their circumstances including lack of tenure and poor access to banking and loan, bars them from accessing the government support as discussed by Jain et al. (2018) and also restricts their access to financing to address their cash flow problems.

Lack of awareness of the available support forces households to turn to other financial arrangements such as savings clubs or informal finance if they still want an LPG connection, such as households in clusters 1 and 2. Two households we interviewed took out an informal loan, loans which are often on high interest rates. One household borrowed the money from a family member and one household saved for months to be able to make the payment. Rizwana (names of respondents have been changed), a native of Bangalore, switched to LPG because of pressure from neighbours who complained of the constant smoke emerging from their house. Her family paid INR 8000 (ca. USD 110) for a double cylinder connection for which they received a loan from a local money lender. Despite getting the connection three months prior to our conversation, they were still paying the lender up to INR 1000 per week. They are receiving a sum of INR 100 in subsidies after each refill. Her husband, a daily wage labourer, supports her and their three children.

Table 3, shows clusters 1 and 2 had a significant proportion of households like Rizwana's who despite little awareness of government clean cooking initiatives did avail of financial support in the form of subsidies for refills and a free stove. Other households we interviewed mentioned that despite promises of regular subsidies, many of the households have not been receiving any. Interestingly, these households expressed no inclination or interest to receive the subsidy either, as they felt the INR 100-300 they may receive would do little to help with the costs.

*3.2.2. Electricity access*

According to the World Bank (2018), India has an urban electrification rate of over 99% and indeed all interviewed households had regular access to electricity of some sort. However, this statistic often ignores the difficulty in getting metered access to electricity, and one third of our interviewed households relied on illegal connections. Despite the difficulty expressed by some households in accessing a legal metered connection, lack of access to a regular source of electricity was not an issue. Indeed the only group of households in our survey who reported limited access to electricity were those in cluster 3 with a high proportion of recent migrants living in non-notified slums, as seen in Table 3. Only 41% of households in this group had regular electricity access.

During our conversation with Meena at Nayandahalli, a ward with a high migrant population due to its proximity to industrial areas, she stated that the authorities have been coercing the community to pay for metered connections. However, they are resisting until they are granted land rights. Similar stories of respondents being asked to pay up to INR 16,000 (ca. USD 225) for a metered connection came up during several of the interviews. Tangled wires precariously hanging from one streetlight providing electricity to the surrounding houses are a common sight.

Table 3 shows that clusters 1,2 & 4 whose households migrated more than a generation ago use more electricity than recent migrants in cluster 3. The more established a household is the more time they will have had to acquire electrical

appliances, as well as gain legal tenancy or move to a property with recognised tenancy, facilitating access to a metered connection. Ahmad and Puppim de Oliveira (2015) similarly found that access to utilities such as electricity and water were associated with the uptake of LPG among slum households.

The cost of electricity was not seen as a major barrier for most households, with metered households paying monthly bills between INR 100-500. Naseema expressed that despite difficulty in making the payment every month, with two school age children at home, they don't have any choice. Naseema is a tea seller, and her husband is a rickshaw driver and together they earn between INR 200-400 daily, which they use to support their family of six.

#### *3.2.3. Involuntary transitions*

Lack of affordable alternative fuels was a key narrative for uptake of LPG in interviews, but this was not apparent from the survey data. Historically, kerosene was subsidised by the state and distributed through the Public Distribution System (PDS) to enable access to low cost cooking fuels. However as subsidies have been rolled back, in an attempt to encourage the uptake of cleaner cooking fuels (Jaocb, 2017), there has recently been a ban of the sale of kerosene in PDS shops. Additionally, the availability of firewood is also dwindling owing to rapid urbanisation. With the two most accessible and affordable sources of traditional cooking fuels restricted, households are forced to switch to LPG. While studies have addressed the impact of kerosene subsidy withdrawal elsewhere in South East Asia (Lam et al., 2016), the impact of such measures on cooking fuel choice in India have not been studied in detail.

Nearly two thirds of interviewees who used LPG, cited a lack of affordable kerosene as a driver of their transition. The emerging black market prices for kerosene of INR 70-100 (ca. USD 1-1.50) per litre, were considerably higher than the INR 15 per litre at the PDS shops. While this may appear to have had the desirable effect of nudging households towards cleaner cooking fuels, it does so at a cost. As highlighted above, households often lack access to the financial tools that can make this transition easier, and none of these households made

use of available, albeit insufficient, financial support. In fact, a novel finding in our study was that such a measure can even have the unintended consequence of forcing some households to switch back to using firewood. Parvathy who lives with her husband and four children in a self-constructed temporary dwelling, has been using firewood for the last four years since her local PDS shop stopped providing kerosene. She also stated that her children were falling sick frequently due to the smoke.

*3.2.4. Frugal energy practices*

Households are required to constantly compromise on their energy consumption. Past studies have shown that even if households 'switch' to cleaner fuels, they continue to use the existing fuel as well as the new fuel to meet their energy needs and this practice of fuel stacking was prevalent in the interviews and surveyed households. For example, despite having both electricity access as well as an LPG connection, some households opted to use firewood for water heating which is both cheaper and quicker. Janaki, who lives with her ailing husband and works as a daily wage labourer, uses a portable kerosene stove which requires a refill every five days, for which she spends INR 100 per refill. To try and reduce this recurring expense, they cook rice over rotis, which cooks faster. Sometimes, they go up to two days relying on outside food such as plain buns, when kerosene is either not available or they are unable to meet the cost.

The hours spent cooking or using light in the household provide a proxy for time spent on energy related practices in the household. Table 3 shows that across all clusters except for cluster 3, households spend between 3 to 4 hours cooking each day, however there is greater variation in hours of lighting. While cooking satisfies a basic need to eat, lighting may be a proxy for other activities in the household. Whether children doing homework, watching television, or doing small jobs, households can adjust their practices and routines to the resources available. Mariamma, a resident of Rajagopal Nagar, with both her and er husband, relies entirely on their son's income to meet their daily expenses. "I don't use the fan nor light during the day and spend my time sitting outside

the house to reduce my electricity bill" she tells us. She uses firewood for water heating despite having an LPG connection and does not own a refrigerator because she says it would increase the bill further.

#### *3.2.5. LPG Safety and Health Concerns*

The harmful health impact of firewood and kerosene was not a cause for concern amongst most interviewees. When asked whether they were worried about their own health or the health of their children, interviewees often showed little concern. Pachiamma, who has been relying on kerosene for over 40 years, spoke of her fear of using LPG since it might burst or cause a fire in the house; a finding seen in other recent studies by Osano et al. (2020) and Sharma et al. (2020). She told us she is not worried about the smoke caused by kerosene. She shares a small pucca house (a pucca house is a permanent house built of concrete, stone, metal or clay brick) with two others and the cooking is done indoors. Urmila, who has been using LPG for ten years, said that she in fact preferred using kerosene since the food tasted better and she did not see indoor smoke as an issue either.

Interestingly findings in a recent study by Mani et al. (2020) suggested that prior awareness of health benefits of LPG over biomass were not a driver of uptake, and more likely households are made aware upon adoption. Only one household we interviewed showed active knowledge of the health benefits LPG can have in a household. She told us that 7 years earlier, the local community leaders in collaboration with a private gas company, organised a meeting in their community to discuss the health benefits of switching to LPG. However, she did point out that it was the INR 1000 (ca.USD 14) subsidy along with the free stove, that ultimately drove households to switch to an LPG stove. Nonetheless our findings do align with those of (Gould et al., 2020); that messaging, perceptions, and education would appear to have a role to play in clean energy transitions.

*3.2.6. Difficulty in prioritising clean energy*

Households are unable to prioritise clean energy in their financial decisions."We don't even have toilets, where will we get the money to buy LPG", one interviewee named Rama told us outside her home as her neighbours nodded in agreement. Discussions were often centred around stories of mounting health care bills, school fees and loans that are being cleared as the 'more important' household expenses. LPG was not a key priority for the households interviewed.

Although a few households told us that they had discussed the possibility of purchasing LPG, such ambitions were quickly dismissed due to the lack of money and other spending priorities. The 'lumpy' payments for LPG were seen as a major barrier. Naseema who relies on firewood and kerosene says, "We just took a loan of INR 25,000 for festival and other household expenses, we cannot afford to take more loans". For Ramadan, an Islamic festival celebrated in the month of May, she had to purchase new clothes and gifts for her family of six, leaving very little behind for other expenses.

*3.2.7. Lack of strong community and political networks*

Finally, a recurring theme that emerged almost across all households was the lack of any political or community network. "Nobody visits us. During election time people will come for votes, but that is it.", says Radha, who is a widowed housewife living with her late husband's family. Socio-cultural groupings along lines of religion and caste can often play a role in functioning and organisation of a community. As shown in Table 3, clusters 4 and 5 have over 50% of households belong to religious minorities, and 57.6% and 69.0% of households are classed as OBC (Other Backward Caste) respectively. They also display relatively low biomass consumption, and the majority of households use Kerosene or LPG. This may point to differing social norms and community perceptions about the use of these fuels for cooking. It could also reflect access to resources related to their standing in society, or community network. This supports the findings of Saxena and Bhattacharya (2018), who found that structural inequalities experienced by certain caste and religious communities restricted access to energy

goods.

When asked about the role of sangams (local term for informal Micro-Finance Institutions (MFIs) and Savings Clubs), households often lacked interest in participating in these networks. The reasons ranged from lack of time due to work commitments to lack of trust in these groups. Latha, who lives with her parents and her daughter, told us that despite being aware of the local MFI, she does not trust them. "In this community, all the 'big' people are selfish and enjoy the benefits themselves", she told us. This sentiment came up in four other interviews, with two women having lost their money to people who claimed to represent a sangam. A few women also spoke about the fear of taking loans from sangams due to the fear of inability to pay the money back. Only five households spoke of helpful neighbours who are willing to share information and mobilise financial support in times of need.

## 4. Transition Pathway Characterisation

A clustering of the correlation network of the coded interviews indicates six different groups of interviewees with common narratives of energy use identified as groups A to F. The households in these six different groups discussed a combination of the issues discussed in the previous section. For example interview group A are affected by difficulty prioritising clean energy but are also affected by issues surrounding electricity connection, and lack of a strong community or political network. Conversely interview group B have reliable metered access to electricity, and have good community and political networks, while managing their finances to pay for cleaner fuels, while also being aware of health issues related to fuel use. A table with a detailed breakdown of key discussion themes for each of six clusters can be found in the supplementary information.

Recall from Section 2 that each interviewee is also associated with the survey cluster they are found to be closest to. As the next step, each interviewee is further clustered on 2 dimensions - their interview grouping and their survey cluster. By doing so, we can identify or infer plausible and distinct pathways

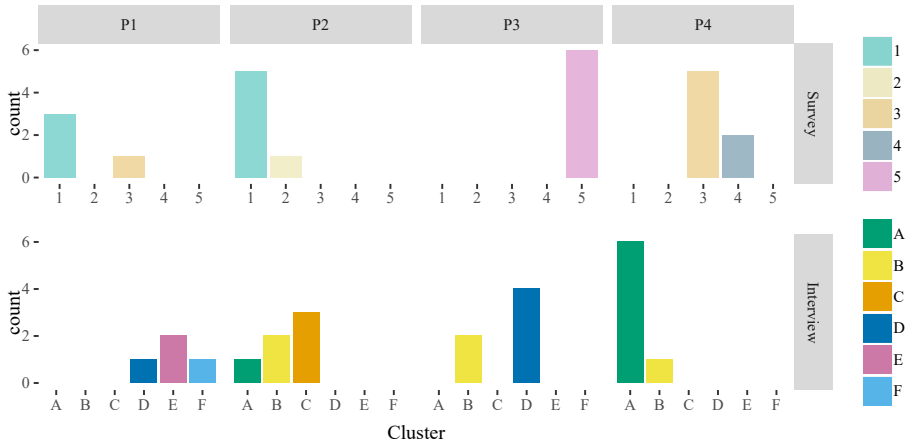



Figure 5: Proportion of interview and survey clusters represented in the four second-stage clusters.

that can help households with similar characteristics and narratives transition to clean cooking fuel. Through this we identify four distinct pathways across interviewed households. The four distinct transition pathways each have a unique data driven definition of the challenges and barriers to clean cooking transition that they present, which are described in Table 4, and the proportion of each constituent cluster in each pathway is shown in Figure 5. A plot of clustering results can be found in the supplementary information.

Transition pathway P1 detailed in Table 4 concerns households in mostly notified slums, who are at least second generation migrant families, with an even split between daily and non-daily wage earners. This pathway consists of households in survey clusters 1 and 3, and interview groups D, E, and F. These household are most unlikely to use LPG and have moderate prevalence of kerosene use. There is a low proportion of religious minorities in this group, and these households have a lack of strong community networks, with many being unaware of available support for clean cooking fuel. They often have reliable electricity with a metered connection, but have frugal fuel stacking practices for example using collected firewood to boil water or cook rice to save money. The interviewed households in this group discussed how cost and availability

Table 4: Key attributes and narratives for transition pathway clusters

| Clust. | Key Attributes | Key Narrative |
|---|---|---|
| P1 | Notified slum: 61.8%<br>Daily wage earners 55.3%<br>Biomass use: 388 kWh<br>LPG prevalence 1.5%<br>Kerosene prev. 24.0%<br>Minority religion 13.3%<br>Migrated 28 years ago | • Reliable electricity access with metering;<br>• Frugal energy practices with multiple fuels;<br>• Unaware of available support for clean fuel;<br>• Fridge ownership aspirations;<br>• Kerosene restriction leads to involvement in informal markets;<br>• Lack of strong community networks. |
| P2 | Notified Slum 82.8%<br>Daily wage earners 41.6%<br>Biomass Use: 406 kWh<br>LPG prevalence: 3.8%<br>Kerosene prev.: 37.2%<br>Minority religion 15.8%<br>Migrated 34 years ago | • Fear of LPG safety/preference for kerosene;<br>• Cost of kerosene has driven uptake of LPG and firewood;<br>• Have other financial priorities such as home improvement of purchasing a fridge;<br>• May have good community network but skeptical of informal finance initiatives. |
| P3 | Notified Slum 37.9%<br>Daily wage earners 63.6%<br>Biomass Use: 86 kWh<br>LPG prevalence: 32.8%<br>Kerosene prev. 51.7%<br>Minority religions 37.9%<br>Migrated 51 years ago | • Electricity access and metered connections;<br>• May have paid for own connections but do receive some subsidies for fuel;<br>• Have community or political networks;<br>• Have felt pressure to use LPG from lack of availability/cost of kerosene. |
| P4 | Notified Slum 30.6%<br>Daily wage earners 85.6%<br>Biomass Use: 214 kWh<br>LPG Penetration 5.4%<br>Kerosene Use 20.2%<br>Minority religions 16.3%<br>Migrated 20 years ago | • Electricity access concerns, pressure to pay for meter;<br>• LPG not a financial priority;<br>• Lack of awareness/access to support;<br>• Lack of community and political network;<br>• Recent migrant wage labourers;<br>• Informal community/no tenure rights. |

restrictions on kerosene had driven them to informal markets, and that they had financial aspirations other than using LPG, such as purchasing a fridge.

Transition pathway P2 consists of mostly second or third generation households in notified slums, where a majority of households are paid weekly or monthly. These households are part of survey clusters 1 and 2 and interview groups A, B, and C. They are the most prolific users of biomass fuels and few such household use LPG. Safety concerns regarding LPG and a preference for kerosene may help explain this. These households have been forced to use LPG or revert to firewood as a result of kerosene shortage and cost increase. These households have good community networks but are skeptical of semi-formal MFIs and savings clubs, and usually switching to LPG is not an aspiration or financial priority. Rather these households would prioritise acquiring a fridge or improvements to their home.

LPG penetration was highest amongst households on transition pathway P3. These are households in survey cluster 5 and interview groups B and D. These households are surprisingly mostly in non-notified slums (or undefined areas adjacent to notified slums) and daily wage earners. However they have the lowest biomass use and highest use of petroleum fuels for cooking as well as metered electricity access. These households often belong to minority religions and OBCs and have good community and political networks. Head of household literacy rate is higher than amongst the mean household. They have also felt pressure to switch cooking fuel due to kerosene shortage and cost, however have been able to access some subsidies and benefits to switch to LPG.

The final transition pathway P4 is analogous to the situation of daily wage labourers, many of whom have migrated to the city for work. They are mostly living in non-notified slums or sometimes 'blue tent' informal settlements, and have limited awareness or difficulty accessing benefits such as subsidies or financial rebates for LPG use. LPG is often not a financial priority amongst this group, and their irregular electricity access is of more concern with many being pressured to pay for a meter. These households often lack community or political networks and have limited access to even semi-formal finance. The

precarious nature of their daily wage employment can make managing finances difficult, and their lack of tenure makes access to support a problem.

While our method is able to identify key determinants of clean cooking adoption which align with those found in other studies, the transition pathways identified by this second stage clustering provide important additional information about the specific combinations of barriers to clean fuel and household characteristics that were not apparent from the interview or survey analysis alone. Unlike rural areas, amongst low-income households in urban areas there is far greater heterogeneity and our method is able to distinguish these different typologies of low income household, and identify their needs and context to inform policy design. This is a key novelty of our method with respect to more straightforward quantitative clustering or predictive analytical methods. Our method allows us to track how different factors work together to define different pathways to clean fuel and highlight the barrier or challenge present with each of these.

These transition pathways offer insight into how a household will respond to changes in energy provision and policy in different ways. An example of this concerns pathway P1 and P2's response to kerosene restrictions. Pathway P1 have poor community networks, and little knowledge of existing government support for clean fuels. Pathway P2 do not financially prioritise LPG and may have safety concerns about LPG, as well as distrusting informal finance initiatives. With the restrictions on kerosene at ration shops, households on pathway P1 responded by turning to informal markets for kerosene, while households on pathway P2 either adopted LPG or if they could not access financing reverted to using biomass.

The integrated qualitative and quantitative dataset has allowed us to infer these pathways and identify households with different socio-economic circumstances that may share a pathway in transitioning to clean cooking. For example pathway P4 is characterised by lack of awareness and access to government support for clean cooking, lack of community and political networks, and poor access to other utilities. However two very different groups of households, from

different survey clusters, were associated with this pathway. Both recent migrant wage labourers and longer term retired or widowed residents in notified slums appear to face some similar barriers to accessing clean cooking.

### *4.1. Limitations and Further Work*

The descriptive quality and high resolution of our survey data provide a greater level of detail on energy use habits among low-income urban households in India, and make an important contribution to the limited body of knowledge on low-income urban households. However, our data are limited in applicability by specifically pertaining to a specific agro-climatic, social, and political geography: namely Bangalore. Further studies across different states would be required to test the extent to which one could borrow strength across households located in different physical and socio-political conditions.

Furthermore, this work has focused on descriptive analysis of the data to gain information on the variations of barriers faced by households on their path towards clean cooking transitions. Whilst these outcomes can be used to tailor and fine-tune energy policies to maximize their reach across households, they cannot be used directly to predict their impacts.

## 5. Conclusions and Policy Implications

This study of low-income households in Bangalore provides a detailed insight into behaviours and decision making surrounding clean cooking transitions in poor urban households. Energy use and fuel choices vary considerably due to the interaction of a wide range of socio-economic and behavioural determinants. Firewood was used by all households surveyed to some extent and all households used more than one fuel in the household. However, just over 10% of households primarily made use of LPG for cooking.

The four transition pathways identified in this paper indicate that some households are at greater risk of being trapped using biomass fuels, particularly those in non-notified slums and without strong community networks. Each

of the four pathways highlight different barriers to transition and an integrated strategy of interventions is required to address these. For some households better access to more reliable financing is needed to help deal with the issue of cash flows resulting from being in daily or weekly wage employment. Interventions could implement alternative financing arrangements that allow households to pay for their cylinder in daily or weekly installments, such as methods employed with mobile enabled pay-as-you-go solar home systems in Kenya (Rolffs et al., 2015).

There is also a need for awareness and behaviour changing initiatives for the more established households and communities with less awareness of available support and inaccurate perceptions of risks and safety of biomass and LPG use. These could be targeted to relevant wards and combined with promotional efforts for the LPG uptake scheme. Households in non-notified slums can struggle to access much needed support for cleaner fuels. Their precarious living circumstances and limited access to infrastructure need to be addressed to facilitate their adoption of cleaner fuels. Lack of tenure rights and banking prevent these households accessing current initiatives, targeted interventions could either use specific criteria for access to subsidy schemes for those in such circumstances or indeed this could be addressed as part of a wider initiative to improve living standards and legal status of those in non-notified slums. This would support the argument of Sankhyayan and Dasgupta (2019) that access to energy cannot be viewed in isolation of other socio-economic development indicators.

Although the characteristics we identify alone do not define a transition pathway, they do enable a deeper understanding of groups of households likely to follow one or more transition pathways to clean cooking.

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## 7. Data Availability

Anonymised and processed versions of the datasets used in this study are available in the Apollo repository, https://doi.org/10.17863/CAM.59870. Due to the sensitive nature of some questions asked in this study, survey respondents were assured raw data would remain confidential and would not be shared.

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