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LETTER

Association of personal network attributes with clean cooking adoption in rural South India

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Abstract

Adoption of liquefied petroleum gas (LPG) is the primary policy approach in India to transition rural poor communities toward clean cooking behavior. Prior clean cooking studies show that affordability, accessibility, and awareness impact LPG adoption in India. There is scarce research that explores the association of personal networks of community members in their LPG adoption. In this cross-sectional study, we use standard egocentric personal network analyses and multivariate logistic regression models to examine the association of structure and composition of personal networks with LPG adoption in poor communities. Our results show that higher proportions of peers owning LPG are associated with higher likelihood of LPG ownership in the respondents (OR = 41.30, 95% confidence interval: 16.86–101.20, $p = 0.00$). This study on personal network characteristics in clean cooking research offers a germane foundation for further large scale personal network studies on clean cooking adoption in poor communities.

1. Introduction

Traditional cooking systems relying on solid fuels such as firewood, charcoal, animal dung, and crop residue are widespread in rural India, particularly among those living in poverty [1, 2]. These traditional stoves and fuels have been documented to cause adverse health outcomes, and impinge on the quality of life for both those using them in their households as well as those who live in an area where these stoves are extensively used. Recent estimates show household air pollution (HAP) accounted for approximately 600 000 people premature deaths in 2019 [3], making it one of the leading causes of preventable mortality in India. Conditions including lung cancer, chronic obstructive pulmonary disease, high blood pressure, reduced cognitive abilities, and tuberculosis have been conclusively linked to HAP exposure [2, 4–9]. Women and children are the most likely to spend significant amounts of time with and near traditional stoves, and are therefore more impacted by harmful emissions [1, 10]. HAP is a pressing public health crisis that warrants unceasing attention. Cleaner cooking systems such as liquefied petroleum gas (LPG) need to supplant traditional cookstoves [11–13]. Prior research has shown that factors pertaining to affordability, accessibility, and awareness impact LPG adoption in rural poor communities of India [12, 14, 15]. Multiple studies have also documented that behavior change strategies have significantly contributed to LPG uptake [12, 15, 16].

Personal networks contribute in shaping our behaviors and decisions [17]. Individuals construct a personal community around themselves [18]. Structure and composition of personal relationships with peers offer access or create barriers to new

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opportunities or ideas for individuals. Personal networks are conduits of social influence [19]. Studies have shown that personal networks of an individual impact adoption of evidence-based interventions [20, 21]. Instances include: (a) adoption of contraceptives [22]; (b) knowledge transfer [23, 24]; (c) stroke recovery [25]; (d) diffusion of technological innovation [23, 26, 27]; and (e) social support [28]. A 2018 study in an economically disadvantaged community in Zimbabwe found that if someone in a person's social network adopted a new technology, that person was also more likely to adopt the technology [29]. Thus, a fundamental tenet is that personal networks are instrumental in impacting behavior. However, there is no systematic study exploring the association of personal networks with adoption and/or use of clean cooking systems such as LPG in poor communities. The association of personal networks with LPG adoption behaviors ought to be tested more widely. Women tend to be the primary cook in most cultures. They play a critical role in adoption of cleaner cooking interventions like LPG. It is important to explore the association of personal networks of women and LPG adoption in their respective households.

The purpose of this study is to explore the association of personal network characteristics with adoption of LPG in rural households of India. We adapted PERSNET, a standard personal network survey instrument [18, 20] to collect network data from women (primary cook) of 195 rural households from 35 habitations (available online at stacks.iop.org/ERL/16/064087/mmedia). We adjusted for perception based factors and demographic characteristics of the respondents in our model. We leveraged data collected using a household LPG adoption questionnaire administered for the same study [30]. The operationalization of the key variables in the study is described in detail in section 2.

2. Methods

2.1. Study design and participants

This study is part of a larger (parent) National Institutes of Health funded case-control study [30]. The parent case-control research project has a study sample of 510 households below the poverty line, from 35 rural habitations of Thambalapalle and Peddamandyam *mandals* (block) in Chittoor district of Andhra Pradesh state in southern India. The parent study employs a cross-sectional design. The study respondents for the research project were the women from each of the 510 households. Inclusion criteria for the parent study were: rural household with an adult female member (>18 years' age), woman respondent who was able to provide consent for the study, the woman respondent who was the primary cook of the house, women respondent resided in the household for the last 12 months, women respondent planned to reside in the household for at least 12 months from the date of enrollment for the study. A sample size of 255 households was selected correspondingly for the case group (LPG adopter households) and control group (non-LPG households). An additional inclusion criterion for the case group (LPG adopter households) was that the household must have received the first LPG cooking tank in the last 12 months within the date of enrollment for the study.

For the study on personal network analysis, we randomly selected a subset of 100 households each from the case and the control group of the parent study. Data collection for network analysis was undertaken from June 2016 through January 2018. The primary outcome for this study was LPG adoption, a dichotomous variable with categories yes or no. A hundred households from case group had adopted LPG (category: LPG adopters) while 100 households from control group had not adopted LPG (category: non-LPG adopters) and were still cooking on traditional stoves. We deleted entries from five respondents (two from LPG adopters and three from non-LPG adopters) during data cleaning owing to missing demographic data. The total analysis sample comprised 195 respondents. All participants provided verbal consent to participate in the network study. The study was also approved by the Boston College Institutional Review Board (IRB #18.271.01). We collected the personal network data by adapting PERSNET, a standard network survey instrument [18, 20]. We collected the demographic data using a standard field-tested LPG adoption questionnaire [30].

2.2. Network measurements

Personal network analyses or egocentric social network analyses focus on the structure and composition of the networks surrounding a target individual [31] referred to as ego or respondent. The set of individuals reported by the egos (or respondents) to whom they are directly connected are called alters or peers. The key components of personal networks include: (a) a focal node (called ego or respondent); (b) nodes to whom ego is directly connected to (called alters or peers); and (c) the ties among these nodes. In personal network analysis, the structure and composition of these ego networks in the sample are examined.

In this study, a trained enumerator led the personal network data collection in the field. The main sections of our personal network instrument were: (a) name generator; (b) name inter-relator; and (c) name interpreter.

(a) Name generator: the survey began with two name generator questions to prompt identification of individuals (peers) who give advice, socialize with, and support the respondents.

(b) Name inter-relator: after eliciting the network members, a second set of questions was administered to explore the structure of the personal networks. For this study, the questions explored the existence of connections (ties) among the respondents and their corresponding peers.
(c) Name interpreter: finally, the composition of these networks was probed with name interpreter questions. Corresponding with the aim of the study, the question explored if peers of the respondents had adopted LPG stoves or not.

Personal network analysis involves examination of patterns of association between them [20]. We analyzed three measures of network structure and one measure of network composition in this study [20]. These are described below.

(a) Network size: This is typically measured by the total number of nodes in the network after excluding the node of the respondent. For instance, if a respondent reports having seven connections, the network size is 7.
(b) Mean degree: It is the average number of ties of a network member, excluding the respondent. Mean degree describes the distribution of ties in a personal network.
(c) Network density: This is a measure of network cohesiveness and is the ratio of actual ties to the maximum possible ties. Network density is measured as: $[2 \times L]/[N \times (N - 1)]$; where L is the number of actual ties, and N is the number of nodes in the personal network. A personal network with a relatively higher network density is more clustered and close-knitted. Network density is a continuous variable varying from 0 through 1.
(d) We analyzed one measure of network composition: LPG homogeneity. This measure examines the proportion of network members (or peers) who own an LPG stove. For instance, if a respondent reports having five connections as peers, and all these five connections have LPG, then the LPG homogeneity is 1. If a respondent reports that three out five connections have LPG, then the LPG homogeneity is 0.6. LPG homogeneity is a continuous variable varying from 0 through 1. The value 0 indicates none of the peers have LPG, while the value 1 indicates all peers having LPG.

To summarize, we statistically examined four network measures namely network size, mean degree, network density, and LPG homogeneity.

2.3. Statistical analysis

We analyzed the association of personal network measures with LPG adoption with three sequential steps routinely followed in studies on personal network analyses for evidence-based public health interventions [20, 25]. These three steps are discussed below.

2.3.1. Step 1

Using bivariate analysis, we compared the demographic and network variables between LPG adopters (case group) and non-LPG adopters (control group) or traditional stove users. We used unpaired two-tailed t-test or Mann–Whitney U-test (for non-parametric distribution) for continuous variables. We used chi-square test for categorical variables.

2.3.2. Step 2

We then used multivariate logistic regression model analysis to explore the association of LPG adoption with the network measures. We built two separate models. Model 1 is an unadjusted regression model. This model includes the four network measures (network size, mean degree, network density, LPG homogeneity). We tested these measures and ensured that there is no multi-collinearity. Model 2 explores the association of these four network measures after adjusting for demographic and perception based predictors. This was undertaken to ensure that network measures maintain their association with LPG adoption even when adjusted for demographic and perception based predictors. The demographic predictors used are: (a) age of the respondent in years; (b) average monthly income of the household; (c) marital status of the respondent; (d) highest education received by the respondent (women) and by the male head of household; and (e) caste of the respondent.

Evidence suggests that our personal networks influence our mental models, which consequently shape our decision toward adoption of evidence-based interventions [20, 27, 32–37]. Perceptions toward clean cooking also shape mental models, which in turn influence adoption of clean cooking technologies [38, 39]. Perceptions toward clean cooking could be shaped from personal observations over time or through participation in awareness campaigns. Thus, to examine the true association of personal network attributes with LPG adoption, it was crucial to control for the perception based predictors. Thus in model 2, in addition to the demographic predictors, we adjusted for three perception based predictors that have routinely found traction in clean cooking literature [12, 15, 16]. They are:

(a) Availability of biomass: this dichotomous variable (option: yes/no) examined if respondents perceive that the biomass is easily available to them for traditional stove use. Evidence shows that if respondents feel that biomass is easily available, then the likelihood to adopt LPG is low.

(b) LPG safety: this dichotomous variable (option: yes/no) examined if respondents perceive LPG stove as an unsafe technology for their households.
(c) Awareness campaigns attended: this dichotomous variable (yes/no) explored whether the respondents have attended awareness campaigns on clean cooking. Participation in clean cooking awareness campaigns increase the likelihood of LPG adoption [12, 16, 40].

Both the models used 95% confidence interval and a p-value of 0.05 for significance. We compared the relative fit of the models using the AIC estimates.

2.3.3. Step 3

To further corroborate the association of significant personal network characteristic with LPG adoption, we undertook the following analysis: (a) we developed separate personal network montage for the LPG adopters and non-adopters; and (b) we developed separate density plots for LPG adopters and non-adopters to explore the pattern of association of the significant personal network characteristic with LPG adoption. We used Stata version 15 for univariate and multivariate regression analyses, and RStudio 4.0.3 for network montage and graphs.

3. Results

3.1. Bivariate analyses

Table 1 summarizes the results of bivariate analysis. Out of 195 study participants in the sample, 98 of them (50.26%) adopted LPG (referred to as LPG adopters), and the average age was approximately 38 years (SD = 11.02). 97 respondents had not adopted LPG (referred to as non-LPG adopters), and the average age of these respondents was approximately 41 years (SD = 15.79). There were no significant demographic differences between those who adopted and did not adopt LPG. Most of the participants were married (89.80% vs 83.51%, $p = 0.21$). Most of the sample belonged to the other backward castes (OBC) (57.44%) followed by scheduled caste/scheduled tribe (SC/ST) (27.18%). Those who adopted LPG were relatively more likely to belong to the general caste (20.41% vs 10.31%, $p < 0.001$), more likely to belong to OBC (70.41% vs 44.33%, $p < 0.001$), and less likely to belong to SC/ST (9.18% vs 45.36%, $p < 0.001$). There were no significant differences between LPG adopters and non-LPG adopters with reference education levels of the respondent ($p = 0.11$) or the education levels of the primary male decision maker ($p = 0.44$). However, LPG adopters had higher average household monthly income (in Indian National Rupees (INR)) (3326 vs. 2662 INR, $p < 0.01$). Regarding perception based predictors, LPG adopters were relatively less likely to state that biomass was easily available (1.02% vs 29.90%, $p < 0.001$), were less likely to report that LPG was unsafe (3.06% vs 21.65%, $p < 0.001$). There was no significant difference between the two groups on clean cooking awareness campaigns attended ($p = 0.38$). In terms of network structure, LPG adopters had a smaller network size (7.00 vs 7.31, $p < 0.01$), and the average peer in network had fewer connections (mean degree 4.90 vs 5.12, $p = 0.01$). There was no significant difference in the density of personal networks between the two groups (0.98 vs 0.96, $p = 0.33$). In terms of network composition, respondents who adopted LPG presented higher scores for LPG homogeneity (0.79 vs 0.50, $p < 0.001$).

3.2. Multivariate model analyses

3.2.1. Network analyses

We developed two regression models clustered by habitation (Table 2). The models were built following a block approach—including variables in blocks to isolate the effects. The first model (unadjusted model) included the four network predictors. The structural attributes of the networks: network size, network density, and the mean degree were not significant. The compositional attribute of the networks: LPG homogeneity was strongly significant. In model 1, a 1 unit increase in the proportion of peers adopting LPG was associated with an increase of approximately 68 times in the odds of adopting LPG by the respondents (OR = 68.26, 95% confidence interval: 16.15–288.48, $p < 0.01$). For instance: if the proportion of peers adopting LPG increases from 0 to 0.2 (an increase of 0.2 units), it leads to a corresponding increase in the likelihood of LPG adoption by the respondents by approximately 13.65 times (0.2×68.26). LPG homogeneity varied from 0 through 1. The value 0 indicates none of the peers have LPG while the value 1 indicates all the peers have LPG. Thus, the results from model 1 also show that if all the peers of a personal network of a respondent own LPG, it increases the likelihood of the respondent to also have LPG by approximately 68 times.

In model 2 we adjusted for demographic and perception based predictors to test the association of the network predictors with LPG adoption. Similar to model 1, LPG homogeneity was statistically significant, albeit there was a reduction in the strength of the association. A 1 unit increase in the proportion of peers owning LPG was significantly associated with increased odds of LPG adoption among respondents (OR = 41.30, 95% confidence interval: 16.86–101.20, $p = 0.00$). For instance: if the proportion of peers adopting LPG increases from 0 to 0.2 (an increase of 0.2 units), it leads to a corresponding increase in the likelihood of LPG adoption by the respondents by approximately 8.26 times (0.2×41.30). As mentioned, LPG homogeneity varies from 0 through 1. Thus, model 2 shows that if all the peers of a personal network of a respondent have LPG, it increases the likelihood of the respondent to also adopt LPG

Table 1. Bivariate description—percentage (frequency) or mean (SD), of outcome and predictor variables ($N = 195$).

Measure	Adopted LPG ($n = 98$)	Did not adopt LPG ($n = 97$)	p-value[a]
Network predictors			
Network size	7.00 (2.26)	7.31 (1.18)	<0.01
Network density	0.98 (0.06)	0.96 (0.18)	0.33
LPG homogeneity	0.79 (0.23)	0.50 (0.27)	<0.001
Mean degree	4.90 (2.52)	5.12 (1.52)	0.01
Perception based predictors			
Availability of biomass (yes)	1.02% (1)	29.90% (29)	<0.001
LPG tank unsafe (yes)	3.06% (3)	21.65% (21)	<0.001
Awareness campaigns attended (yes)	5.10% (5)	7.00% (7)	0.38
Demographics			
Age (years)	38.21 (11.02)	41.54 (15.79)	0.37
Average monthly income (INR)	3,326.02 (3,102.04)	2,661.86 (1,287.34)	<0.01
Marital status (1 = married)	89.80% (88)	83.51% (81)	0.21
Highest level of education of the respondent (female)			
None	58.16% (57)	74.23% (72)	0.11
Below or up to class 4	7.14% (7)	4.12% (4)	
Class 5 to class 8	21.43% (21)	10.31% (10)	
Class 9 to class 10	8.16% (8)	9.28% (9)	
Class 11 to class 12	4.08% (4)	1.03% (1)	
College	1.02% (1)	1.03% (1)	
Highest level of education of the head of the household (male)			
None	42.86% (42)	42.27% (41)	0.44
Below or up to class 4	1.02% (1)	4.12% (4)	
Class 5 to class 8	28.57% (28)	26.80% (26)	
Class 9 to class 10	15.31% (15)	13.40% (13)	
Class 11 to class 12	5.10% (5)	4.12% (4)	
College	4.08% (4)	1.03% (1)	
Not applicable	3.06% (3)	8.25% (8)	
Caste of the respondent[b]			
General	20.41% (20)	10.31% (10)	<0.001
OBC	70.41% (69)	44.33% (43)	
SC/ST	9.18% (9)	45.36% (44)	

[a] p-value calculated from unpaired two-tailed t-test or Mann–Whitney U-test for continuous variables and $\chi 2$ test and Fisher's exact test for categorical variables, p values were reported.

[b] General caste groups are considered as relatively the least disadvantaged communities. Scheduled tribes (STs) are traditionally marginalized. Scheduled castes (SCs) are economically and socially disadvantaged communities. They have also been traditionally marginalized. Other backward castes (OBCs) form a large group that is heterogeneous and is also considered by the constitution of India as being 'economically and socially backward'.

by approximately 41 times, after adjusting for other predictors in the model. From both the models, it can be concluded that that higher the proportion of peers adopting LPG, higher was the likelihood for respondents to also adopt LPG, even after adjusting for demographic and perception based predictors in the model. The association of LPG homogeneity with LPG adoption from model 2 is also demonstrated by the predicted probability curve in figure 1.

3.2.2. Covariate analyses

Respondents who perceived that biomass is easily available to them had a lower likelihood to adopt LPG (OR = 0.01, 95% confidence interval: 0.00–0.11, $p = 0.00$). Respondents who perceived LPG as unsafe also had a lower likelihood to adopt LPG (OR = 0.05, 95% confidence interval: 0.02–0.13, $p = 0.00$). Attending awareness campaigns on clean cooking was not significant (OR = 1.41, 95% confidence interval: 0.09–23.03, $p = 0.81$). In terms of the demographic predictors, a unit increase in monthly income was associated with a 4% increase in the probability of adopting LPG (OR = 1.04, 95% confidence interval: 1.01–1.06, $p = 0.01$). Married respondents were about four times more likely to adopt LPG than their non-married counterparts (OR = 4.73, 95% confidence interval: 1.12–19.97, $p = 0.03$). Respondent's educational status was not a consistently significant predictor. OBC communities or other minorities, compared to the general castes were not significantly associated with adopting LPG. Belonging to the SC/ST groups was significantly associated with a 95% decrease in the odds of

Table 2. Binomial logistic regression analysis of LPG adoption based on network predictors, perception based predictors and demographics, with clustering at the habitation level ($N = 195$).

Measure	Model 1 OR (95% CI)	p-value	Model 2 OR (95% CI)	p-value
Network predictors				
Network size	1.80 (0.12–27.40)	0.67	1.27 (0.05–30.43)	0.88
Density	65.42 (0.00–3.43e + 07)	0.53	34.47 (4.0e-06–2.9e + 08)	0.66
LPG homogeneity	68.26 (16.15–288.48)	<0.01	41.30 (16.86–101.20)	<0.01
Mean degree	0.51 (0.03–8.68)	0.64	0.72 (0.03–19.29)	0.85
Perception predictors				
Availability of biomass (Ref: no)			0.01 (0.00–0.11)	0.00
Yes				
Unsafe LPG (Ref: no)			0.05 (0.02–0.13)	0.00
Yes				
Attending campaigns (Ref: no)			1.41 (0.09–23.03)	0.81
Yes				
Demographics				
Age (years)			1.76 (0.29–10.54)	0.54
Average monthly income (INR-Sqrt)			1.04 (1.01–1.06)	0.01
Marital status (Ref: other)				
Married			4.73 (1.12–19.97)	0.03
Highest level of education of the respondent (female) (Ref: none)				
Below or up to class 4			2.65 (0.55–12.80)	0.22
Class 5 to class 8			2.04 (0.64–6.56)	0.23
Class 9 to class 10			0.22 (0.08–0.62)	0.00
Class 11 to class 12			11.70 (1.44–95.12)	0.02
College			0.12 (0.01–1.17)	0.07
Highest level of education of the male head of the household (Ref: none)				
Below or up to class 4			0.02 (0.00–1.22)	0.06
Class 5 to class 8			0.42 (0.13–1.32)	0.14
Class 9 to class 10			0.71 (0.24–2.07)	0.53
Class 11 to class 12			0.62 (0.11–3.58)	0.59
College			0.25 (0.07–0.84)	0.03
Not applicable[a]			6.55 (0.95–44.99)	0.06
Caste of the respondent (Ref: general)				
OBC			0.54 (0.18–1.63)	0.27
SC/ST			0.05 (0.01–0.41)	0.01
Goodness-of-fit statistics				
AIC	1.16		0.87	
BIC	−786.11		−794.08	

[a] Not applicable is used when there is no male decision maker in the household; Ref. stands for reference category; OR stands for odds ratios, and 95% CI stands for 95% confidence intervals.

adopting LPG compared to those belonging to the general castes (OR = 0.05, 95% confidence interval: 0.01–0.41, $p = 0.01$).

3.3. LPG homogeneity: personal network montage and density plots

Figures 2(a) and (b) corroborate results of the multivariate regression models. The network montage in figures 2(a) and (b) shows the network size of the respondents and type of stove (LPG or traditional stoves) owned by the respondent's peers. Figure 2(a) shows the personal network arrays of case group (LPG adopters) respondents in the sample organized by the stove ownership of their peers. Within the first few rows we see a scattered mix of LPG and non-LPG peers. The overwhelming uniformity

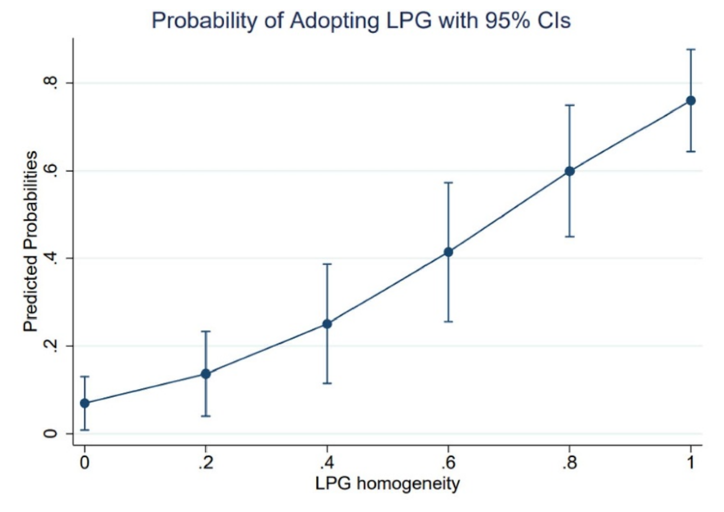

Figure 1. Predicted probability of LPG adoption. The marginal effects curve for model 2 showing the association of predicted probability of LPG adoption with LPG homogeneity, after adjusting for all other predictors. The probability of adopting LPG increases among respondents with an increase in the proportion of their personal networks also owning LPG.

of color in the latter half of the montage shows that respondents that were LPG owners had a homogenous network where their network peers were also predominantly LPG owners. This is visually juxtaposed against figure 2(b), that shows the control group respondents (non-LPG adopters) and their corresponding peers. In figure 2(b), a majority of non-LPG owners had peers who were also non-LPG owners. The pattern changes only toward the last few rows in figure 2(b) where only five non-LPG owners had peers who were all LPG owners.

Figure 3 further demonstrates our results with two density plots of LPG homogeneity. The peak of a density curve shows highest concentration of data points. In figure 3, the plot on the left is the density curve for non-LPG respondents. The peak of the curve is at LPG homogeneity value of slightly more than 0.5. This indicates that the highest concentration of respondents have peer groups in which only 50% of their peers have LPG. The plot on the right is the density curve for LPG respondents, which is in contrast. The peak of the curve is at LPG homogeneity value of approximately 1. This indicates that the highest concentration of respondents have peer groups in which almost all the peers also have LPG. Visuals from the personal network montage and the density plots provide further validation to the results from the logit models.

4. Discussion

4.1. Network measures

The results show that compositional characteristic namely LPG homogeneity was associated with LPG adoption. Increase in peers having LPG increases likelihood of the respondents to also own LPG. The data were cross-sectional, so the directionality of the association is unknown. However, following two key insights could be drawn from this foundational study of personal networks in stove adoption research:

(a) Despite awareness campaigns, education, increase in income, and similar socio-economic status, there are distinct groups of people that define their cooking behavior in these rural households. A shared identity in terms of cooking behavior could clearly be observed in the personal networks of respondents in these communities. One group constitutes respondents with significantly higher number of peers having LPG than that in the other group. Diffusion of information across distinct groups are difficult and gradual [41]. The finding partly contributes to our knowledge on why there is gradual transition in clean cooking adoption in poor communities. Behavior change is difficult when individuals are embedded in their own homophilic groups. Frequent conversations with people with similar thought process in cooking behavior create a social eco-system where transition to clean cooking is slow.

(b) To address HAP challenges, numerous governments and international agencies have implemented clean cooking welfare policies and schemes. For instance, the Government of India rolled out its flagship welfare program (*Pradhan Mantri Ujjwala Yojana*) to provide the rural poor with access to LPG at subsidized costs. Although there is a surge in adoption, however there are rural interiors where uptake and use is still a challenge. Targeted awareness campaigns and behavioral change strategies are implemented to shift the mental models

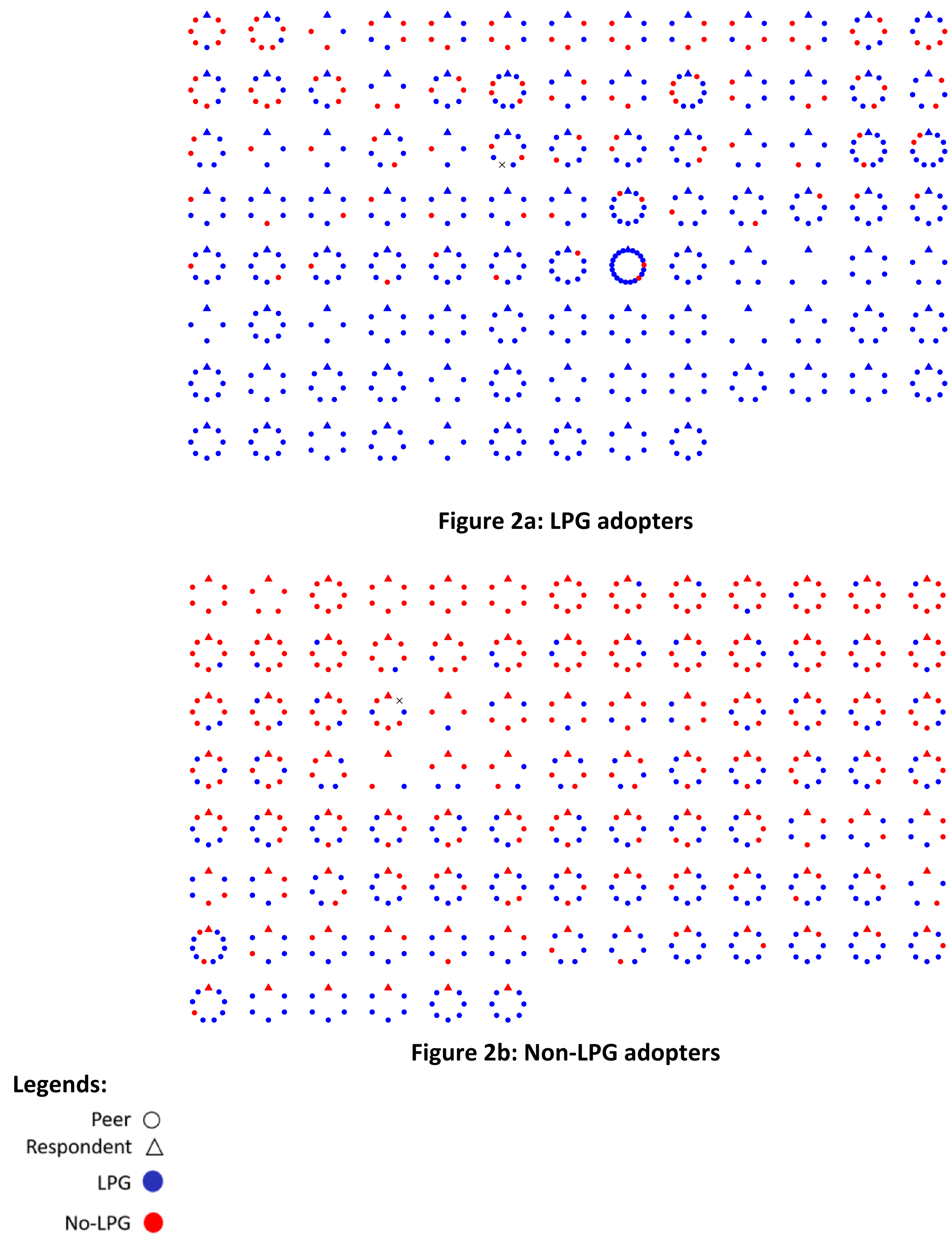

Figure 2. (a) Personal network montage of the LPG adopters. The array shows that respondents who own LPG have a higher proportion of peers who have adopted LPG. (b) Personal network montage of the non-LPG adopters. The array shows that respondents who do not own LPG have a higher proportion of peers who have not adopted LPG.

of those rural poor households. Dissemination of awareness campaigns could be insufficient without exploring how attributes of personal ties could shape mental models and behaviors. In gender and class segregated communities, personal networks could be instrumental in shaping decisions toward LPG adoption. A 'domino effect' either due to peer pressure or peer-led motivation could partly contribute in transitioning to LPG. Opinion leaders could be identified by unpacking structure and composition of personal networks in these communities. Leveraging personal networks and opinion leaders to disseminate information on clean cooking technologies could be an effective instrument in improving the reach and uptake of LPG in

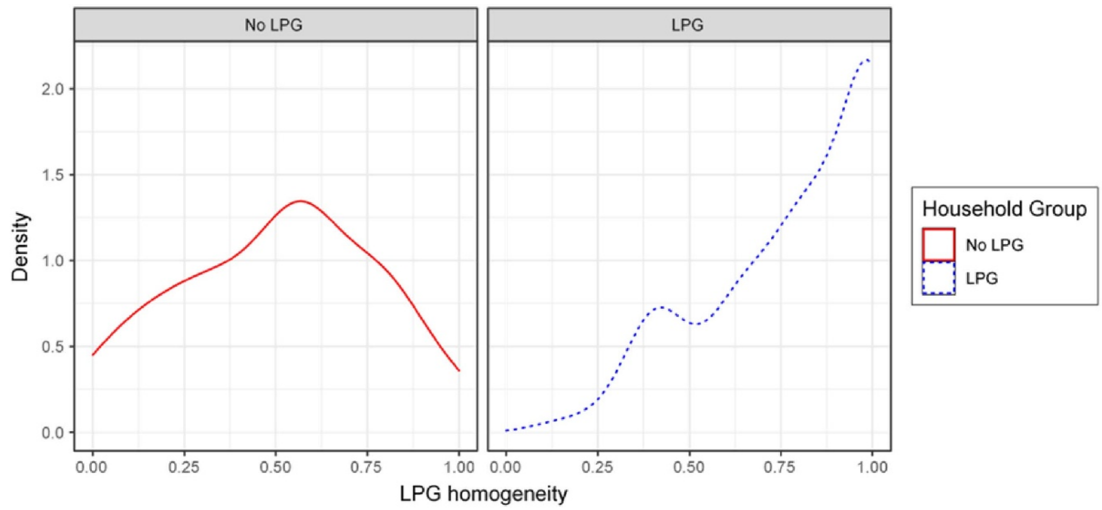

Figure 3. LPG density plot by stove ownership. In LPG households, unlike non-LPG, the highest concentration of respondents in the data have peer groups where almost all the peers also have LPG.

rural poor communities where HAP remains widespread.

4.2. Covariates

The results also offer additional points of consideration for research focused on clean cooking in rural poor communities. For instance, the results of the logit models indicate a lower likelihood of LPG adoption in the case where a source of biomass is nearby. This reinforces the evidence that convenience in accessing biomass motivates rural households to continue using traditional stoves especially in case of deficit in adequate awareness. Perception of LPG as unsafe was negatively associated with adoption, denoting continued gaps in knowledge despite pervasive awareness campaigns. Scholars have emphasized the importance of other social and cultural factors in fuel choice and use patterns [42]. The finding that belonging to SC/ST groups was associated with a decrease in probability of LPG adoption underscores the enduring caste divisions in rural India where historically disadvantaged groups continue to face exclusions in access to improved resources.

4.3. Limitations of the study

There are seven key limitations of this study. They are listed below.

(a) This was a cross-sectional study. Experimental studies and longitudinal data are needed to build on these findings, and further explore the temporal effect of personal networks on stove adoption and use.
(b) The study did not account for: 1. strength of ties of personal networks; and 2. demographic homogeneity of the respondents. Inclusion of these network attributes could provide additional evidence on the role of networks in clean cooking adoption research.
(c) The study focused on association of networks with adoption of LPG, but falls short in exploring the use of LPG. Further studies must explore role of personal networks in both LPG uptake and its use.
(d) While this study witnessed a clear separation on the two groups of LPG and traditional stoves, there are numerous instances wherein energy deficit households stack LPG or clean stoves with traditional stoves. Structure and composition of networks of such households should be explored in future studies.
(e) The geographical location of the peers could play a role in their adoption of LPG, and by extension impact the likelihood of LPG adoption among respondents. Reported peers who live in villages proximal to urban areas could have a higher likelihood to take up LPG. Including network size in the model partly captured the likelihood of counting those peers who live closer to urban areas.
(f) Interaction with LPG distributors is less likely, at least, for this study. Only two LPG distributors supplied LPG tanks and stoves to all the households in this study. We do not rule out the likelihood of the impact of LPG distribution on the LPG uptake in larger multi-town studies.
(g) Typical of a survey based study, there could be issues of recall bias. Also, the retrospective nature of the study could have led to decreased response validity.

5. Conclusion

To our knowledge, this is the first ever study in clean cooking adoption research where personal network analyses were deployed. Through an exploration of personal network characteristics associated with LPG adoption, our study offers novel determinants that could shape LPG adoption. Analyses of personal networks unpacked the interesting aspect that communities similar in socio-economic attributes had distinct social groups based on their cooking behavior. Four factors that clearly merit further investigation and could be built on this study are: (a) extent of LPG use among peers; (b) impact of network attributes of women vs. men from the same household; (c) strength of network ties; and (d) threshold of peers' LPG adoption that lead to stove transition among respondents. Further studies could leverage on the current study, and build on our findings to take a deeper dive to understand how these personal ties impact LPG uptake and by extension clean stove adoption and use.

Data availability statement

The data generated and/or analysed during the current study are not publicly available for legal/ethical reasons but are available from the corresponding author on reasonable request.

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Conflict of interest

The authors declare no conflict of interest.

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