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Assessment of household energy utilization patterns in Uganda: A latent class analysis

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Abstract

This study aims to identify classes and patterns of household energy utilization and the predictive factors that determine class membership. Energy is an essential part of a household's socio-economic status. By examining the household's energy utilization patterns, we can better understand how to formulate and implement efficient strategies for adopting clean energy. This study aims at identifying homogenous classes with respect to their energy patterns in Uganda and examining predictive factors of household class membership. The study uses data on 2,138 households from the 2019/2020 Uganda National Household Survey. Using latent class analysis models, a data-driven method, the study identified four latent household classes; 'Solar-firewood' (41%), 'Electricity-charcoal' (33%), 'Moderate energy-user' (19%) and 'Low energy-user' (7%). Results from the study show that the main drivers of household energy choice for cooking and lighting were age, education level, housing conditions and wealth status of the household head. This study contributes to understanding the classes and patterns of household energy utilization patterns in Uganda. These findings may help policymakers predict which latent class a household falls into in

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order to guarantee efficient targeting of household energy utilization policies and strategies seeking transition to cleaner energy sources.

Keywords
energy, tropical communities, quantitative analysis, families, environment

Introduction

Several energy sources have been used for various household uses such as cooking and lighting (Avila et al., 2017; Kojima et al., 2016; Streatfeild, 2018). Over 2 billion people in developing countries rely on accessible energy sources for their daily energy needs (Nzabona et al., 2021). In Uganda, firewood and charcoal are the leading sources of energy for cooking (UBOS, 2021). This trend raises environmental issues because of greenhouse gasses and air pollution (Namaalwa et al., 2009), and more people are likely to die annually due to respiratory infections (Lambe et al., 2015; Ogundipe et al., 2018). Through its agencies, Electricity Regulatory Authority and Rural Electrification Agency, the government of Uganda has made efforts to increase the supply and access to electricity, particularly in the rural areas of the country. However, the proportion of households using grid electricity reduced from 22% in 2016/17 to 19% in 2019/20, while solar PV increased from 18% to 38% (UBOS, 2021). This clearly indicates that, in spite of government efforts, the majority of the households are still not on grid electricity. In Uganda, like most African countries, most households find it expensive to connect to renewable sources such as grid electricity (Aarakit et al., 2021; Blimpo & Cosgrove-Davies, 2019).

Energy is an essential part of household's socio-economic welfare (Wolde-Rufael, 2006). The benefits of households connecting to grid electricity include improving household socio-economic welfare, preventing environmental degradation and a country's sustainable development. In addition, access to affordable, reliable and sustainable energy is widely recognized as an essential input towards achieving Sustainable Development Goal 7 in Africa (Chirambo, 2018). Previous household energy studies report that most households in Uganda were heavily reliant on fuel wood as the primary source of energy (Behera & Ali, 2017; Drazu et al., 2015; Nzabona et al., 2021). Studies in Kenya have also shown that firewood and charcoal utilization for cooking is on the rise (Lung & Espira, 2019). These results underscore the need to identify distinct sub-groups of households who are distinguished by their choice and utilization of energy sources. It is, therefore, important to understand the classes and patterns of household energy utilization and factors determining membership in order to formulate strategies and policies that lead to households adopting clean power and safer energy sources.

Latent class analysis (LCA) is a statistical technique that identifies categorical latent variables on the basis of observed categorical variables (Muthén & Muthén, 2000). The analysis identifies qualitatively different sub-groups within populations that share certain outward characteristics (Weller et al., 2020). LCA estimates conditional latent class membership probability (and assigns individuals to their most likely class based on this conditional probability) and item response probability (Henry & Muthén, 2010). The conditional membership probability represents the probability that an individual belongs to a latent class, conditional on the answers to the indicators. Therefore, LCA is a useful methodology for identifying potential households for intervention rather than explicitly based on their socio-economic and demographic characteristics such as income levels (Petersen et al., 2019).

This study aims to identify classes and patterns of household's energy utilization and predictive factors that determine class membership. The objectives of this study are: (1) to use statistical methods to group households into distinct sub-groups or classes based on their adopted energy utilization choices; and (2) to identify predictors of these classes in the general population. In particular, our research questions are: how are households distributed in their choice and utilization of energy sources? What pattern explains household choice of energy sources? What socio-economic and demographic factors determine the choice of energy source preferred by the households? To what extent do the factors determine the energy choice preference?

Theoretical background

This study is anchored on previous work on the energy ladder model (Kowsari & Zerriffi, 2011; Van der Kroon et al., 2011). The model describes a pattern of how households switch from biomass energy sources to modern energy sources as their economic status improves (Waleed & Mirza, 2022). The switch is influenced by socio-economic characteristics of the households, supply, availability and accessibility of the energy sources and government interventions that affect the price of energy options (Pachauri & Jiang, 2008). The model assumes that as the households' socio-economic status improves they switch from less efficient biomass fuels to modern fuels that they consider more efficient (Nzabona et al., 2021). However, some studies have established that as income increases, households use a mix of energy sources, a norm referred to as the 'energy stacking' model (Katutsi et al., 2020; Mainimo et al., 2022; Medina et al., 2019). The energy stacking model hypothesizes that households use a variety of energy sources regardless of income level (Choumert-Nkolo et al., 2019; Nguyen et al., 2019). Both the energy ladder and the energy staking models compliment each other in understanding households' energy choices (Katutsi et al., 2020).

Literature review

Several approaches have been used to study household's energy choice and utilization patterns, including structural equation models (Kimutai et al., 2022; Soltani et al., 2020; Zhang et al., 2018), Multinomial logit/probit models (Katutsi et al., 2020; Wassie et al., 2021) and cluster analysis (Ofetotse et al., 2021; Rhodes et al., 2014; Yang et al., 2018). The findings of these studies indicated that a household's energy choice and utilization were significantly influenced by several factors including occupation, age, gender, income level and education level of household head, household size, location and dwelling type. Most households in rural areas adopt solar PV for lighting because of a lack of connection to the national grid. Household heads with relatively high income and education who reside in urban areas are more likely to use electricity for cooking and lighting, while their counterparts in rural areas use firewood for cooking.

In his study, Lee (2013) established that household size, the share of adults in the household and gender in combination explain the utilization of firewood and electricity, while Drazu et al. (2015) studied household energy consumption patterns in Uganda and established energy demand is dominated by solid energy fuels.

Kowsari and Zerriffi (2011) stated that household energy choices depend on household decisions emanating from a complex interaction between household characteristics (economic, socio-demographic and behavioural) and exogenous factors like physical environment as well as energy policies and supply. In addition, Katutsi et al. (2020) investigated the drivers of fuel choice for cooking amongst households and established that households' energy choices differ due to differences in socio-economic settings, environmental factors and cultural factors.

There is an information gap in the current evidence since policy-intervention targets are based on 'average' households; not taking into account households' differences based on their energy utilization choices and patterns. This research fills the gap by identifying classes and patterns of households' energy utilization and predictive factors that determine class membership. Previous studies have used the LCA model to identify underlying classes of households with multidimensional behaviours such as electricity usage (Song & Leng, 2020), agricultural technology adoption (Bizimungu & Kabunga, 2018) and beverage purchases amongst British households (Berger et al., 2020).

This study contributes to literature by adding the LCA approach of identifying classes of household energy utilization, as well as analyzing their causes, outcomes and predictors. This analysis is very important to favour the development of future efficient strategies and to induce households to adopt clean power and safer energy resources. Therefore, for informed policymaking, it is also important to identify which category of households ought to be targeted by what kind of policy interventions.

The remainder of this paper is structured as follows: The 'Materials and methods' section presents data sources, indicator variables, data analysis and ethical considerations. The 'Results' section settin out household descriptive statistics, latent classes and covariates is followed by 'Discussion, Study limitations' and 'Conclusions and policy implications' sections, respectively.

Materials and methods

Data sources

This study uses secondary data collected in the 2019/2020 Uganda National Household Survey (UBOS, 2021). The UNHS 2019/2020 is the seventh in the series of household surveys conducted by UBOS aimed at collecting high quality and timely data on socio, demographic and economic characteristics of the household population. The survey provides representative estimates for the 15 sub-regions and the country as a whole. The survey followed a two-stage stratified sampling design where enumeration areas were drawn from each of the sub-regions with probability proportional to size, followed by selection of households using systematic random sampling. A total of 13,732 households were interviewed. For this study, we extracted 2,138 households from the national data set, representing those who responded to questions about energy sources for lighting and cooking. This sub-sample was comparable by age, sex and regional distribution to the national sample (UBOS, 2021). Hence, this study is based on a nationally representative sample of households in Uganda.

Indicator variables

The main indicator variables for this study are sources of energy for cooking and lighting. The UNHS 2019/2020 collected information on sources of energy for cooking by asking respondents ‘What source of energy does this household mainly use for cooking?’ The sources of energy for cooking captured during the survey were national grid electricity, solar power, generator electricity, thermal plant electricity, gas, biogas, paraffin, charcoal, firewood, cow dung, grass and others. For this study, the energy sources for cooking are categorized as electricity, kerosene, charcoal, firewood and others.

The survey also collected information on sources of energy for lighting by asking respondents ‘What source of energy does this household mainly use for lighting?’ The sources of energy for lighting captured during the survey were national grid electricity, solar power, generator electricity, thermal plant electricity, gas, biogas, paraffin, candles, firewood, cow dung, grass, dry cells and others. For this study, the energy sources for lighting are categorized as electricity, solar, paraffin, dry cells and others.

Also collected in the survey were households’ socio-economic and demographic characteristics, such as head of household’s age, sex, wealth status, education level and marital status, type of dwelling, type of kitchen and cooking stove used, source of firewood and occupancy tenure.

Analytical model

The mathematical LCA model is described below following the works by Weller et al. (2020) and Dolšak et al. (2020).

Let the energy choices observed on the n households ($\mathfrak{X}_i = x_{i1}, x_{i2}, \ldots, x_{i5})^T$, $i = 1, 2, 3, \ldots, n$, and $j = 1, 2, \ldots, J$; where x_{ij} ε $\{1, 2, \ldots, C_j\}$ where C_j is the number of categories that the response of household i to energy source j can assume.

Assuming that there are K latent classes of the households, that is, each x_i comes from some unobserved class k ε $\{1, 2 \ldots K\}$.

If Y is the latent variable indicating the class from which a household belongs, then prior distribution shows that P(Y), is the probability that a randomly selected household belongs to a particular class, k (i.e., class membership probabilities). Let $P(Y = k) = \eta_k$. The class membership probability is the likelihood that a household is properly classified, enabling each household to be categorized into the best-fitting class.

The class conditional distribution describes the distribution of energy choices given that a household in class k answers item j in category c, that is, $x_j = c$ given $Y = k$,

$$f_k(x) = P(x_j = c|Y = k)$$

The assumption (or axiom) of conditional independence says that the joint distribution of x's under independence is the product of the marginal. It implies that within a class all the x's will be uncorrelated. Given membership in class k, responses to the individual households are independent of each other, then,

$$f_k(x) = \prod_{j=1}^{J} P(x_j = c|Y = k)$$

Let π_{jk} be the probability that a household in class k has a positive response to item j (item-response probabilities), then the class conditional distribution is:

$$f_k(x) = \prod_{j=1}^{J} \pi_{jk}^{x_j}(1 - \pi_{jk})^{1 - x_j}$$

Therefore, the unconditional distribution of x is obtained by weighting the conditional distribution by η_k and add them up:

$$f(x) = \sum_{k=1}^{K} \eta_k \prod_{j=1}^{J} \pi_{jk}^{x_j}(1 - \pi_{jk})^{1 - x_j}$$

The posterior distribution, $P(Y = k|x)$, gives the probability of belonging to group k given a set of items; that is, using Bayes' theorem

$$P(Y = k|x) = \frac{f_k(x)\eta_k}{f(x)}$$

This is a probabilistic model with JK latent class parameters π_{jk} and η_k for $k = 1, 2 \ldots K$; $j = 1, 2 \ldots J$. This helps to assign households to classes given their responses to a set of items.

The latent class parameters are estimated by a maximum likelihood model estimation approach using a log-likelihood function given by:

$$L(\pi, \eta) = \sum_{i=1}^{n} log\left[\sum_{k=1}^{K} \eta_k \prod_{j=1}^{J} \pi_{jk}^{x_j}(1 - \pi_{jk})^{1 - x_j}\right]$$

Subject to constraints

$$\sum_{k=1}^{K} \eta_k = 1; \qquad \sum_{c=1}^{C_j} \pi_{cjk} = 1$$

Latent class models are estimated by iteratively adding potential classes to determine which model is the best fit to the data. The number of latent classes depends on a combination of factors including model fit, class size and interpretability (Weller et al., 2020). To assess the model fit and determine the appropriate number of latent classes, a combination of some model fit indicators and statistical tests were used. These include the Bayesian information criterion (BIC), the Akaike information criterion (AIC), Lo–Mendell–Rubin likelihood ratio (LMR) and the bootstrapped parametric likelihood ratio test (BLRT) (Dolšak et al., 2020; Killian et al., 2019; Nylund et al., 2007). According to Weller et al. (2020), good fit models are indicated by the lowest absolute values of AIC and BIC. The significance probabilities of the class models were established using the LMR and the BLRT at a 5% level. The null hypothesis is that the latent class model would be accepted when the *p*-value is greater than 0.05.

The data were analyzed using the Latent Gold 5.0 statistical package (Vermunt & Magidson, 2013) and STATA software version 15 (StataCorp, 2007). First, households' general characteristics were analyzed in terms of frequencies, percentages, means and standard deviation. Second, a series of LCA models were fitted for five binary indicators namely: energy source for lighting, energy source for cooking, type of kitchen, primary cooking stove and source of firewood. Thirdly, multinomial logistic regression analysis was used to predict the household's latent class membership against the different covariates. This aimed at establishing which household factors were key drivers of switching from reference energy utilization latent class to other classes. The regression model assumes that the household's probability varies depending upon their observed covariates (Dolšak et al., 2020). The logistic regression function produces relative risk ratios (RRRs), at a 95% confidence interval, which indicates that the covariate is significantly associated with an increase (or decrease) in the risk of membership in a specified latent class relative to a reference latent class corresponding to a different level on the covariate (Lanza & Rhoades, 2013).

Results

Household characteristics by energy sources for lighting and cooking

This section presents the household characteristics. Table 1 shows that most household heads were male (68%), with an average age of 37 years (SD = 15), married (69%) and having attained primary education (44%). In terms of geographical coverage, the majority of households were in the central region of Uganda (32%) and living in rural areas (58%). In addition, they lived in their own dwelling units (69%), comprising 1–3 sleeping rooms (90%), with an average household size of four people (SD = 2.4) and 60% of the households were classified as 'poor'.

Table 1. Percentage of households reporting energy sources used for lighting and cooking by selected household characteristics.

		Energy sources for lighting					Energy sources for cooking				
Household characteristics		Electricity	Solar	Paraffin	Dry cells	Other	Electricity	Kerosene	Charcoal	Firewood	Other
Overall ($n = 2138$)		28.2	31.7	10.4	12.5	17.2	1.8	0.6	32.7	58.9	6.1
Sex of household head ($n = 2131$) $\chi^2 = 34.69$ $p = 0.000$							$\chi^2 = 31.49$ $p = 0.000$				
Male	68.7	68.2	73.6	72.5	70.5	56.6	73.0	91.7	66.2	67.5	89.2
Female	31.3	31.8	26.4	37.5	29.5	43.4	27.0	8.3	33.8	32.5	10.8
Age of Household head (years) ($n = 2131$) $\chi^2 = 34.4$ $p = 0.000$							$\chi^2 = 134.4$ $p = 0.000$				
15–29	45.5	45.0	39.4	44.6	47.8	56.3	48.7	83.3	49.1	39.8	76.2
30–39	20.8	24.7	21.3	18.9	18.3	16.4	32.4	8.3	26.4	18.1	14.6
40 and above	33.7	30.3	39.3	36.5	34.0	27.3	18.9	8.3	24.4	42.1	9.2
Marital status ($n = 2138$) $\chi^2 = 123.7$ $p = 0.000$							$\chi^2 = 447.7$ $p = 0.000$				
Married	68.9	58.0	75.5	70.7	78.7	66.6	63.2	8.3	66.8	75.9	21.4
DivorcedWidowed	19.8	19.9	18.6	23.4	18.3	20.9	15.8	16.7	19.9	20.1	18.3
Never married	11.3	22.1	5.9	5.9	3.0	12.5	21.1	75.0	13.3	4.1	60.3
Number of sleeping rooms ($n = 2132$) $\chi^2 = 54.2$ $p = 0.000$							$\chi^2 = 33.6$ $p = 0.000$				
1–3	90.6	91.9	84.1	96.0	90.3	96.1	97.4	100.0	94.4	87.3	95.2
4 and above	9.4	8.1	16.0	4.1	9.7	3.9	2.6	0.0	5.6	12.7	4.8
Household size ($n = 2132$) $\chi^2 = 43.1$ $p = 0.000$							$\chi^2 = 70.3$ $p = 0.000$				
1–6	81.7	87.7	77.6	88.7	79.1	89.1	91.9	100.0	90.5	78.3	96.2
7–10	13.9	10.0	19.1	9.9	18.7	9.6	8.1	0.0	8.5	18.3	3.1

(continued)

Table 1. Continued.

Household characteristics	Energy sources for lighting						Energy sources for cooking				
	Electricity	Solar	Paraffin	Dry cells	Other		Electricity	Kerosene	Charcoal	Firewood	Other
[illegible]	[illegible]	[illegible]	3.3	1.4	2.2	1.4	[illegible]	0.0	1.0	3.3	0.8
Region ($n=2138$) $\chi^2=271.7$ $p=0.000$						$\chi^2=390.0$ $p=0.000$					
Central	32.1	67.3	26.4	21.6	5.6	10.9	70.3	75.0	56.0	15.8	47.7
Eastern	25.7	14.8	24.0	49.1	45.9	17.5	5.4	16.7	15.1	32.4	23.9
Northern	23.0	5.2	21.9	14.9	42.9	44.3	18.9	0.0	13.7	29.4	13.9
Western	19.2	12.7	27.7	14.4	5.6	27.3	5.4	8.3	15.2	22.5	14.6
Education level ($n=2138$) $\chi^2=618.6$ $p=0.000$						$\chi^2=438.4$ $p=0.000$					
None	13.0	3.5	11.5	9.9	12.3	33.4	0.0	0.0	3.9	19.3	5.3
Primary	44.1	20.4	51.3	65.3	67.5	40.2	26.3	16.7	26.8	55.2	38.2
Secondary	29.0	42.0	28.1	21.6	17.5	22.0	36.8	41.7	43.7	20.1	32.1
Post-secondary	13.9	34.2	9.2	3.2	2.6	4.4	36.8	41.7	25.6	5.4	24.4
Occupancy tenure ($n=2132$) $\chi^2=478.9$ $p=0.000$						$\chi^2=795.3$ $p=0.000$					
Owner occupied	69.0	35.8	83.9	79.7	86.2	77.4	36.8	16.7	38.4	91.3	31.8
Free	6.3	8.5	4.7	5.4	5.6	6.9	2.6	0.0	7.3	4.6	19.8
Rented	24.7	55.7	11.4	14.9	8.2	15.7	60.5	83.3	54.3	4.1	48.4
Primary cooking stove ($n=2130$) $\chi^2=658.2$ $p=0.000$						$\chi^2=320.0$ $p=0.000$					
3-stone	52.6	9.5	63.8	73.4	76.1	72.9	7.9	0.0	3.0	86.8	2.4
Traditional	19.8	35.3	17.0	13.1	12.3	8.8	29.0	0.0	43.0	8.6	1.6
Improved	21.0	43.1	15.4	9.0	9.0	11.1	52.6	33.3	52.4	4.5	0.0
No cooking	6.6	12.2	3.8	4.5	2.6	7.2	10.5	66.7	1.6	0.1	95.9
Type of kitchen ($n=2117$) $\chi^2=259.9$ $p=0.000$						$\chi^2=427.1$ $p=0.000$					

(continued)

Table 1. Continued.

		Energy sources for lighting					Energy sources for cooking				
Household characteristics		Electricity	Solar	Paraffin	Dry cells	Other	Electricity	Kerosene	Charcoal	Firewood	Other
Inside	16.8	23.5	13.7	11.3	13.2	17.6	31.6	58.3	27.8	9.9	16.4
Outside, built	46.8	28.0	62.9	62.4	60.5	27.9	29.0	0.0	23.6	64.1	6.4
Makeshift	36.4	48.6	23.4	26.2	26.3	54.6	39.5	41.7	48.6	26.1	77.3
Wealth status ($n = 2132$)	$\chi^2 = 116.1$ $p = 0.000$						$\chi^2 = 37.3$ $p = 0.000$				
Poor	60.4	46.0	53.7	73.7	63.7	82.5	52.0	63.6	48.8	65.8	63.6
Middle	37.8	49.7	44.6	26.4	34.8	17.5	44.0	36.4	48.8	32.5	35.5
Richer	1.8	4.3	1.7	0.0	1.5	0	4.0	0.0	2.3	1.7	0.8

With regards to energy utilization patterns, Figure 1(a) shows that the majority of the households were using solar (32%) followed by electricity (28%) for lighting, while Figure 1(b) shows that firewood (59%) and charcoal (33%) were the predominant sources of energy for cooking. In terms of cooking, most households were using a three-stone (53%) as their primary cooking stove, with outside-built kitchen (47%) and the bush/forest (71%) was their source of firewood.

Table 1 further shows that all the household characteristics were statistically significantly associated with energy sources used for lighting and cooking ($p < 0.05$).

Latent classes

Table 2 presents the model fit statistics derived from the LCA. After assessing one to five-class solutions, a four-class model was identified as the optimal

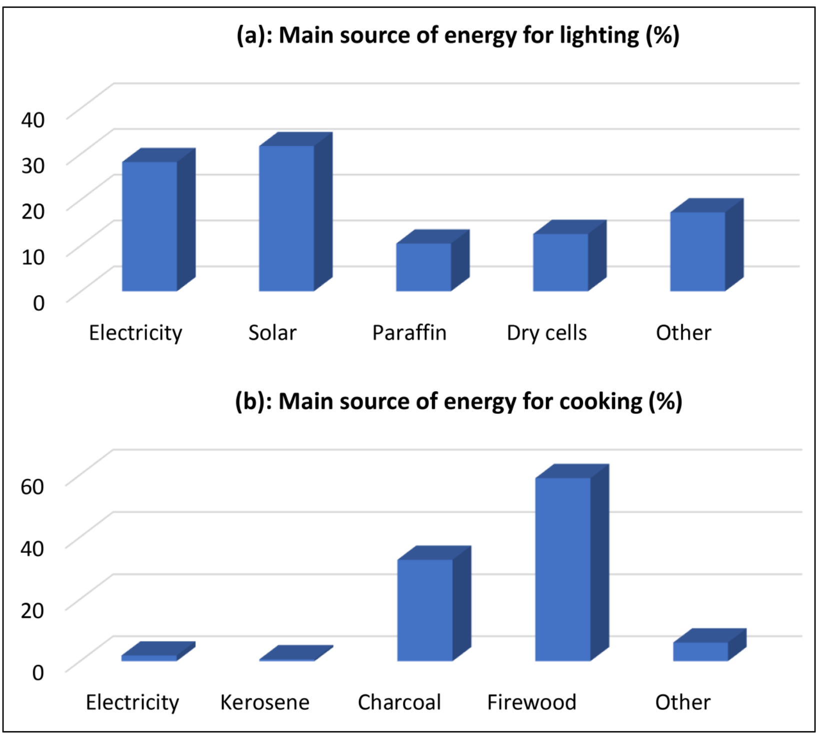

Figure 1. (a) Main source of energy for lighting (%). (b) Main source of energy for cooking (%).

solution that best fits the data by its lowest BIC value, fewer parameters and a smaller log-likelihood ratio. The five-class model also showed adequate goodness-of-fit statistics; however, the BIC value was slightly higher than for the four-class model. Therefore, the result implies that four groups of households have been identified in the data based on their energy utilization heterogeneity.

Results indicate that of the 2,138 households assessed, most of them fall in latent class 1 comprising 878 households (41%), while the least number is in class 4 with only 139 households (7%), as shown in Table 3. Since each individual household must belong to one and only one class, then the sum of individual class sizes (class 1–4) must be equal to the total households assessed. For each class, we estimated the conditional probability of energy sources for lighting and for cooking, primary cooking stove, type of kitchen and source of firewood. The higher the conditional probability, the more that item is considered sufficient to influence classification labelling.

Class 1 members are characterized by the highest probability of using solar (0.69) for lighting, firewood (0.68) for cooking, a three-stone stove (0.65), their source of firewood is their own plantation (0.92) and they have an outside built kitchen (0.72). This class is labelled as 'Solar-firewood' households. These probabilities suggest that members in this class use traditional energy sources for cooking and have their own dwellings with an outside-built kitchen. The significantly high probability of using solar for lighting suggests that these households have limited or no access to grid electricity.

Class 2 members mostly use electricity (0.78) for lighting; charcoal (0.98) for cooking, use improved cooking stoves (0.81) and have their kitchen inside dwellings (0.58). Accordingly, this class can be labelled as 'Electricity-charcoal' households.

Class 3 shows similar patterns with class 1 concerning using firewood (0.32) for cooking and a three-stone stove (0.34), except that they have bush/forest as their source of firewood and utilize makeshift kitchens. In addition, they use other sources of energy (e.g., torch and dry cells) for lighting (0.64). Therefore, these members are labelled 'Moderate energy-use' households.

Class 4 members exhibited significantly lower probabilities of using electricity (0.11) for lighting and are more likely (0.96) to use other energy sources, for example, gas for cooking, or not cooking at all (0.91). This class shows the lowest probabilities of using traditional energy sources for lighting and cooking. Accordingly, we label this class as 'Low energy-use' households.

Predictors of latent class membership

After identifying the latent classes in the data, household socio-economic and demographic characteristics were included in the multinomial logistic

Table 2. Model fit statistics for LCA models.

		LL	BIC(LL)	AIC(LL)	Npar	L^2	df	*p*-value	Class.Err.
Model1	1-Cluster	−13,729.4107	27,635.1769	27,504.8215	23	11,864.6252	2115	2.1e-1328	0.0000
Model2	2-Cluster	−11,693.6748	23,747.7281	23,481.3496	47	7793.1533	2091	6.4e-644	0.0051
Model3	3-Cluster	−11,329.4194	23,203.2404	22,800.8389	71	7064.6426	2067	1.3e-536	0.0054
Model4	4-Cluster	−11,181.6049	23,091.6343	22,553.2098	95	6769.0134	2043	8.6e-498	0.0809
Model5	5-Cluster	−11,104.6337	23,121.7149	22,447.2674	119	6615.0711	2019	1.0e-480	0.0870
Model6	6-Cluster	−11,046.4284	23,189.3274	22,378.8569	143	6498.6605	1995	2.4e-469	0.1050

Table 3. Description of latent class membership.

Cluster size	Class 1 41.1% (878)	Class 2 33.7% (721)	Class 3 18.7% (400)	Class 4 6.5% (139)
Energy source for lighting				
Dry cells	0.1762	0.0370	0.1981	0.0510
Electricity	0.0719	0.6526	0.0005	0.5044
Others	0.0510	0.0756	0.5909	0.2319
Paraffin lantern	0.1673	0.0392	0.0915	0.0727
Solar	0.5336	0.1955	0.1190	0.1400
Energy source for cooking				
Charcoal	0.0180	0.9465	0.0004	0.0017
Electricity	0.0000	0.0438	0.0074	0.0253
Firewood	0.9779	0.0040	0.9889	0.0011
Kerosene	0.0000	0.0057	0.0000	0.0575
Other	0.0041	0.0000	0.0033	0.9144
Primary cooking stove				
3-stone	0.8347	0.0111	0.9433	0.0031
Improved	0.0605	0.5418	0.0086	0.0005
No cooking	0.0012	0.0159	0.0000	0.9960
Traditional	0.1036	0.4312	0.0480	0.0004
Source of firewood				
Bush/Forest	0.6186	0.1173	0.9233	0.7125
Market	0.1325	0.8002	0.0345	0.1015
Own Plantation	0.2489	0.0825	0.0422	0.1860
Type of kitchen				
Inside	0.0708	0.2856	0.1577	0.2038
Makeshift	0.1135	0.4854	0.5832	0.7610
Outside Built	0.8157	0.2290	0.2591	0.0352

regression model to explore the effect of covariates on latent class membership. The latent classes were the dependent variable for the model to assess the predictors of latent class membership and the covariates were as follows:

- Age of household head: 15–24 years, 25–34 years, 35–44 years, 45–54 years and 55+ years
- Marital status of household head: Never married, Married, Divorced or Widow
- Education level of household head: None, Primary, Secondary and Post-secondary
- Number of sleeping rooms: 1 room, 2–3 rooms and 4+ rooms

- Occupancy tenure: Free dwelling, Owner occupancy and Rented dwelling
- Self-reported wealth status: Poor, Middle and Rich

A multinomial logistic regression analysis was performed to estimate the RRR of covariates on latent class membership in each class relative to the reference class (Class 1). The estimates measure the percentage change in the probability of class membership when the value of the covariate changes by 1 category and all other variables are kept constant at their means. The results are presented in Table 4.

```
Multinomial logistic regression                 Number of obs     =      1,453
                                                LR chi2(45)       =    1137.94
                                                Prob > chi2       =     0.0000
Log likelihood = -1234.8915                     Pseudo R2         =     0.3154
```

Based on the likelihood ratio chi-square test [LR $\chi^2(45) = 1137.97$, $p = 0.00$], the model containing the full set of predictors represents a significant improvement in fit relative to a null model (no predictors). Therefore, we can infer that at least one population slope is non-zero. The McFadden's pseudo R-square (Pituch & Stevens, 2016) indicates that the model represents a 31.5% improvement in fit relative to the null model.

Class 2 vs class 1. When Class 2 was compared with Class 1 as a reference group, marital status-married (RRR = 0.32, $p = 0.000$); number of sleeping rooms – 2–3 rooms (RRR = 0.62, $p = 0.018$); education level – secondary (RRR = 5.27, $p = 0.000$) and postsecondary (RRR = 9.50, $p = 0.000$); occupancy tenure – owner occupancy (RRR = 0.34, $p = 0.001$), rented dwelling (RRR = 7.21, $p = 0.000$) and wealth status-middle (RRR = 1.43, $p = 0.035$) were significant predictors of household latent class membership. The RRR for the 'married' dummy variable indicates that the risk of falling in Class 2 for married household heads is 0.32 times that of never-married household heads. This means that married household heads are at less risk of falling into Class 2 and at a greater risk of falling into Class 1 than the never married household heads. With regards to the number of sleeping rooms in the dwelling, the RRR of the '2–3 room' category indicates that the risk of falling in Class 2 for household heads in 2–3 rooms' dwellings is 0.62 times that of household heads in 1-room dwellings. This means that with an increasing number of sleeping rooms in a dwelling, the risk that a household head falls in Class 2 decreases, whereas the risk of falling in Class 1 increases. The RRR of the 'secondary' category of variable indicating education level

Table 4. Multinomial logistic regression of covariates on latent class membership.

	Comparison group (Ref = Class 1)					
	Class 2		Class 3		Class 4	
Covariates	RRR	*p*-value	RRR	*p*-value	RRR	*p*-value
Age – *15–24 years (Ref)*						
25–34 years	1.32	0.262	0.70	0.119	1.28	0.413
35–44 years	1.42	0.303	0.34*	0.002	0.71	0.978
45–54 years	1.11	0.775	0.25*	0.000	0.13	0.059
55+ years	1.06	0.867	0.25*	0.000	0.09*	0.030
Marital status – *Never married (Ref)*						
Married	0.32*	0.000	0.58	0.133	0.03*	0.000
Divorced or widow	0.89	0.749	0.57	0.178	0.28*	0.002
Number of rooms – *1 room (Ref)*						
2–3 rooms	0.62*	0.018	0.87	0.468	0.17*	0.000
4+ rooms	0.39*	0.006	0.67	0.295	0.30	0.145
Education level – *None (Ref)*						
Primary	1.74	0.104	0.23*	0.000	0.66	0.447
Secondary	5.27*	0.000	0.15*	0.000	1.32	0.616
Postsecondary	9.50*	0.000	0.12*	0.000	3.76*	0.030
Occupancy – *Free dwelling (Ref)*						
Owner occupancy	0.34*	0.001	0.88	0.729	0.51	0.109
Rented dwelling	7.21*	0.000	0.87	0.772	4.11*	0.001
Wealth status – *Poor (Ref)*						
Middle	1.43*	0.035	0.32*	0.000	1.01	0.965
Rich	0.97	0.968	0.04	0.988	0.58	0.677

*Significant coefficient at 5% level.

(RRR = 5.27, $p = 0.000$) and 'post-secondary' category (RRR = 9.50, $p =$ 0.000) means that with increasing education of the household head, the risk of falling into Class 2 increases whereas the risk of falling into Class 1 decreases. The RRR for the 'rented dwelling' category (RRR = 7.21, $p =$ 0.000) indicates that the risk of falling in Class 2 for household heads occupying rented dwellings is 7.21 times of that those who are in a free dwelling. This means that household heads who occupy rented dwellings were at a higher risk of falling into Class 2 than those in free dwellings, and at a decreased risk of falling into Class 1. The RRR for the 'middle' category (RRR = 1.43, $p = 0.035$) indicates that the risk of a household head in the middle wealth status falling into Class 2 is 1.43 times that of a household head in the poor wealth status. It also indicates that with each one-unit increase in wealth status, the relative risk of falling into Class 2 is multiplied by a factor of 1.43. This means that household heads with an increasing wealth status were at a greater risk of falling into Class 2 than those with decreasing wealth status, and at a decreasing risk of falling into Class 1.

Class 3 vs class 1. Results from comparing Class 3 with Class 1 as a reference group showed that age – 45–54 years (RRR = 0.25, p = 0.000) and 55+ years (RRR = 0.25, p = 0.000); education level – primary (RRR = 0.23, p = 0.000), secondary (RRR = 0.15, p = 0.000) and postsecondary (RRR = 0.12, p = 0.000); and wealth status – middle (RRR = 0.32, p = 0.000) were significant predictors of household latent class membership. The RRR for the '45–54 years' and '55+ years' categories indicate that the risk of falling into Class 3 for a household head aged 45 years and above is 0.25 times that aged 15–24 years, and at a greater risk of falling into Class 1. The RRR of the 'Primary' dummy variable (RRR = 0.23, p = 0.000), 'Secondary' dummy variable (RRR = 0.15, p = 0.000) and 'Postsecondary' dummy variable (RRR = 0.12, p = 0.000) mean that, with increasing education of the household head, the risk of falling into Class 3 decreases whereas the risk of falling into Class 1 increases. The RRR for the 'middle' category (RRR = 0.32, p = 0.000) indicates that the risk of a household head in the middle wealth status falling into Class 3 is 0.32 times that of a household head in the poor wealth status. This means that household heads in the middle wealth status were at less risk of falling into Class 3 than those in the poor wealth status, and at an increased risk of falling into Class 1.

Class 4 vs class 1. When Class 4 was compared with Class 1 as a reference group, age – 55+ years (RRR = 0.09, p = 0.030); marital status – married (RRR = 0.03, p = 0.000) and divorced or widow (RRR = 0.28, p = 0.002); number of rooms – 2–3 (RRR = 0.17, p = 0.000); education level – postsecondary (RRR = 3.76, p = 0.030); and occupancy tenure – rented dwelling (RRR = 4.11, p = 0.001) were significant predictors of household latent class membership. The RRR for the '55+ years' dummy variable indicates that the risk of falling into Class 4 'Low energy-use households' for a household head aged 55 years and above is 0.09 times that aged 15–24 years and at a greater risk of falling into Class 1. The RRR for the 'married' category indicates that the risk of falling in Class 4 for married household heads is 0.03 times that of never-married household heads. This means that married household heads are at almost zero risk of falling into Class 4 and at a greater risk of falling into Class 1 than the never married household heads. With regards to the number of sleeping rooms in the dwelling, the RRR of the '2–3 rooms' category indicates that the risk of falling in Class 4 for household heads in 2–3 rooms' dwellings is 0.17 times that of household heads in 1-room dwellings. This means that with an increasing number of sleeping rooms in a dwelling, the risk that a household falls in Class 4 decreases, whereas the risk of falling in Class 1 increases. The RRR of the 'postsecondary' category (RRR = 3.76, $p = 0.030$) indicates that the risk of a household head who attained post-secondary education falling into Class 4 is 3.76 times that of a household head with no education. This means that with increasing education of the household head, the risk of falling into Class 4 increases whereas the risk of falling into Class 1 decreases. In addition, The RRR for the 'rented dwelling' category (RRR = 4.11, $p = 0.001$) indicates that the risk of falling in Class 4 for household heads occupying rented dwellings is 4.11 times of that those who are in a free dwelling. This means that household heads who occupy rented dwellings were at a higher risk of falling into Class 4 'Low energy-use households' than those in free dwellings, and at a decreased risk of falling into Class 1.

Discussion

The main aim of the study was to identify groups of households as a function of their energy utilization patterns in Uganda, while the specific objective was to analyze the predictive factors of belonging to these groups in the general population. By applying LCA, this study identified segments of Ugandan households that are similar in energy utilization choices, namely 'Solar-firewood' households (Class 1), 'Electricity-charcoal' households (Class 2), 'Moderate energy-users' households (Class 3) and 'Low energy-users' households (Class 4).

This study has identified a number of socio-economic and demographic factors that influence household membership to the latent classes. The estimated parameters show significant effects of age and education level of the household head, as well as the number of sleeping rooms in the dwelling, occupancy and self-reported wealth status. This item-response analysis suggests that household energy utilization in Uganda can be broadly grouped as a pattern of energy sources for lighting and cooking, namely solar-firewood and electricity-charcoal. This finding is in line with a previous study done by Ling et al. (2020); however, other studies have grouped household energy utilization patterns by single energy sources (Aarakit et al., 2021; Lee, 2013; Lusambo, 2016). Our study provided a point of view from which to group household energy utilization in Uganda through identifying different patterns of energy for lighting and cooking.

Amongst the four latent classes, the 'Solar-firewood' households' class was the largest, accounting for 41% of the total sample. These households are characterized by high probabilities of using solar for lighting and firewood for cooking. UBOS (2021) data indicates that 27% of Ugandan households used solar for lighting, while 73% used firewood for cooking. The likelihood of a household falling into this class increases with the age of the household head. Specifically, it has been established that an increase in the age group of the household head increases the probability of being in this class, adding substantially to previous studies by Kazoora et al. (2015), Lusambo (2016) and Nzabona et al. (2021). The use of solar for lighting and firewood for cooking by older household heads is likely to be associated with their relatively lower financial position as they get older. Because of complex financial needs, older household heads tend to focus on affordable and easily accessed sources of energy compared to other sources such as electricity. This class is also associated with households based in rural areas of Uganda that have limited or no access to grid electricity. Solar energy has significant potential in Uganda since the majority of households live in rural areas with limited access to grid electricity. In addition, the continued use of firewood leads to environmental degradation, reduction of soil fertility and climate change. The declining soil fertility will negatively affect households' agricultural productivity and livelihood.

The 'Electricity-charcoal' households' class had high probability of using electricity for lighting and charcoal for cooking. This class constituted about 33% of the total sample. UBOS (2021) indicates that 21% of Ugandan households used charcoal for cooking, while 19% used grid electricity for lighting and 1% for cooking. This clearly shows that access to national grid electricity is still relatively low.

Consistent with existing literature in the field, our results show that with increasing education level of the household head, the risk of falling into 'Electricity-charcoal' households class increases whereas the risk of falling into 'Solar-firewood' households class decreases. For instance, a household head with secondary education is 5.3 times more likely to fall in the 'Electricity-charcoal' households' class than one with no education at all, and a massive 9.5 times if that head has been exposed to postsecondary education. A plausible explanation is that education increases the chances of accessing income-generating opportunities, thus enabling such household heads to afford buying electricity and charcoal for their energy needs. Conversely, household heads with no formal education are more likely to fall into 'Solar-firewood' households' class probably because they cannot afford to buy electricity or charcoal. This implies that the higher the education level of household heads, the more likely they are to choose Electricity-charcoal over the Solar-firewood energy. In accordance with previous studies, education is a significant predictor of household energy consumption in Uganda (Kyasimire, 2019; Lee, 2013; Namaalwa et al., 2009).

The education level of the household head plays an important role in predicting household latent class membership (Gould et al., 2020).

The occupancy tenure of dwelling and number of sleeping rooms used by the household are also important factors in predicting household latent class membership. Specifically, we find that with an increasing number of sleeping rooms in a dwelling, the risk that a household head falls in ‘Electricity-charcoal’ class decreases, whereas the risk of falling in ‘Solar-firewood’ class increases. The increase in the number of sleeping rooms increases the energy demand for household occupants. This should not be a surprise considering that large housing spaces are more energy intensive. It becomes economical to use the relatively cheaper forms of energy (solar and firewood) than using electricity or charcoal. The findings of this study are comparable to the results of Mainimo et al. (2022) and Crentsil et al. (2019), who reported that household size was a major hindrance to the utilization of clean and modern energy sources. In addition, household heads who occupy rented dwellings were at a higher risk of falling into the ‘Low energy-users’ class than those in free dwellings. Different from the members in the other three classes, households in the ‘Low energy-users’ class are characterized by relatively low probabilities of using electricity for lighting but a high probability of using gas for cooking or not cooking at all. Most times, property owners have full control of the energy decisions on behalf of the tenants. The energy utilization of tenants is subject to tenants’ agreements, which may affect their rights to decide on household energy requirements. Studies elsewhere have similarly indicated that housing conditions are associated with household energy utilization (Kazoora et al., 2015; Kojima et al., 2016; Nzabona et al., 2021).

The study results provide empirical evidence that a household head’s wealth status influenced the class membership, with the ‘poor’ having more chances of falling into the ‘Solar-firewood’ class. Conversely, household heads in the middle class had reduced chances of falling into the ‘Solar-firewood’ class. Wealthy households can afford to use electricity or charcoal compared to their ‘poor’ counterparts. This finding is consistent with the energy ladder concept which stipulates that economic growth shifts households towards cleaner and modern energy sources (Kowsari & Zerriffi, 2011). Wealth status has been reported to influence household’s energy utilization choices in sub-Saharan Africa (Baek et al., 2020; Chirambo, 2018).

Study limitations

The limitations of this study include the cross-sectional design of the 2019/2020 UNHS, thus caution should be used when interpreting the results in terms of causal inferences. In addition, since the information is recorded retrospectively, it might be prone to recall bias, with reporting becoming less accurate over time. The availability of only quantitative data limited analysis of other pertinent energy-related issues such as the reason for, attitudes towards and implications of households; energy choices. Therefore, further research is needed to include the outlined variables. A similar study could be conducted on panel UNHS data of previous periods.

Conclusions and policy implications

This study has confirmed latent classes of households based on their energy utilization patterns and assessed their predictors. In Uganda, the majority of households use solar followed by electricity for lighting, while firewood and charcoal were the main sources of energy for cooking (UBOS, 2021). Using LCA, a data-driven method, we identified four household latent classes, namely, 'Solar-firewood', 'Electricity-charcoal', 'Moderate energy-use' and 'Low energy-use' households. This approach enabled us to perform model-based data clustering to identify households with similar patterns of energy choice and provide important insights to this field. The results show that the most important drivers of household energy choice for cooking and lighting were age, education level, housing conditions and wealth status of the household head. This information can help policymakers predict which latent class a household falls into, which allows better targeting of energy policy interventions.

The higher percentage of households falling into the 'Solar-firewood' class presents an environmental challenge resulting from deforestation. Nevertheless, household energy utilization policies and strategies seeking the transition to cleaner energy sources can be based on these findings. For instance, to mitigate the effects of relying on firewood, government needs to sensitize households on conserving the environment and the dangers of degrading it. Furthermore, government should promote utilization of cleaner energy sources by supporting households to access affordable electricity. Government providing incentives to the private sector to invest in energy-efficient technologies such as cook-stoves, liquefied petroleum gas, biogas and solar systems could also assist the transition to cleaner energy sources.

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Author's contribution

RT conceptualized the study, analyzed the data and drafted the manuscript. FB participated in data analysis and advised on manuscript development. Both authors read and approved the manuscript.

Data availability statement

The data is available upon request from the first author.

Declaration of conflicting interests

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