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# Unveiling determinants of household lighting preferences in rural Tanzania: insights for sustainable energy access

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## Abstract

This paper investigates the determinants and prospects of household lighting choices in rural Tanzania using a Multinomial Logit Regression Model. The analysis is based on data from 4671 households, focusing on three lighting options: electricity, solar energy, and candle lighting. The results reveal significant factors influencing these choices, including household head characteristics, household size, marital status, education, employment status, number of rooms, and income. Key findings indicate that the age of the household head negatively influences the likelihood of choosing grid-electricity, while having a male head of household significantly reduces the probability of opting for any lighting option. Larger household size is negatively associated with choosing electricity and candle lighting. Marital status shows that married households are more likely to use candle lighting. Employment status positively impacts the likelihood of adopting all three lighting options, with employed household heads being more likely to choose modern lighting solutions. Income levels are crucial, as higher income significantly increases the probability of selecting electricity and candle lighting, but not solar energy. These findings provide valuable insights for policymakers and stakeholders aiming to enhance sustainable energy access in rural Tanzania. It highlights the importance of addressing socio-economic factors to promote the adoption of modern and sustainable lighting technologies.

**Keywords** Household lighting, Rural tanzania, Multinomial logit regression, Sustainable energy, Socio-economic determinants

## Introduction and background

In Tanzania, understanding household lighting preferences in rural areas is timely for designing effective policies to enhance sustainable energy access important for economic empowerment and development (Brew-Hammond, 2010; Ko et al., 2016). Tanzania joins international efforts to improve on clean energy supply, access and utilization. Despite improvements in energy supply world-wide, many rural households still use inefficient and harmful lighting sources, such as kerosene lamps (Padmavathi & Daniel, 2013a, b; Yao et al., 2016). Transitioning to modern solutions, such as solar-powered lights, is key for sustainable development (Lay et al., 2013a, 2013b, 2013c; Sovacool et al., 2011) in case the household choices and preference are incentivized to opt for clean energy choices as part of implementation of Sustainable Development Goal Number 7 (Affordable clean energy strategy) (United Nations, 2015). This requires more studies to understand behavioral choices towards clean energy especially in rural areas where the world depend on supply of clean air with no industrial by-product pollutants. Understanding lighting energy preferences informs targeted interventions to promote sustainable energy adoption (Amaral et al., 2020a, 2020b, 2020c; Kempton et al., 2007a, 2007b, 2007c) which will lead

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to achievement of Sustainable Development Goal No.7(United Nations, 2015). Strategies may include solar lighting subsidies, educational campaigns, and infrastructure development to enhance energy availability (Barnes & Floor, 1996; Newell et al., 2019). Despite all government, donor agents and rural communities' efforts to invest in rural lighting energy, there are many factors that affect clean energy lighting choices. Higher income households are more likely to adopt modern lighting solutions due to better affordability (Brew-Hammond, 2010). Studies by Brew-Hammond, (2010) and that of Lay et al., (2013a, 2013b, 2013c) highlight the importance of affordability. Their findings emphasize that both the initial investment cost and ongoing operational expenses significantly influence energy access decisions. For rural households, the consideration of cost and income is crucial when evaluating energy options (Kowsari & Zerriffi, 2011a, 2011b; Peters et al., 2019a, 2019b). Heltberg, (2004a, 2004b) and Sovacool, (2014) conducted studies on lighting choices among rural households in Tanzania. Their research primarily focused on technological aspects, emphasizing the need for appropriate know-how to make energy accessible in remote areas. However, these studies did not extensively explore socio-economic factors, leaving a gap in understanding the broader implications of energy choices. Despite technological advancements, socio-economic factors continue to shape energy access decisions. Factors such as cultural norms, community dynamics, and income disparities influence energy access and utilization. Therefore, any sustainable energy solution must consider not only technological feasibility but also the socio-economic context, such as cultural context. The study conducted by Elrayess et al., (2022a, 2022b) investigated culture as one of social factor related to energy choices. Cultural practices and social norms significantly shape energy preferences within communities. These influences extend to attitudes toward adopting new technologies, particularly in the context of clean energy consumption. Cultural transformation may happen through education and awareness creation as highlighted by several studies such as the research by Urmee et al., (2009) who highlights the correlation between education and awareness of modern lighting technologies. Higher education levels often lead to greater openness to adopting energy-efficient solutions. On cultural research, Clancy et al., (2011) emphasize the role of gender dynamics, the study emphasized women as primary users and decision-makers in household energy consumption and their influence on energy choices. In addition, the same study (Clancy et al.,

2011) findings explains role of socio-cultural norms within a community as it affects energy preferences. Attitudes toward energy sources being shaped by collective beliefs and practices.

The study on availability and reliability of energy access conducted by Lee et al., (2016) and Aklin, (2018a, 2018b) emphasizes the importance of energy infrastructure availability. Reliable access to energy significantly impacts household choices.

Heltberg, (2004a, 2004b) and Sovacool, (2014) demonstrate that environmental consciousness drives preferences for cleaner energy options. Households increasingly favor sustainable lighting solutions due to heightened awareness of environmental impacts. Moreover, health considerations during choices of energy sources have been increasingly observed in connection with environmental protection. The study on household Fuels choice by Adhvaryu et al., (2023a, 2023b) and Kitole et al., (2023) highlights health implications associated with household fuels. For instance, their study findings showed that indoor air pollution from traditional fuels can lead to low birth weight and neonatal mortality. Other findings recommend the adaptation of clean energy technologies choices. The adoption of clean energy technologies, such as affordable solar lamps, depends on their reliability, durability, and ease of use (Kempton et al., 2007a, 2007b, 2007c; Sovacool et al., 2011). The Bhutan Case Study research by Das et al., (2014) examining factors influencing renewable energy choices. The study aimed to understand how attitudes toward clean energy adaptation impact household lighting preferences among 5728 households surveyed in the Bhutan Living Standard Survey (BLSS) of 2007. The findings shows that the age of the household head, household size, education, income, and geographic location influenced energy choices. On the same dimension, Scholten, (2014) conducted a study on the decision-making processes of rural households regarding lighting options at global level. The findings highlighted several key factors influencing these decisions, including economic, social, and infrastructural elements. The study revealed that many rural households continue to use kerosene for lighting despite its health risks and the availability of modern alternatives like solar energy. This persistence is partly due to the high initial costs of solar systems and a lack of trust in their long-term reliability. Despite existing literature, social factor research on socio-economic factors driving household lighting choices in rural Tanzania in particular. Are scant. This is a driving force to embark on this area to understand the preference choices towards clean energy as part of implantation of SDG No.7 (United Nations, 2015) good for the environmental protection, specifically to:

- Identify Household Lighting Preferences: Investigate the lighting preferences of rural households in Tanzania, including their current lighting sources, usage patterns, and preferences for modern alternatives.
- Analyze Determinants of Lighting Choices: Explore the factors influencing household lighting decisions.

Significantly, the study in this paper will guide the policy towards understanding the determinants of household lighting preferences, policymakers can design targeted interventions to promote sustainable energy access. These interventions may include subsidies for solar lighting, awareness campaigns, and infrastructure development lighting sources to discourage Har harmful kerosene lamps lighting and encourage shifting to modern alternatives to improve health, outcomes and reduce environmental impact. Furthermore, there are education and economic empowerment opportunities that can be realized from access to reliable lighting. Access to reliable lighting can positively impacts education (study hours, reading, and learning) and also reliable lighting can boost economic activities (productive work after sunset). This study is also important as an opening debate for sustainable development, Insights from this study can contribute to achieving Sustainable Development Goal 7 (Affordable and Clean Energy) by promoting sustainable energy solutions in rural areas to accelerate sustainable development within the context of clean and sustainable energy.
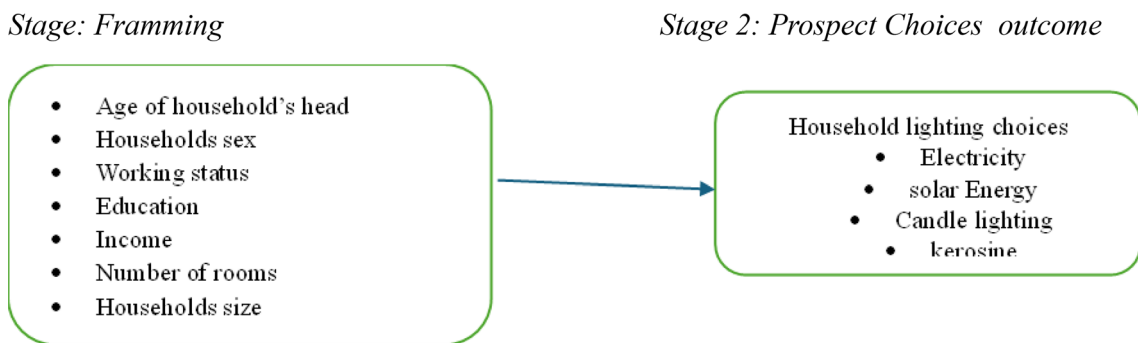
### Analytical framework and methodology

In rural Tanzania, where grid electricity is not universally available, analyzing household lighting choices is crucial. Our research investigates the factors influencing decisions regarding lighting options (e.g., electricity, solar energy, candles, kerosene) using insights from Prospect Theory (Kahneman et al., 2016a, 2016b). A fundamental concept in Prospect Theory is the value function, which describes how individuals evaluate outcomes relative to

a reference point (Killingsworth et al., 2023). In rural settings, income levels, poverty, and other inequalities serve as critical reference points, impacting decision-making. Rural poverty is a significant challenge in Tanzania, particularly given its agrarian economy and dependence on agriculture for livelihoods (Theodory & Kitole, 2024). Individuals exhibit risk aversion for gains and loss aversion for losses when choosing lighting options, a phenomenon discussed by Lovallo et al., (2020) regarding risk-taking and aversion behavior among investors. This aligns with behavioral economics and psychology literature, where the effect of loss aversion is well-documented (Wang & Fischbeck, 2004a, 2004b). In addition, Prospect Theory incorporates probability weighting functions and decision weights, capturing the nuances of human decision-making under uncertainty (Van Vliet et al., 2016). It is essential to recognize that Prospect Theory serves as a descriptive model, offering insights into actual decision behavior rather than prescriptive guidelines. Unlike other econometric analyses focused on numerical estimates, Ruggeri et al., (2020) advocate for using Prospect Theoretical models to address strategic issues and choices, such as lighting choices in rural Tanzania. Like how investors decide on investment portfolios strategically, households consider electricity installation an investment with specific returns and associated risks. The framing of gains and losses is constructed in the brain, creating mental models towards gains from household lighting modes (Bromiley & Rau, 2022; Spellman, 2023).

### Conceptualization

This study employs a statistical research design, utilizing datasets from the Tanzania Panel Survey of 2020/2021 collected by the National Bureau of Statistics (NBS) to investigate the determinants of household lighting choices in rural Tanzania, as presented in Fig. 1. Figure 1 illustrates the two stages in Prospect Theory (Balcaen, 2021; Tversky & Kahneman, 1992a, 1992b; Wu et al., 2020). Stage 1 presents a set of independent variables (the

*Stage: Framming*                                            *Stage 2: Prospect Choices  outcome*

- Age of household's head
- Households sex
- Working status
- Education
- Income
- Number of rooms
- Households size

Household lighting choices
- Electricity
- solar Energy
- Candle lighting
- kerosine

**Fig. 1** Conceptual framework. Stage: framming, Stage 2: prospect choices outcome

value), which are factors influencing decision-making. Employing Prospect Theory, we describe the decision processes based on the available options or valuable alternatives for any of the four household lighting choices. We assume three frames for decision-making: (1) editing the outcome ($\pi$), where individual alternatives are ordered according to a certain heuristic (Jiang & Chen, 2023). The possibilities of lighting households are heuristic in nature, as presented by Pachur et al., (2017) as illustrated in Fig. 1.

In Fig. 1, Stage 1 demonstrates that rural households are assumed to decide which outcomes to consider equivalent, set a reference point, and then regard lesser outcomes as losses and greater ones as gains. This phase aims to edit framing effects (Miti et al., 2021) and resolve isolation effects stemming from individuals' propensity to isolate consecutive probabilities instead of treating them together. The editing process can be viewed as composed of coding, combination, segregation, cancellation, simplification, and detection of dominance, as used by Heutel, (2019) in similar research on energy efficiency and environmental protection.

The second phase is the evaluation phase, where we deduce that people behave as if they compute a value in terms of utility (Shao & Wang, 2022). The editing stage, as discussed above, retains values that lead to potential outcomes and their respective probabilities. Individuals then choose the alternative outcomes with higher utility, resulting in additive or cumulative utility (Häckel et al., 2017). Borrowing from Kahneman and Tversky (1979) and Bleichrodt et al., (2009). We propose the following model reflecting on the two stages illustrated in Fig. 1:

$$V = \sum_{i=1}^{n} \pi(p_i) v(x_i)$$

where

V=overall expected utility of the outcomes to the individual making the decision

$(x_i = x_1.x_2.\ldots\ldots\ldots.x_n)$      =Individual      potential outcomes.

$(p_i = p_1.p_2\ldots\ldots\ldots p_n)$ = potential; outcomes respective probabilities.

$v$= a function that assigns a value to an outcome which is s-shaped and asymmetrical.

Losses are perceived as more painful than gains are pleasurable, a phenomenon known as loss aversion, particularly in situations where information is scarce and unevenly distributed, such as in rural areas (Woodford, 2012). Woodford, (2012) demonstrated the connection between prospect theory and the challenge of information asymmetry. Despite the information generated by government actors, individuals, particularly those in rural areas with low levels of education, have limited

capacity to process and utilize this information effectively. This situation contrasts with the expected utility theory, which assumes a rational agent is indifferent to the reference point and fully informed, an assumption not applicable to rural settings.

Barberis, (2001) highlighted that the magnitude of risk and expected wealth significantly influence return-on-investment choices, which, in turn, measure expected utility. In expected utility theory, individuals do not concern themselves with the framing of losses and gains. The probability weighting function, $\pi(p_i)v(x_i)$ encapsulates the tendency of individuals to overreact to low-probability events and underreact to high-probability events. Passing through the reference point. Let $(x_i, p_i : y_i, g_i)=$ prospect outcome:

$x_i$ = prospect with outcome and the associate probability $p$

and $i$ = 1st., 2nd, 3rd . . . . . . . . . . . nth.

$y_i$ = prospect with outcome y and the associate probability

g and i = 1st., 2nd, 3rd . . . . . . . . . . . nth.

Furthermore, if $(x_i, p_i : y_i, g_i)$ is regular prospect, then either $p + q <= 1$ or $x \geq 0 \leq y$. However, these outcomes and their probabilities has nothing to do with $1 - p - q$:

$$V(x, p : y, q) = \pi(p)v(q) + \pi(y)v(q), \text{ moreover if } (p + q) = 1$$
$$\text{and either } x > y > 0 \text{ or } x < y < 0,$$

$$\text{then } V(x, p : y, q) = v(y) + \pi(p)\left[v(x) - v(y)\right]$$

From the above Prospect Theory (Kahneman & Tversky, 1988), analytical approach in their influential paper introduced prospect theory, which explains how people's decisions are influenced by their attitudes toward risk, uncertainty, loss, and gain. It has significant contribution in analyzing rural Tanzania energy choices as we are dealing with behavioral economics and decision-making energy choices research and therefore, we deduce that:

$$v(y) + v(-y) > v(x) + v(-x) \text{ and } v(-y) + v(-x) > v(x) + v(-x)$$

From the perspective of the value function, decision-makers define their reference points based on deviations from a reference point. According to Levy and Levy (2002), the decision for gains is generally concave, while for losses, it is convex, resulting in an S-shaped curvature. This model provides a more robust framework for understanding decision-making behavior compared to the Random Utility Theory (RUT). The decision curve for losses is steeper than for gains, indicating that decision-makers perceive the impact of losses more strongly than gains. Consequently, individuals tend to

prefer alternatives that minimize losses over those that offer significant gains (Pasquariello, 2014a, 2014b).

If $(x, p) = (y, pq)$ when loss is driving force for rural areas to make decision on which lightening model to prefer, then $(x, pr)$ is not preferred. While based on the benefits the grid electricity provides (prospects) in terms of what could be perceived as return and gains the grid electricity provides, still the rural areas decision-makers (head of the household) may prefer other alternatives after the editing stage. Hence, $(y, pq)$ is not preferred to $(y, pqr)$.

Back to our first assumption equation, follows that $\pi(p)v(x) + \pi(pq)v(y)$ leading to $\pi(pr)v(x) \leq \pi(pq)v(y)$.

Then, we have:

$$\frac{\pi(pq)}{\pi(p)} \leq \frac{\pi(pqr)}{\pi(pr)}$$

This inequality implies that for a fixed ratio of probabilities, the decision weights are closer to unity when probabilities are low than when they are high. This finding is consistent with studies conducted by Kamuzora, (2024), which suggest that poverty is largely a mental construct when studying women investors in Morogoro region. Prospect theory effectively explains how the poor tend to undermine potential gains by framing their decisions primarily in terms of avoiding losses, particularly regarding installation capacity and current costs. Consequently, the future returns on investing in grid electricity are not prioritized; instead, the potential losses are of greater concern. Similar findings are supported by Tversky and Kahneman (1992a, 1992b), who elaborated on the significance of loss aversion in decision-making. In addition, research by Kahneman and Tversky (1979) indicates that individuals tend to overweigh certain outcomes in low-probability scenarios and underweight them in high-probability scenarios, reinforcing the impact of perceived losses on decision-making behavior.

Hence, the probability weighting function (.) is a never linear. Let $x.y.0, p > p\prime$ and $p + q = p\prime + q\prime < 1$ prospect $(x, p\prime : y, q\prime)$ which dominates prospect (x, p': y, q'), this mean that $\pi(p\prime)v(x) + \pi(q\prime)v(y)$ gives us:$\prime$

$$\frac{\pi(p) - \pi(p')}{\pi(q') - \pi(p)} < \frac{v(y)}{v(x)}$$

Hence,     $y \to x, \pi(p) \mapsto \pi(p') - \pi(q);$     however, $p - p' = q' - q,$

Thus, losses are perceived as more painful than gains are pleasurable, a phenomenon known as loss aversion, particularly in situations where information is scarce and unevenly distributed, such as in rural areas (Woodford, 2012). Woodford (2012) demonstrated the connection between prospect theory and the challenge of information asymmetry. Despite the information generated by government actors, individuals, particularly those in rural areas with low levels of education, have limited capacity to process and utilize this information effectively. This situation contrasts with the expected utility theory, which assumes a rational agent is indifferent to the reference point and fully informed, an assumption not applicable to rural settings. Barberis, (2001) highlighted that the magnitude of risk and expected wealth significantly influence return-on-investment choices, which, in turn, measure expected utility. In expected utility theory, individuals do not concern themselves with the framing of losses and gains. The probability weighting function, $\pi(p_i)v(x_i)$ encapsulates the tendency of individuals to overreact to low-probability events and underreact to high-probability events.

From the perspective of the value function, decision-makers define their reference points based on deviations from a reference point. According to Levy and Levy, (2002), the decision for gains is generally concave, while for losses, it is convex, resulting in an S-shaped curvature. This model provides a more robust framework for understanding decision-making behavior compared to the Random Utility Theory (RUT). The decision curve for losses is steeper than for gains, indicating that decision-makers perceive the impact of losses more strongly than gains. Consequently, individuals tend to prefer alternatives that minimize losses over those that offer significant gains (Padmavathi & Daniel, 2013a; Pasquariello, 2014a, 2014b). This inequality implies that for a fixed ratio of probabilities, the decision weights are closer to unity when probabilities are low than when they are high. This finding is consistent with studies conducted by Kitole and Genda, (2024), which suggest that poverty is largely a mental construct. Prospect theory effectively explains how the poor tend to undermine potential gains by framing their decisions primarily in terms of avoiding losses, particularly regarding installation capacity and current costs. Consequently, the future returns on investing in grid electricity are not prioritized; instead, the potential losses are of greater concern.

At this level, we would assume that the decision to install grid electricity follows a linear function. However, due to fear or possibly greed of the household decision maker, this decision may not be valued linearly as one might expect (Chen & Chen, 2016a, 2016b). Generally, individuals are inclined to install grid electricity as their income increases. However, dominated alternatives are eliminated during the editing phase and only brought to the evaluation phase. In our context, the dependent variables (age of the household head, household sex, working status, education, income, number of rooms, and household size) serve as editing criteria. The second

phase involves deciding on lighting alternatives prospect choices among grid electricity installation (A), solar energy (B), and candle lighting (C). This study has shown that option A violates the expected dominance from the perspective of prospect theory. It is possible that prospect A dominates B, B dominates C, but C dominates A. Consequently, a logistic model was employed to analyze the three possible outcomes of rural lighting decisions, as utilized by Scholten, (2014). Scholten, (2014) conducted a study on the decision-making processes of rural households regarding lighting options. Table 1 below is on operationalization of the variables, easements and hypotheses.

Table 1 displays the dependent variables representing the decisions or choices made by individual heads of households under uncertain conditions. According to prospect theory, individuals evaluate potential losses and gains relative to a reference point, often their current wealth or status quo, and are more sensitive to losses than to equivalent gains. The dependent variables in Table 1 reflect these decisions made under uncertainty, showing that household heads choose among four modes of lighting (electricity, solar energy, candles, and kerosene) based on probabilities related to their characteristics in rural areas.

In this study, Table 1 outlines the four lighting choices, drawing on Schwartz's (2008) application of prospect theory to estimate health-related decision choices. The dependent variables encompass factors related to gains, losses, probabilities, and the reference point. The table describes the measurement of variables, including estimated values, scales used, and expected signs in the logistic regression model intended to estimate the outcome (choice of lighting), following Kahneman and Tversky's (1979) Prospect Theory. This methodological approach ensures robust estimation of model parameters and facilitates a comprehensive analysis of the factors influencing household lighting decisions. It enhances the study's contribution to the existing literature on energy access and rural development in Tanzania. The independent variables shown in Table 1, which influence behavioral decisions regarding lighting modes, include age, sex, education, marital status, working status, household income, family size, and number of rooms occupied.

The study employed two econometric models, specifically the logit model and truncated regression (Tobit), to address its dual objectives. The first objective investigated the factors influencing decision-making in choosing household lighting at the framing stage (at the editing stage). Choosing Truncated Tobit choice was necessitated because of the binary nature of the dependent variables presented by the four outcomes. This outcome stage, representing the decision of the

**Table 1** Variable operationalization, measurement and hypothesis

| Variables | Measurement | Categories | Expected sign |
|---|---|---|---|
| Multiple | Operationalization | (Scale) | Sign |
| Dependent variable | | | |
| Households lighting choices | Households' choices for lightening in rural areas | Binary | + |
| (Dependent variables) | 1 For electricity | Binary(yes = 1) | + |
| | 2 For solar energy | Binary(yes = 1) | + |
| | 3 Candle | Binary(yes = 1) | + |
| | 4 Kerosene | Binary(yes = 1) | + |
| Independent variables | | | |
| Age | Number of yeas the head of household has lived | Continuous | + |
| Sex | 1 if a household is male | Binary | + |
| | 0 if a household is female | | 0 |
| Education | Households' years of schooling | Continuous | + |
| Marital status | Head of Households' marital status | Binary | + |
| | 1 for married | (Yes = 1) | + |
| | 0 unmarried | (N0 = 0) | 0 |
| Working status | 1 If a household is working (employed) or 0 not working | Binary | + |
| | Working (Yes = 1) | Yes = 1 | + |
| | Not working (No = 0) | No = 0 | 0 |
| Households' income | Amount of money households earn from various sources | Continuous | + |
| Family size | Number of household members | Continuous | + |
| Number of rooms occupied | Number of rooms a household occupy | Continuous | + |

household head regarding which mode of lighting to choose. The household head could select from four lighting alternatives. Given this binary outcome, the study considered two viable options for analysis: the binary logistic model and the binary probit model, as utilized by Adanguidi, (2021a, 2021b). The binary logistic model was selected over the probit model for several reasons. Firstly, the binary logit model exhibits slightly flatter tails, making it more accurate in estimate the choices following Prospect Theory with S-shaped distribution out outcomes explained earlier. In contrast, the probit curve approaches the axes more quickly, potentially leading to inaccuracies in estimation (Maddala et al., 2002).

The multinomial logit regression model was specifically employed to identify the determinant factors associated with the likelihood of household lighting decisions. In the logit model, the response variable was the heads of household's decision to engage, represented by binary values of 1 or 0, where 1 indicated the chosen alternative and 0 represented the non-chosen alternatives. The selection of this econometric model was driven by its effectiveness in addressing the issue of heteroscedasticity (Green, 2008; Arora et al., 2020; Barberis et al., 2001), ensuring a robust analysis of the factors influencing household lighting choices. The logit model's capability to handle binary outcomes and its suitability for this specific research context made it the preferred choice for unraveling the intricacies of household lighting decisions.

Hence, the probability (Pi) that a head of household has chosen alternative A, B,C or D to light the house is as follows:

$$Z_i = \beta_0 + \sum_{i=1}^{n} \beta_i X_i$$

where $\beta_0$ is constant and $Z_i$ is equal to one (1) indicates householder has chosen one of the alternative and zero (0) otherwise; this means: The equation represents a binary choice model involving the estimation of the probability of the household decision making (Z) as a function of explanatory variables (Xs = alternative energy lightening their house). Mathematically, this is represented as

$$Prob(Z = 1) = F(\beta' X_i)$$

$$Prob(Z = 0) = F(1 - \beta' X_i)$$

where $Z_i$ is the observed response for the $i^{th}$ observation of the response variable Z. This means that $Z_i$ =1 for alternate chosen sectors and $Z_i = 0$ for not choosing the alternative under consideration. $X_i$ is a set of either Age of household's head. Households sex, working status, Households sex,

Education level, Income levels, Number of rooms or Households size defined as explanatory variables/

Those explanatory variables are associated with the $i^{th}$ individual decision, which determine the probability of choosing one of the alternatives for lightening the house (P). The function may take the form of a normal, logistic or probability function. The Logit model uses a logistic cumulative distributive function to estimate, P given Z by

$$P\left(Y = \frac{1}{X}\right) = \frac{e^Z}{1 + e^Z}$$

$$P\left(Y = \frac{0}{X}\right) = 1 - \frac{e^Z}{1 + e^Z}$$

$$Z = \Pr(Y = 1/X_1, X_2 \ldots . X_n) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$

The coefficient $\beta_p$ is the change regresses probability that Y=1 associated with a unit (one p household decision on lightening) change in X's holding constant the other regresors. The empirical model for the Logit model estimation is specified as follows:

$$Z = Logit(P) = ln\frac{P}{1 - P} = \beta_0 + \beta_1 X_1 + \beta_2 X_2$$
$$+ \beta_3 X_3 + \beta_4 X_4 + \ldots . . \beta_{12} X_{12} + \varepsilon_i$$

where $ln(\frac{P}{1-P})$ is the log-odds in favor of the head of the household's chance of choosing the lightening alternative among the exixiting four alternatives or it is the logarithm of the ratio of probability of increase the chance of choosing that specific lightening alternative (p) to probability of not of not being chosen (1-p). The empirical model used to estimate the logit regression model of the factors for influence choices among households is as follows:

**Table 2** Social–economic status of the heads of households who made lighting energy prospect choices

| Variable | Category | Frequency | Percentage |
|---|---|---|---|
| Sex | Male | 3581 | 76.66% |
| | Female | 1090 | 23.34% |
| Marital status | Unmarried | 1835 | 39.28% |
| | Married | 2.36 | 60.72% |
| Working status | Working | 3291 | 70.46% |
| | Not working | 1380 | 29.54% |
| Lighting choices | Electricity | 586 | 12.55% |
| | Solar Energy | 3903 | 83.56% |
| | Candle Lighting | 107 | 2.29% |
| | Kerosene | 75 | 1.61% |

$$Y_i = \beta_0 + \beta_1 Dmale + \beta_2 Dagr + \beta_3 Dacc + \beta_4 DEmp$$
$$+ \beta_5 Dprc + \beta_6 lnExt + \beta_7 lnAge + \beta_8 lnEdu$$
$$+ \beta_9 lnFsz + \beta_{10} lnAgW + \beta_{11} lnExp + \varepsilon_i$$

## Results

The results in Table 2 indicate that, on average, households have approximately six members. The average age of household members is 48.7 years, with a minimum age of 17 years and a maximum age of 98 years.

Table 2 describes the socio-economic status of the households, revealing significant discrepancies in individual household incomes. The findings provide insights into the demographic characteristics and lighting choices of households in rural Tanzania participating in the study. Most respondents are male (76.66%), with the remaining 23.34% being female, indicating that the majority of household heads in rural areas are male. This gender distribution suggests a predominantly male representation, highlighting the need for gender-inclusive strategies in rural electrification initiatives.

Regarding marital status, a significant proportion of households are married (60.72%), while 39.28% are unmarried. The high percentage of married households, along with those having working members, may influence household lighting choices. In terms of employment status, 70.46% of households have at least one working member, while the remaining 29.54% do not.

Table 3 shows the lighting choices among households, with solar energy being the most prevalent choice (83.56%), followed by electricity (12.55%). A smaller percentage of households use candle lighting (2.29%) or kerosene (1.61%). The dominance of solar energy as a lighting choice aligns with sustainable practices, highlighting the potential success of renewable energy interventions, but still, it could be the availability of grid-energy sources in rural areas.

The wide standard deviation in household size and age indicates considerable variability in these aspects. The total household income exhibits a substantial range, with an average of 11,873,218 Tanzanian Shillings and a significant variation (standard deviation of 29,346,330).

The average years of education stand at 6.4, with limited variability. The number of rooms in households averages 2.32, with a relatively low standard deviation of 0.686, suggesting consistency in housing conditions.

Table 3 findings suggest diverse household compositions and economic situations in rural Tanzania. The substantial standard deviation in household size, age, and income underscores the need for nuanced analyses to understand the factors influencing lighting choices. Higher variability in income may indicate disparities in economic well-being among participating households. The consistent number of rooms may imply commonality in housing infrastructure in rural areas.

Table 4 presents the results of the odds ratio test. This test provides insights into how each predictor variable affects the likelihood of using solar energy or candle lighting relative to electricity within the given dataset. Odds ratios represent changes in odds; values close to 1 indicate minimal impact, while values significantly different from 1 suggest stronger associations (Gigerenzer & Todd, 1999). The findings from the odds ratio test are interpreted as follows:

- *Household Age:* The odds ratio for solar energy and candle lighting relative to electricity is approximately 1.001. This suggests that household age has minimal impact on the odds of using solar energy or candle lighting compared to electricity.

**Table 4** Odds ration test

| Variable | Electricity | Solar energy | Candle lightening |
|---|---|---|---|
| Household Age | 0.98 | 1.001 | 1.001 |
| Head of the household (Male) | 0.266 | 0.287 | 0.159 |
| Household Size | 0.86 | 1.094 | 0.745 |
| Married Status (Married) | 1.066 | 1.312 | 3.604 |
| Education in years | 1.012 | 0.977 | 0.086 |
| Employment Status(working) | 0.679 | 2.086 | 2.557 |
| Number of Rooms | 1.017 | 0.729 | 1.017 |
| Household TTHIncome | 3.679 | 0.972 | 6.479 |

**Table 3** Description of social–economic status spread

| Variable | Obs | Mean | Std. Dev | Min | Max |
|---|---|---|---|---|---|
| Households size | 4671 | 5.604 | 3.199 | 1 | 38 |
| Household Age | 4671 | 48.703 | 15.509 | 17 | 98 |
| Total Household income | 4671 | 11, 873,218 | 29,346,330 | 733, 001 | 1.814, 000, 000 |
| Years of Education | 3891 | 6.369 | 1.441 | 1 | 14 |
| Number of rooms | 4563 | 2.318 | 0.686 | 2 | 4 |

- *Head of the Household (Male):* The odds ratio for solar energy and candle lighting relative to electricity is significantly less than 1 (0.266). This indicates that households with male heads are less likely to use solar energy or candle lighting compared to electricity.
- *Household Size:* The odds ratio for solar energy and candle lighting relative to electricity is approximately 0.86. Like household age, this suggests that household size has minimal impact on the odds of using solar energy or candle lighting compared to electricity.
- *Married Status (Married):* The odds ratio for solar energy and candle lighting relative to electricity is slightly greater than 1 (1.066). This implies that married households are slightly more likely to use solar energy or candle lighting compared to electricity.
- *Education in Years:* The odds ratio for solar energy and candle lighting relative to electricity is approximately 1.012. Again, education level has minimal impact on the odds of using solar energy or candle lighting compared to electricity.
- *Employment Status (Working):* The odds ratio for solar energy relative to electricity is significantly greater than 1 (2.086). This indicates that working households are more likely to use solar energy compared to electricity.
- *Number of Rooms***:** The odds ratio for solar energy and candle lighting relative to electricity is approxi-

mately 1.017. The number of rooms has minimal impact on the odds of using solar energy or candle lighting compared to electricity.
- *Household Total Income* The odds ratio for solar energy relative to electricity is significantly greater than 1 (3.679). Higher household income is associated with increased odds of using solar energy compared to electricity,

Furthermore, we tested the Log Likelihood Ratios, which are crucial for assessing the overall performance and validity of the Multinomial Logit Regression Model presented in Table 5.

Table 5 shows the robustness of the employed model. We employed the Log Likelihood Ratio (LLR) test, as applied by many researchers (Kim et al., 2003; Polcari, 2013a, 2013b; Sur, 2019). The LLR test yielded a Chi-squared value of 572.44 and a *p* value of 0.0000, demonstrating the statistical significance of the model and indicating its superior fit. This suggests that the included variables collectively play a substantial role in elucidating the variance in decision-making choices among the four lighting modes in rural areas of Tanzania. The low *p* value indicates that the observed disparities in likelihoods across categories are not attributable to chance. Moreover, the positive Log Likelihood Ratio value reinforces the model's adequacy.

**Table 5** Results from estimations of the Multinomial Logit Regression Model

| Variables | Electricity | | Solar energy | | Candle lighting | |
|---|---|---|---|---|---|---|
| | Coeff | P > Z | Coeff | P > Z | Coeff | P > Z |
| Households age | − 0.02* | 0.035 | 0.004 | 0.614 | 0.001 | 0.885 |
| Head of Households sex | | | | | | |
| Male | − 1.331** | 0.016 | − 1.247** | 0.018 | − 1.844*** | 0.004 |
| Households size | − 0.142** | 0.016 | 0.09 | 0.100 | − 0.294*** | 0.000 |
| Marital status | | | | | | |
| Married | 0.655* | 0.069 | 0.272 | 0.415 | 1.283** | 0.013 |
| Education years | 0.0642 | 0.524 | − 0.023 | 0.805 | 0.082 | 0.521 |
| Employment Status | | | | | | |
| Working | 1.168*** | 0.000 | 1.052*** | 0.000 | 0.940** | 0.009 |
| Number of rooms | 0.017 | 0.959 | − 0.315 | 0.312 | 0.0169 | 0.968 |
| Income | | | | | | |
| lnTTHIncome | 1.303*** | 0.000 | −0.028 | 0.898 | 1.868*** | 0.000 |
| _cons | − 17.750 | 0.000 | 4.855 | 0.190 | − 29.146 | 0.000 |
| Multinomial logistic regression | | Number of observations = 4671 | | | | |
| | | LR chi2(24) = 572.4 | | | | |
| | | Prob. > ch2 = 0 | | | | |
| Log likelihood = − 1828.9524 | | Prob > chi2 = 0.00 | | | | |
| | | Pseudo R2 = 0.135 | | | | |

*p < 0.01, **p < 0.05, *p < 0.1*

In practical terms, this implies that the chosen predictor variables effectively capture the diversity in household lighting choices, providing a dependable foundation for assessing the influence of socioeconomic and demographic factors on the probability of selecting electricity, solar energy, or candle lighting within rural Tanzanian households. Notably, as kerosene usage was negligible in this context, it was deemed unnecessary to include it in the analysis using the LLR method in Table 5.

The results presented in Table 5 reveal that the age of the household head was statistically significant at a 10% significance level ($P=0.035$) in influencing households' decisions regarding lighting choices. Specifically, the findings suggest that for each 1-year increase in the household head's age, there is a corresponding decrease of 0.02 in the relative log odds of selecting electricity. Conversely, there is an increase of 0.004 in the relative log odds of opting for solar energy or candlelight.

The findings further indicate that male-headed households significantly influence the choice of electricity usage, with a 10% significance level ($P=0.016$). In addition, the significance levels for choosing solar energy and candle lighting were recorded at $P=0.018$ and $P=0.004$, respectively. Being a male head of the household is associated with a decrease of 1.3313 in the relative log odds of choosing electricity compared to alternative options. Furthermore, there is a decrease of 1.2477 in the relative log odds of opting for solar energy in comparison to choosing both candlelight and electricity.

Household size was found to be statistically significant at a 10% significance level ($P=0.016$) in influencing households' choices regarding the decision on lighting mode, particularly grid electricity. The significance level was recorded at $P=0.0000$ for selecting candle lighting over grid electricity installation and solar energy. A one-unit increase in household size is associated with a decrease of 0.1422 in the relative log odds of selecting grid electricity compared to alternative options. Conversely, there is a 0.0903 increase in the relative log odds of opting for solar energy compared to not selecting it. In addition, there is a decrease of 0.2943 in the relative log odds of choosing candle lighting compared to not selecting it.

Married households were found to be statistically significant at a 10% significance level ($P=0.069$) in influencing households' choices regarding the installation of grid electricity, with a significance level of 5% ($P=0.013$) for selecting candle lighting. Being married is associated with a 0.6555 increase in the relative log odds of choosing grid electricity compared to alternative options. In addition, there is a 0.2721 increase in the relative log odds of selecting solar energy compared to not choosing it and opting for other alternatives.

Furthermore, the employment status of the head of the household was found to be statistically significant at a 1% significance level ($P=0.000$) in influencing the household's choice to use electricity. Specifically, being employed is associated with a 1.1690 increase in the relative log odds of choosing electricity over other options. For selecting solar energy, the significance level is 1% ($P=0.000$), while for choosing candle lighting, it is 5%.

In addition, the logarithm of total household income was also found to be statistically significant at a 1% significance level ($P=0.000$) in influencing the decision to install grid electricity. A one-unit increase in income is associated with a 1.3035 increase in the relative log odds of choosing to install electricity compared to not installing it. This relationship is significant at the 1% level for choosing candle lighting.

## Discussion

The findings reveal that the age of the household head significantly influences the decision to install grid electricity. Similar results were reported by Emmanuel (2021), indicating that total household income plays a statistically significant role in influencing lighting choices between electricity and candle lighting. The age factor was also significant in the choice of fuel lighting energy in Bhutan (Das et al., 2014). In addition, Wassie et al., (2021) found that the age of the household head significantly impacts electricity choices for lighting in Ethiopia.

Furthermore, the study highlights that male-headed households significantly influence the decision to use grid electricity. Being male is associated with a decrease in the relative log odds of choosing electricity. This finding differs from that of Giri and Goswami, (2017), who found that female-headed households significantly influence the choice of solar energy for lighting in Nepal. Similarly, Huizenga et al., (2023) and Wassie et al., (2021) found that female-headed households were significantly associated with the installation of grid electricity for lighting in Ethiopia. This is because many households in rural areas of Tanzania are headed by males compared to Nepal and Ethiopia.

An increase in household size is associated with a decrease in the relative log odds of choosing grid electricity and an increase in the relative log odds of choosing solar energy. This finding aligns with Giri and Goswami, (2017), who found that family size significantly influences the choice of solar energy for lighting in Nepal. In addition, Onsongo, (2019) and Emmanuel, (2021) found that household size is statistically significant in influencing lighting choices for grid electricity and candle lighting. Similarly, Wassie et al., (2021) found that household size is significant in solar choices for lighting in Ethiopia.

Employment status is also a significant factor. Being employed is associated with an increase in the relative log odds of choosing grid electricity and solar energy. This is like Das et al., (2014) in Bhutan, who attributed the choice of fuel lighting energy to income and the employment status of the household head. Income differences are evident in influencing lighting choices in Tanzania as well as in Bhutan for choosing fuel to light houses.

Finally, an increase in total household income is associated with an increase in the relative log odds of deciding to use and install grid electricity. This finding contrasts with Giri and Goswami, (2017), who found that household total income significantly influences the choice of solar energy for lighting in Nepal, rather than grid electricity. In addition, Khundi-Mkomba et al., (2020) indicated that households in the richer class have higher odds of using solar panels compared to others. Emmanuel, (2021) also found that household total income is statistically significant in influencing lighting choices for grid electricity and candle lighting. Furthermore, Choumert-Nkolo et al., (2019) revealed that income, education, and environmental factors significantly influence household lighting choices in rural settings.

## Conclusion

This study provides valuable insights into the significant factors influencing household lighting preferences in rural Tanzania. The analysis has revealed compelling findings regarding the impact of various socio-economic variables on households' lighting choices.

Key Findings:

- *Household Age:* Older households showed decreased odds of choosing electricity compared to alternative sources like solar energy and candle lighting.
- *Household Head Gender:* Male-headed households significantly influenced the decision to opt for grid electricity and the ability to install solar lighting.
- *Household Size:* Larger households showed decreased odds of choosing grid electricity and candle lighting but increased likelihood of selecting solar energy. This suggests that larger families, with lower income, have fewer possibilities to install grid electricity in rural areas.
- *Marital and Employment Status:* Married and employed households respectively showed higher odds of choosing various lighting options.
- *Household Income:* Higher income levels were associated with increased odds of choosing electricity and candle lighting, while decreasing the odds of choosing solar energy.

## Recommendations

Based on these findings, policymakers and stakeholders can derive key recommendations to enhance rural electrification initiatives in Tanzania:

- *Awareness Campaigns and Financial Incentives:* Implement targeted awareness campaigns and financial incentives to encourage older households to adopt electricity.
- *Income Generation and Employment Opportunities:* Create opportunities for income generation and employment in rural areas to empower households economically and promote the adoption of modern lighting technologies.
- *Innovative Financing Models:* Explore innovative financing models to make sustainable energy solutions more accessible, accompanied by robust education campaigns highlighting their long-term benefits.

Incorporating these policy recommendations, grounded in the study's findings, will contribute to creating an enabling environment for rural households in Tanzania to opt for sustainable lighting energy. By addressing age-related concerns, income disparities, employment dynamics, and financial constraints, policymakers can foster a more inclusive and sustainable approach to rural electrification.

**Declarations**

**Ethics approval and consent to participate**
Not applicable.

**Consent for publication**
Not applicable.

**Competing interests**
No competing interests to declare.

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## Publisher's Note