ASSESSING THE DETERMINANTS OF HOUSEHOLD BIOMASS DEMAND AND WILLINGNESS TO PAY FOR IMPROVED ENERGY SOURCES IN ADAMAWA STATE, NIGERIA

Aliyu Alhaji Jibrilla
Department of Economics
Adamawa State University,
aliyu518@adsu.edu.ng

Godwin Boniface
Department of Economics
Adamawa State University,
gboniface2@gmail.com

Adamu Jibrilla
Department of Economics
Adamawa State University,
jibrilla653@adsu.edu.ng

***Corresponding author:**
Aliyu Alhaji Jibrilla
Department of Economics
Adamawa State University, Mubi
aliyu5189@adsu.edu.ng

ABSTRACT

Dependence on biomass for cooking and heating in rural Nigeria significantly contributes to deforestation, air pollution, and severe health issues, which may disproportionately affect women and children. This study investigates the factors influencing biomass consumption and the potential for transitioning to cleaner energy sources in Adamawa State. Employing a mixed-methods approach of data collection, including quantitative surveys and qualitative interviews, we examine how socioeconomic, demographic, and environmental factors shape energy choices. Results indicate that while environmental awareness is linked to clean energy adoption, demographic factors such as household size and age exert a substantial influence on biomass use. Contrary to the Energy Ladder model, income and education levels do not directly impact biomass consumption, aligning more with the Energy Stacking model. These findings highlight the complex interplay of factors affecting household energy decisions. Policy recommendations focus on enhancing environmental awareness, expanding clean energy access, and leveraging economic incentives to accelerate the transition to cleaner energy sources.

Keywords: *biomass consumption, clean energy, Adamawa State, Nigeria, energy transition, sustainable development, energy stacking.*

1. Introduction

Energy is a fundamental driver of economic growth and development (McGuirk, 2014; Elfaki et al., 2021). It powers industries, creates jobs, and improves living standards. Household energy consumption, encompassing lighting, cooking, heating, and transportation, is essential for human well-being (Rapu et al., 2015). However, access to clean and affordable energy remains a significant challenge in many developing countries. Rural households in these regions often rely heavily on traditional biomass fuels such as firewood and crop residues for their energy needs (Ruppel & Althusmann, 2016). This reliance has severe health and environmental consequences. Indoor air pollution from biomass combustion is a leading cause of respiratory diseases and premature deaths, particularly among women and children (Timilsina & Malla, 2012; Jakub, 2021). Furthermore, deforestation and climate change are exacerbated by the unsustainable use of biomass (Hemstock et al., 2020). Despite global efforts to promote clean cooking solutions (Rafaj et al., 2018), progress in transitioning from biomass to cleaner fuels has been slow, especially in Sub-Saharan Africa. Millions of people in this region continue to rely on wood fuels and charcoal for their daily energy needs, with women, children, and marginalized communities bearing the brunt of the negative impacts (Bensch, Jeuland & Peters, 2021; Dagnachew et al., 2020; Ghebreyesus, 2024).

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Nigeria, a populous African nation, grapples with significant energy challenges. Traditional fuels, primarily firewood and charcoal, constitute about 70% of household energy supply (Madukwe, 2014; Energy Commission of Nigeria, 2021). This reliance contributes to deforestation, environmental degradation, and severe health issues (Bruce et al., 2002; Sovacool, 2012; World Health Organization [WHO], 2016; Guerrero-Lemus, Shephard, Guerrero-Lemus & Shephard, 2017; Johnson et al., 2020). Poverty and inefficient energy use are closely linked, especially in rural areas. For instance, Northeast Nigeria, with a 72.2% poverty rate, relied on traditional fuels for 95.9% of its energy consumption (Adamu et al., 2020).

Factors like fuel availability, accessibility, and poverty contribute to the prevalence of traditional fuels (Kumar, et al., 2020). Impoverished communities bear disproportionate energy costs from unimproved sources due to limited financial capacity to adopt cleaner alternatives. Remote areas face additional challenges, including limited energy services and higher operational costs for providers (Nnaji et al., 2021). Indoor air pollution (IAP) from inefficient biomass combustion is a critical health risk linked to premature deaths and various health issues (World Health Organization [WHO], 2016).

Understanding the factors influencing household energy choices is crucial for promoting cleaner energy adoption. Previous research primarily focused on "willingness to pay," neglecting other determinants of energy decisions (Jotaworn et al., 2023; Afriyie et al., 2024; Tadele & Kalyebara, 2023). This study adopts a broader approach, examining socioeconomic, cultural, and environmental factors influencing households' willingness to transition to cleaner energy sources in Adamawa State, Nigeria.

While the importance of LPG and electricity for sustainable development is recognized, existing research often overlooks these specific alternatives, concentrating on overall household energy consumption (Nnaji et al., 2012). Studies on cleaner energy adoption in other regions are limited, and the unique context of Adamawa State, Nigeria, remains understudied. This research aims to fill this gap by examining the factors influencing biomass consumption and households' willingness to transition to cleaner energy sources in the region.

This study is justified by pressing need for sustainable energy solutions to address deforestation, indoor air pollution, and associated health risks in Adamawa Sate. The region's contribution to deforestation and CO2 emissions underscores the importance of transitioning to cleaner energy sources. Moreover, by focusing on willingness to transition rather than solely on willingness to pay, this research offers a comprehensive understanding of household energy decision-making. The findings will inform effective energy policies and contribute to global efforts to combat energy poverty and environmental degradation.

2. Literature Review

2.1 *Theoretical Review*

Two prominent theories offer valuable insights into household energy choice and consumption patterns. The first theory is the Energy Ladder (EL) model. The Energy Ladder (EL) model, proposed by Hosier and Dowd (1987) and further developed by Schlag and Zuzarte (2008), provides a foundational framework for understanding the progression of household energy consumption. It posits a hierarchical sequence of fuel types, with households ascending the ladder as their income increases. Lower-income households typically rely on traditional biomass fuels like firewood, crop residues, and animal dung due

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

to affordability and availability. As income grows, households may transition to intermediate fuels like charcoal and kerosene, offering improved efficiency and convenience. Ultimately, higher-income households tend to adopt modern energy sources such as electricity, liquefied petroleum gas (LPG), and solar, characterized by greater efficiency, cleanliness, and convenience (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008).

While the EL model suggests a linear progression, the Energy Stacking (ES) model, as outlined by Kitole, Tibamanya, and Sesabo (2023), acknowledges the more complex reality of household energy consumption, particularly in low-income contexts. This model proposes that households often combine multiple fuel sources simultaneously to meet their energy needs. Factors such as affordability, accessibility, cultural preferences, and specific energy demands influence the combination of fuels used. For instance, a household might rely on biomass for cooking while using electricity for lighting (Boyce & Lewis, 2001).

The EL and ES models offer complementary perspectives on household energy choices. The EL model provides a useful starting point by highlighting the role of income in fuel transitions (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008), while the ES model emphasizes the practical constraints and diverse strategies employed by households (Kitole, Tibamanya, & Sesabo, 2023; Campbell et al., 2003, Heltberg, 2004). Understanding the limitations of the EL model, especially in low-income settings, is crucial for developing effective energy policies and interventions.

2.1 *Empirical Review*

Empirical research has identified a range of factors influencing household energy choices beyond income. Socioeconomic factors, including household size, education, and income, exert a substantial influence on household energy choices. Research conducted by Kuunibe et al. (2013) and Pandey and Chaubal (2011) underscores this correlation. While these studies provide valuable insights, the relationship between socioeconomic status and energy choice is complex. Factors such as access to alternative fuels, government policies, cultural norms, and occupation can significantly moderate these effects. For instance, households with higher incomes may have greater access to cleaner fuels, while those in rural areas with limited infrastructure may be constrained to traditional biomass. Growing concerns about the environmental and health impacts of biomass combustion have influenced household energy decisions. Studies by Capareda (2011) and Orifah et al. (2019) have shown that households with greater awareness of these issues are more likely to adopt cleaner energy sources. The availability and cost of energy sources are critical determinants of household choices. In many rural areas, limited access to modern fuels like electricity and LPG forces households to rely on traditional biomass (Hanna et al., 2016). Economic constraints also play a significant role, as lower-income households may prioritize affordability over environmental considerations.

While the transition to cleaner energy sources is essential for mitigating environmental impacts and improving public health, several challenges persist. Studies by Mangeni et al. (2023), Sumardjo, Firmansyah, and Dharmawan (2023), and Varkey (2023) emphasize the importance of promoting cleaner-burning fuels like LPG to reduce emissions and improve indoor air quality. However, factors such as urban convenience and perceived alternative value can influence the adoption of these fuels (Wesnawa, Sarmita, & Christiawan, 2023).

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Of significant concern is that, despite the growing global emphasis on clean energy, research on the determinants of clean energy demand in Nigeria remains limited. While studies by Nnaji et al. (2012) and Song et al. (2012) have examined overall household energy consumption, a more focused assessment of factors influencing the adoption of LPG and electricity is needed. Adeleke et al. (2022) made a valuable contribution by investigating factors affecting the willingness to adopt renewable energy technologies (RETs) in South-western Nigeria. However, a more comprehensive understanding of the determinants of clean energy adoption in specific regions, such as Adamawa State, is still required.

This study focuses on Adamawa State due to its limited access to modern energy services and the prevalence of traditional biomass use. By examining the factors influencing the transition from biomass to cleaner fuels like LPG and electricity in this context, the research aims to fill the research gap and provide insights for promoting sustainable energy adoption in Nigeria.

Recent studies have expanded the understanding of household energy choices beyond traditional socioeconomic factors. Research from Thailand (Jotaworn et al., 2023) and Ghana (Afriyie et al., 2024) highlights the importance of consumer preferences, quality, and accessibility in shaping energy decisions. Furthermore, the complex energy landscape, as emphasized by Tadele and Kalyebara (2023), underscores the need for a multifaceted approach to energy policy. Research from Pakistan (Nazir, & Tian, 2022; Mustafa et al., 2023; Saleem & Ulfat, 2024).) supports the inclusion of economic, social, cultural, and environmental factors in policymaking.

2.3 *Theoretical Framework*

To comprehensively understand the factors influencing household energy transitions in Adamawa State, Nigeria, this study adopts a theoretical framework that integrates the Energy Ladder (EL) and Energy Stacking (ES) models. While the EL model posits a sequential progression from traditional to modern fuels based on income (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008), the ES model acknowledges the simultaneous use of multiple fuel sources due to various factors (Kitole, Tibamanya & Sesabo, 2023). This study hypothesizes that a combination of both models is necessary to explain the complex energy consumption patterns in the study area.

Socioeconomic factors, including income, household size, education, and occupation, are critical determinants of energy access and consumption. Larger households may exhibit higher biomass consumption due to increased energy needs (Kuunibe et al., 2013). Moreover, environmental awareness and concerns about the health impacts of biomass use can influence the adoption of cleaner fuels (Capareda, 2011; Orifah et al., 2019).

This study focuses on Adamawa State due to its limited access to modern energy services and the prevalence of traditional biomass use. By examining the factors influencing the transition from biomass to cleaner fuels like LPG and electricity in this context, the research aims to contribute to the broader understanding of household energy transitions in Nigeria.

3.0 Methodology

3.1 Description of Study Area

Adamawa State, located in northeastern Nigeria, serves as the study area due to its diverse energy landscape. Characterized by its varied topography, including the Mandara Mountains and the Nigerian savannah plains, the state's economy relies on agriculture, livestock, and mineral resources. To capture this heterogeneity, Yola North, Numan, and Mubi North Local Government Areas were selected. Yola North represents the urban centre, Numan a mix of rural and semi-urban settings, and Mubi North a densely populated area with both urban and rural characteristics. This selection ensures a comprehensive representation of the state's energy challenges and opportunities.

3.2 Research Design

A mixed-methods approach was employed to comprehensively investigate household biomass consumption and preferences in Adamawa State. Quantitative data on household characteristics, biomass use, and willingness to transition to cleaner energy sources were collected through cross-sectional surveys using Kobo Collect. To complement these findings, qualitative data were gathered through focus group discussions and key informant interviews. This approach allowed for a detailed understanding of the socio-cultural factors influencing biomass use and the potential for alternative energy solutions.

3.3 Population and Sample

3.3.1 Population

The target population comprised all households within the three selected Local Government Areas (LGAs): Yola North (estimated population 307,900), Numan (estimated population 141,200), and Mubi North (estimated population 233,600) (National Population Commission, 2023).

3.3.2 Sampling Strategy

A multi-stage sampling technique was employed to ensure representative data collection across Adamawa State. Initially, LGAs were purposively selected based on economic activity and population density. Subsequently, five wards were randomly chosen from Yola North and Mubi North, while four wards were selected from Numan to achieve geographical coverage. Finally, a systematic random sampling method was used to select 36 households in Yola North, 26 in Mubi North, and 21 in Numan for survey participation. This combined approach effectively integrates quantitative and qualitative data collection, strengthening the research design.

3.3.4 Sample Size Determination

A sample size of 399 households was determined for this study, proportionally distributed across the three selected local government areas. This sample was calculated using Taro Yamane's formula based on the projected total population of 682,700 for the sampled areas, as reported by the National Population Commission in 2023:

$$n = \frac{N}{1 + Ne^2}$$

Where $n =$ sample size, $N =$ Total population, $e =$ error margin (the common error margin of 0.05 i.e. 5% is chosen with, 95% confidence interval).

N = 682,700, e = 0.05 $\quad n = \frac{682{,}700}{1+682{,}700(0.05)^2}$ = 399.766

Below is a table summarizing the estimated population for each local government, along with their corresponding sample sizes, culminating in a total sample size of 399 households:

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Table 1: Sample Size Distribution

A	B	C	D	E	(C x E)
LGAs	Total No. of Wards	No. of Wards Selected	Total Projected Population in the LGA (NPC, 2022)	Sample size drawn from each ward	Sample used from each LGA
Yola North	11	5	307,900	36	180
Mubi North	11	5	233,600	27	135
Numan	10	4	141,200	21	84
Total	**32**	**14**	**682,700**		**399**

Source: National Population Commission (2023) and sample size computed by Research Team Using Taro-Yamani Formula for Calculating Sample Size.

3.4 Data and Methodology

3.4.1 Data

The data for this study were collected through a household survey focusing on firewood and charcoal, the predominant biomass fuels in the study area. While charcoal is considered a cleaner alternative to firewood, both are classified as biomass energy. Key variables included environmental awareness, household income, education level, age, size, and access to alternative energy sources. Occupation, social, and cultural factors were also considered potential influencing factors.

3.4.2 Methods of Data Analysis

A multifaceted approach was employed to analyze the collected data. Descriptive statistics, including mean and standard deviation, were calculated to characterize household biomass demand patterns. Cross-tabulations were used to explore associations between biomass use and household characteristics. To examine determinants of biomass consumption and willingness to transition to cleaner energy sources, impact analyses were performed. Household biomass consumption was categorized into three levels (small, medium, large) and analysed using ordered logistic regression. Household decisions regarding transitioning to cleaner energy sources (willing, neutral, not willing) were analysed using multinomial logistic regression. These models assessed the impact of various factors on these outcomes. Given the focus on transitioning from biomass, the "Not Willing" category served as the baseline for comparison.

3.4.1 Ordered logit model

Households typically consume different level of biomass, depending on the factors influencing that decision. As a result, traditional logistic regression is in appropriate since it can only address the binary dependent variables. As mentioned above, biomass consumption can be ordered in terms of small, medium, and large quantities. In our ordered model, a latent variable Y_i^* represents the unobserved propensity of biomass use, which is influenced by a set of explanatory variables. The model is specified as follows (McCullagh, 1980):

$$Y_i^* = X_i \beta + \varepsilon_i$$

Where:

Y_i^* is the latent continuous variable for observation i.

X_i is a vector of explanatory variables for observation i.

β is a vector of coefficients.

ε_i is the error term, assumed to follow a logistic distribution.

The observed ordinal outcome Y_i is categorized into three levels of biomass use: Low, Medium, and High. These categories are determined by comparing the latent variable, Y_i^* with the following thresholds:

$$Y_i = \begin{cases} 1 & if\ Y_i^* \leq \tau_1 \\ 2 & if\ \tau_1 < Y_i^* \leq \tau_2 \\ 2 & if\ Y_i^* \geq \tau_2 \end{cases}$$

where:

τ_1 is the threshold separating Low from Medium.

τ_2 is the threshold separating Medium from High.

The probability that Y_i falls into category j is given by:

$$P(Y_i = j / X_i) = \Lambda(\tau_j - X_i\beta) - \Lambda(\tau_{j-1} - X_i\beta)$$

$P(Y_i = j / X_i)$ is the probability that the observed Y_i is in category j given the vector of explanatory variables X_i.

$= \Lambda(z)$ is the logistic cumulative distribution function (CDF), defined as $\Lambda(z) = \dfrac{1}{1+e^{-z}}$.

τ_j are thresholds that separate the different categories.

$X_i\beta$ is the linear predictor, where β vector of coefficients for the explanatory variables.

For the category $j = 1$:

$$P(Y_i = 1 / X_i) = \Lambda(\tau_1 - X_i\beta) = \frac{1}{1+e^{-(\tau_1 - X_i\beta)}}$$

For the category $j = 2$:

$$P(Y_i = 2 / X_i) = \Lambda(\tau_2 - X_i\beta) - \Lambda(\tau_1 - X_i\beta) = \frac{1}{1+e^{-(\tau_2 - X_i\beta)}} - \frac{1}{1+e^{-(\tau_1 - X_i\beta)}}$$

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

For the category $j = 3$:

$$P(Y_i = 3 / X_i) = 1 - \Lambda(\tau_2 - X_i\beta) = 1 - \frac{1}{1 + e^{-(\tau_2 - X_i\beta)}}$$

In the baseline model, the vector X comprises environmental awareness, reflecting respondents' ecological consciousness; income level, as a proxy for socioeconomic status; household head age, representing the age of the primary decision-maker in the household; household size; and alternative energy availability, indicating access to clean energy options. To comprehensively explore the determinants of household biomass use and address potential omitted variable bias, we incorporated additional variables representing sociocultural factors: occupation, to account for potential differences in energy access and preferences across sectors, cultural influence, given its hypothesized impact on energy choices through values and social norms, and social influence, to capture the effects of peer pressure and social networks on energy behaviour.

Average Marginal Effects

To better understand the impact of each explanatory variable on the probability of the different levels of biomass use, we computed the Average Marginal Effects . The Average Marginal Effects indicate how a one-unit change in an explanatory variable affects the probability of observing a specific category of biomass use, holding all other variables constant.

The Average Marginal Effects of X_k on the probability of observing category j is given by:

$$\frac{\partial P(Y_i = j / \mathrm{X}_i)}{\partial \mathrm{X}_{ik}} = (Y_i = j / \mathrm{X}_i)\left[\beta_k - \sum_{m=1}^{J-1} P(Y_i = m / \mathrm{X}_i)\beta_k\right]$$

Where:

$P(Y_i = j / \mathrm{X}_i)$ is the probability of the $i-th$ observation falling into category j.

β_k is the coefficient for the $k-th$ explanatory variable X_k .
J is the total number of categories.

For the lowest category: $(Y_i = 1)$:

$$\frac{\partial P(Y_i = j / \mathrm{X}_i)}{\partial \mathrm{X}_{ik}} = \Lambda(\tau_1 - X_i\beta)[1 - \Lambda(\tau_1 - X_i\beta)]\beta_k$$

For the lowest category: $(Y_i = 2)$:

$$\frac{\partial P(Y_i = j / \mathrm{X}_i)}{\partial \mathrm{X}_{ik}} = [\Lambda(\tau_1 - X_i\beta) - \Lambda(\tau_2 - X_i\beta)][1 - \Lambda(\tau_1 - X_i\beta) - \Lambda(\tau_2 - X_i\beta)]\beta_k$$

For the lowest category: $(Y_i = 3)$:

$$\frac{\partial P(Y_i = j / \mathrm{X}_i)}{\partial \mathrm{X}_{ik}} = \Lambda(\tau_2 - X_i\beta)[1 - \Lambda(\tau_2 - X_i\beta)]\beta_k$$

$\Lambda(z), \tau_1, \tau_1, \mathrm{X}_i\beta$ and β_k are as defined above.

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

3.4.2 Multinomial logit model

Household decisions regarding the transition to cleaner energy sources (willing, neutral, not willing) were analysed using a multinomial logistic regression model. To gain deeper insights into the factors influencing the adoption of alternative energy sources, the "Not Willing" category was selected as the baseline for comparison. This approach enables a focused examination of the characteristics and barriers associated with resistance to change. By contrasting the profiles of households unwilling to transition with those that are neutral or willing, the analysis provides a clearer understanding of the determinants of energy choices. The model is specified as follows (McFadden, 1974):

$$P(Y_i = j) = \frac{\exp\left(\beta_{j0} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa}\right)}{1 + \exp \sum_{m=2}^{J} \exp(\beta_{m0} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa})}$$

For $J = 2,3$ and where:

Y_i is the categorical outcome for observation i,

j represents the category of outcome variable, with $J = 3$ total categories,

$X_{i\kappa}$ is the vector of explanatory variables,

K is the number of explanatory variables,

β_{j0} denotes the intercept for category j,

β_k is the coefficient for the $k-th$ explanatory variable for observation i.

The probability of the baseline category ("Not- Willing") is:

$$P(Y_i = 1) = \frac{1}{1 + \exp \sum_{m=2}^{J} \exp(\beta_{m0} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa})}$$

For the "Neutral" category $(j = 2)$:

$$P(Y_i = 2) = \frac{\exp\left(\beta_{20} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa}\right)}{1 + \exp \sum_{m=2}^{J} \exp(\beta_{m0} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa})}$$

For the "Willing" category $(j = 3)$:

$$P(Y_i = j) = \frac{\exp\left(\beta_{30} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa}\right)}{1 + \exp \sum_{m=2}^{J} \exp(\beta_{m0} + \sum_{K=1}^{K} \beta_{j\kappa} X_{i\kappa})}$$

The coefficient β_{jk} reflect the change in the log odds of being in category j (either "Neutral" or "Willing") relative to the baseline category ("Not-Willing") for a unit change in the explanatory variable $X_{i\kappa}$.

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Similar to the ordered logistic regression model, the explanatory variables $X_{i\kappa}$ included environmental awareness, household head age, household size, income level, and alternative energy availability, providing valuable insights for promoting sustainable energy practices in the study area. To further explore potential influences, occupation, cultural influence, and social influence were also incorporated as predictors.

To quantify the change in the predicted probability of transitioning to a cleaner energy source due to a one-unit change in an explanatory variable, while holding all other variables constant, the marginal effect of explanatory variable on the probability of being in outcome category j can be evaluated as follows:

$$\mathrm{ME}_{j\kappa} = \mathrm{P}(\mathrm{Y}_i = j)\left(\beta_{j\kappa} - \sum_{m=1}^{J} \mathrm{P}(\mathrm{Y}_i = m)\beta_{m\kappa}\right)$$

$P(Y_i = j)$ is the probability of being in category j.

β_{jk} is the coefficient for the $k-th$ explanatory variable in category j.
J is the number of outcome categories.

$P(Y_i = m)$ is the probability of being in category m, β_{mk} is the corresponding coefficient.

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Table 1. Correlations and Descriptive Statistic

Variables Samples (N = 399)	Mean	SD	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
(1) Quantity of Biomass use	1.832	.792	1.000											
(2) Willingness to Transition	1.915	.728	-.421***	1.000										
(3) Willingness to Transition	2.692	.939	-.232***	.134***	1.000									
(4) Education Level	13.682	4.87	0.017	-0.037	-0.056	1.000								
(5) Income Level	52208.87	16489.893	.058	.026	-.151***	.781***	1.000							
(6) Household Age	41.707	13.92	.030	-.179***	.101**	-.399***	-.548***	1.000						
(7) Household Size	9.1	2.566	-.011	-.020	.219***	.148***	.092*	.027	1.000					
(7) Alternative Energy Availability	.627	.484	-.301***	.052	.315***	.051	-.037	.082	.394***	1.000				
(9 Occupation (Agriculture)	.301	.459	-.020	.107	.035	.000	.053	-.046	.051	.054	1.000			
(10) Occupation (Non-Agriculture)	.318	.466	.023	-.112**	-.011	-.047	-.078	.109**	-.086*	.105**	-.448***	1.000		
(11) Social Influence	1.91	.816	-.016	.059	.000	.010	.020	.013	-.058	-.054	.006	-.043	1.000	
(12) Cultural Influence	1.83	.619	.013	-.010	-.034	-.033	-.003	.040	.033	.005	.004	.032	-.608***	1.000

*p < .10. **p < .05. ***p < .01.

Descriptive Statistics

Descriptive statistics for the study population (N=399) are presented in Table 1. The mean quantity of biomass use (1.832) suggests moderate reliance on biomass. High willingness to transition (means 1.915 and 2.692) indicates potential for sustainable energy adoption. The population's education level (mean 13.682 years) suggests moderate capacity for technological uptake. Income diversity (mean $52,208.87) may influence energy choices. Larger households (mean 9.1) could correlate with higher energy consumption. Low alternative energy availability (mean 0.627) highlights infrastructure gaps. The occupational mix (agriculture 0.301, non-agriculture 0.318) suggests varied economic base. Moderate social and cultural influence (means 1.91 and 1.83) offers opportunities for behaviour change interventions promoting sustainable energy.

Correlation Analysis

While the correlation analysis reveals valuable relationships between variables (e.g., education and environmental awareness), it's important to consider the potential impact of multicollinearity on our model's interpretability. The strong positive correlation between income and education (0.781) and the negative link between social influence and cultural influence (-0.608) warrant attention, especially when interpreting their individual effects. It's important to note that while these correlations are strong, they fall below the commonly used cut-off of 0.8 for severe multicollinearity concerns. However, even moderate correlations can influence interpretations. The encouraging aspect is that the majority of correlations observed earlier were below 0.5, indicating a generally weak to moderate level of association between most explanatory variables. This reduces the likelihood of severe multicollinearity issues for a significant portion of the model. To gain a more comprehensive understanding of the potential multicollinearity impact and ensure a robust analysis with reliable conclusions drawn from the correlations, we employed the Variance Inflation Factor (VIF) analysis. The VIF results are presented in the table below;

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Table 2. Variance inflation factor

	VIF	1/VIF
Environmental Awareness	1.161	.861
Education Level	2.658	.376
Income Level	3.214	.311
Household Age	1.469	.681
Household Size	1.259	.794
Alternative Availability	1.326	.754
Occupation (Agriculture)	1.394	.717
Occupation (Non-Agriculture)	1.433	.698
Social influence	1.609	.621
Cultural influence	1.609	.621
Mean VIF	1.713	.

To assess potential multicollinearity, correlation analysis (Table 1) was conducted. While some variables exhibited strong correlations (e.g., income and education), subsequent variance inflation factor (VIF) analysis (Table 2) revealed that all values remained below the critical threshold of 5. This suggests multicollinearity is unlikely to be a major issue, allowing us to proceed with confidence with further analysis.

Table 3. Cross-Tabulation of Quantity of Biomass use by Key Demographic and Socioeconomic Factors

Attribute	Value	Large	Medium	Small	Total
Environmental Awareness	1	9	4	24	37
	2	38	67	40	145
	3	77	35	9	121
	4	40	32	24	96
Education Level	7	47	40	21	108
	13	32	25	18	75
	15	50	40	44	134
	17	1	0	0	1
	21	34	33	14	81
Income Level	24001	44	33	17	94
	55001	35	45	25	105
	60000.5	50	30	40	120
	70001	35	30	15	80
Household Age	2	85	55	40	180
	3	67	66	48	181
	4	12	17	9	38
Household Size	2	5	5	0	10
	3	5	0	5	10
	4	9	0	0	9
	5	18	5	0	23
	6	0	14	0	14
	7	0	0	9	9
	8	9	5	25	39
	9	18	44	18	80
	10	34	27	15	76
	11	32	19	20	71
	12	25	19	0	44
	13	9	0	5	14

Alternative Availability	0	37	54	58	149
	1	127	84	39	250
Occupation (Agriculture)	0	121	81	77	279
	1	43	57	20	120
Social Influence	1	63	46	43	152
	2	54	52	25	131
	3	47	40	29	116
Cultural Influence	1	47	40	29	116
	2	100	80	55	235
	3	17	18	13	48

The cross-tabulated results in Table 3 reveal complex patterns in biomass consumption. Awareness levels, while showing some correlation, do not directly predict biomass use. Respondents with the lowest awareness (Level 1) predominantly fall into the small biomass use category. As awareness increases to Levels 2 and 3, a noticeable shift towards larger biomass usage is observed. However, the highest awareness group (Level 4) exhibits a more balanced distribution, suggesting that awareness alone may not directly correlate with reduced biomass use.

Higher educational attainment and income levels also fail to consistently correlate with lower biomass consumption. Respondents with higher educational attainment, particularly those with a diploma (Level 15) or postgraduate degrees (Level 21), demonstrate significant presence in the large and medium biomass use categories. This indicates that education level alone is not a predictor of lower biomass consumption, as higher educated individuals also have substantial representation in large biomass use. Income levels display a mixed pattern concerning biomass use. While medium and high income levels show considerable large biomass use, no clear trend emerges linking higher income levels to lower biomass consumption. This suggests that factors beyond income influence energy choices.

Younger households (Age 2) are predominantly represented in the large biomass use category. As household age increases, a slight decrease in large biomass use is observed, with older households (Ages 3 and 4) showing a more varied distribution across all categories. Significant variation exists in biomass use across different household sizes. Larger households (sizes 9, 10, and 11) exhibit considerable use across all biomass categories. Interestingly, the largest household sizes do not exclusively lean towards large biomass use, highlighting the complex nature of household energy consumption patterns.

Household occupation appears to significantly influence biomass consumption patterns. Agricultural households (Level 1) generally consume larger quantities of biomass compared to non-agricultural households (Level 0). This disparity suggests potential differences in access to alternative energy sources or reliance on biomass between the two groups. Non-agricultural households (Level 0), exhibiting higher biomass usage, may face barriers to adopting cleaner energy options. To address this, targeted interventions providing alternative energy solutions to non-agricultural households are essential.

Cultural factors also play a crucial role in biomass consumption. Households with moderate cultural influence (Level 2) tend to consume more biomass than those with low cultural influence (Level 1).

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

This indicates that cultural norms and practices shape energy choices. While communities with low (Level 1) and high cultural influence may be more adaptable, those with moderate influence (Level 2) often require specific interventions. Culturally sensitive approaches are vital for promoting sustainable energy practices. Social influence also seems to significantly impacts biomass consumption. Households with high social influence (Level 3) generally consume more biomass compared to those with low social influence (Level 1). This highlights the importance of social norms and peer behavior in shaping energy choices. However, households with low social influence (Level 1) exhibit a more varied consumption pattern, suggesting potential openness to alternative energy options. Leveraging social influence through targeted campaigns can accelerate the transition to cleaner energy sources.

Finally, the availability of alternative energy sources does not directly correlate with reduced large biomass use. While areas with alternatives available (Level 1) have larger biomass use cases than areas without alternatives (Level 0), this suggests that availability alone may not drive the transition away from biomass.

4.2 Ordered logit regression results

To identify the most parsimonious and predictive model for biomass consumption, an information-theoretic approach employing the Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) was utilized. A stepwise model-building process incorporating demographic, socioeconomic, and sociocultural variables was undertaken. The final model, characterized by the lowest AIC and BIC values, comprised core demographic and socioeconomic factors. While occupation, social, and cultural influences were considered, their inclusion did not significantly enhance model fit. The predictive performance of the final model, as assessed by McFadden's pseudo-R^2, was modest. This suggests that the model, while capturing some variation in biomass consumption, does not fully explain the phenomenon. This limitation may be attributed to factors such as the ordered nature of the dependent variable, the potential omission of key variables, complex individual consumption patterns, and unobserved influences. To assess the appropriateness of the ordered logit model, the proportional odds assumption was evaluated using the Brant test. The non-significant Brant test result (Table 4) supports the use of the ordered logit model for this analysis.

Table 4. Ordered logistic regression

Variable	Model 1	Model 2	Model 3
Environmental Awareness	-.356*** (.112)	-.355*** (.112)	-.3559*** (.1122)
Education Level	-.004 (.031)	-.001* (.031)	-.0023 (.0310)
Income Level	9.86e-06 (.000010)	9.98e-06 (.00001)	(.00001)
Household Age	.018 (.008)	0.018 (.008)	.0185** (.0083)
Household Size	.095 (.042)	0.104 (.042)	.1030** (.0421)
Alternative Energy Availability	-1.240*** (.226)	-1.317 (.232)	-1.3221*** (.2320)
Occupation (Agriculture)		.274 (.234)	.2751 (.2346)
Occupation (Non-Agriculture)		.365 (.241)	.3599 (.2413)

Cultural Influence			-.0577 (.1948)
Social Influence			-.0914 (.1494)
τ_1	-.074 (.737))	.200 (.756)	-.0618 (.9289)
τ_2	1.611 (.742)	1.893 (.763)	1.6332 (.9330)
R^2McFadden	.066	.069	.070
AIC	818.041	819.458	823.074
BIC	849.952	859.347	870.942
χ^2	56.978***	59.561***	59.945***
Brant Test of PRA	3.54 [.738]		
N	399	399	399

Note: *p < .10. **p < .05. ***p < .01. τ is the *Threshold (latent variable): (τ_1 distinguishes between the lowest and middle) categories of biomass use;* τ_2 distinguishes between the middle category and the highest . A household with a latent score below -0.0745 would fall into the lowest (smaller) biomass use category, between -0.074 and 1.611 into the middle (medium) category, and above 1.611 into the largest category. Figure is square bracket is the probability value.

Table 4 presents the results of the ordered logit regression. It shows that environmental awareness is significantly negatively associated with the quantity of biomass used at the 1% significance level. A one-unit increase in environmental awareness decreases the log odds of higher biomass use by approximately 0.356 units, suggesting that households with greater environmental consciousness are less likely to rely heavily on biomass. Contrary to expectations, education and income levels do not significantly influence biomass use. This suggests that factors beyond socioeconomic status, such as cultural practices or economic constraints, may be more critical determinants of biomass consumption.

Age of the household head is positively correlated with biomass use at the 5% level. A one-year increase in age corresponds to a 0.018 increase in the log odds of higher biomass consumption. Household size is also a significant positive predictor of biomass use. A one-unit increase in household size raises the log odds of higher biomass consumption by approximately 0.103. Conversely, the availability of alternative energy sources is strongly and negatively associated with biomass use at the 1% level of significance level. A one-unit increase in alternative energy availability decreases the log odds of higher biomass consumption by approximately 1.240.

The findings of this study contribute to the broader understanding of household energy choices, particularly in the context of biomass consumption. While the Energy Ladder (EL) model posits a linear progression from biomass to cleaner fuels with increasing income (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008), the results suggest a more complex reality. The significant negative association between environmental awareness and biomass use aligns with the notion of consumers making informed choices about energy sources. However, the lack of significant influence of education and income levels challenges the strict adherence to the EL model, indicating that other factors are at play.

This study's findings are more consistent with the Energy Stacking (ES) model, which acknowledges the use of multiple fuel sources simultaneously (Kitole, Tibamanya & Sesabo, 2023). The positive association between household size and biomass consumption supports this perspective, as larger households may require additional energy sources despite access to cleaner alternatives. Consistent with previous research (Heltberg, 2005; Bansal et al., 2013), demographic factors such as age and household size influence biomass use. Older households, often more accustomed to traditional practices, and larger households with greater energy demands, are more likely to rely on biomass. These findings underscore the importance of targeted interventions addressing the specific needs of these population segments.

The strong negative association between the availability of alternative energy sources and biomass consumption highlights the critical role of expanding access to clean energy options. This aligns with the emphasis on promoting cleaner-burning fuels like LPG to reduce environmental impact and improve public health (Varkey, 2023).

Table 5. Average Marginal Effects on Biomass Consumption

Predictors	$\frac{dy}{dx(1)}$	$\frac{dy}{dx(2)}$	$\frac{dy}{dx(3)}$
Environmental awareness	0.0771***	-0.0182***	-0.0589***
	(0.0234)	(0.0066)	(0.0182)
Education level	0.0009	-0.0002	-0.0007
	(0.0067)	(0.0016)	(0.0051)
Income level	-0.000002	0.0000005	0.0000016
	(0.000002)	(0.0000005)	(0.0000017)
Head of Household age	-0.0039**	0.0009**	0.0030**
	(0.0018)	(0.0005)	(0.0014)
Household size	-0.0206**	0.0049**	0.0158**
	(0.0089)	(0.0023)	(0.0069)
Alternative availability	0.2687***	-0.0635***	-0.2052***
	(0.0443)	(0.0164)	(0.0355)

Note: The estimated coefficients reflect the average marginal effects of explanatory variables on the probability of biomass consumption levels: quantity consumed (small = 1, medium = 2, large = 3). Delta method standard errors are shown in parentheses, with significance levels indicated by stars: *p < .10. **p < .05. ***p < .01.

Table 5 presents the average marginal effects of environmental awareness on the probability of different biomass consumption levels. Results indicate a positive and statistically significant association between environmental awareness and the probability of consuming small amounts of biomass at the 1% level. A one-unit increase in environmental awareness is associated with a 7.7% increase in the probability of consuming small amounts of biomass. This suggests a potential shift towards more efficient biomass use or adoption of cleaner alternatives. Conversely, the probability of consuming medium and large amounts of biomass decreases significantly at the 1% level with increasing environmental awareness. A one-unit increase in environmental awareness is associated with a 1.8% decrease in the probability of consuming medium and a 5.9% decrease in the probability of consuming large amounts of biomass. This suggests a potential overall reduction in biomass consumption among environmentally conscious households.

Contrary to expectations, neither education level nor income level significantly impacts biomass consumption patterns. This indicates that socioeconomic status alone is not a primary determinant of energy choices in this context. However, household demographics seem to influence biomass use. The results indicate a negative and statistically significant association between the head of household's age and the probability of consuming large amounts of biomass at the 5% level. A one-year increase in the head of household's age is associated with a 0.4% decrease in the probability of consuming large amounts of biomass. Household size also matters, as the results indicate a negative and statistically significant association between household size and the probability of consuming large amounts of biomass at the 1% level. A one-unit increase in household size is associated with a 2.1% decrease in the probability of consuming large amounts of biomass. Conversely, there is a positive and statistically significant association between household size and the probability of consuming medium and small

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

amounts of biomass at the 1% level. A one-unit increase in household size is associated with a 0.5% increase in the probability of consuming medium and a 1.6% increase in the probability of consuming small amounts of biomass.

The availability of alternative energy sources presents another interesting finding. Results indicate a positive and statistically significant association between alternative availability and the probability of consuming small amounts of biomass at the 1% level. A one-unit increase in alternative availability is associated with a 26.9% increase in the probability of consuming small amounts of biomass. However, this increase is partially offset by decreases in the probability of consuming medium and large amounts of biomass. There is a negative and statistically significant association between alternative availability and the probability of consuming medium and large amounts of biomass at the 1% level. A one-unit increase in alternative availability is associated with a 6.3% decrease in the probability of consuming medium and a 20.5% decrease in the probability of consuming large amounts of biomass.

The results presented in Table 5 are largely consistent with existing literature on household energy choices, particularly regarding the role of environmental awareness, household demographics, and the availability of alternative energy sources. These findings provide valuable insights into the complex factors influencing biomass consumption levels in households.

First, the positive and statistically significant association between environmental awareness and the probability of consuming small amounts of biomass aligns with studies by Capareda (2011) and Orifah et al. (2019) who highlighted that greater awareness of the environmental and health impacts of biomass use leads to the adoption of cleaner energy sources. The 7.7% increase in the probability of consuming small amounts of biomass with higher environmental awareness suggests that households may be shifting towards more efficient biomass use or cleaner alternatives. This shift is consistent with the notion that increased environmental awareness drives households to adopt practices that reduce their overall biomass consumption.

Conversely, the results indicating a decrease in the probability of consuming medium and large amounts of biomass with increasing environmental awareness are also consistent with the literature. The 1.8% decrease for medium amounts and the 5.9% decrease for large amounts suggest that as households become more environmentally conscious, they reduce their reliance on larger quantities of biomass. This aligns with findings by Capareda (2011) and Orifah et al. (2019), which emphasize that environmental awareness contributes to a reduction in the use of biomass, thus promoting cleaner energy alternatives.

However, the results showing that neither education level nor income level significantly impact biomass consumption patterns present a deviation from some established findings. Studies such as those by Pandey and Chaubal (2011) and Kuunibe et al. (2013) often point to education and income as significant determinants of fuel choice. The lack of significant impact in this context may suggest that other factors, such as environmental awareness and household demographics, are more influential in determining energy choices in this specific setting. This finding indicates the need to consider context-specific dynamics when analysing household energy transitions.

Household demographics also play a crucial role in biomass consumption patterns. The negative and statistically significant association between the age of the household head and the probability of consuming large amounts of biomass is supported by the literature. A 0.4% decrease per year in the probability of consuming large amounts of biomass suggests that older household heads may prefer cleaner fuels, potentially due to greater health awareness or accumulated environmental knowledge. This finding aligns with studies like Kuunibe et al. (2013), which emphasize the influence of household head characteristics on energy choices.

Moreover, the mixed influence of household size on biomass consumption is consistent with existing research. The negative association with large biomass consumption and the positive association with medium and small amounts indicate that larger households diversify their fuel use to manage higher energy demands efficiently. This is in line with findings by Kuunibe et al. (2013), suggesting that larger households have varied energy needs that lead them to use different types of fuels concurrently.

Lastly, the availability of alternative energy sources shows a significant impact on biomass consumption patterns. The positive and statistically significant association with small biomass consumption (26.9% increase) indicates that households might use small amounts of biomass alongside alternative energy sources, supporting the Energy Stacking model (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008; Kitole, Tibamanya & Sesabo, 2023). The decreases in the probability of consuming medium and large amounts of biomass (6.3% and 20.5%, respectively) with greater alternative availability are consistent with the ES model's assertion that access to alternatives reduces reliance on traditional biomass.

In conclusion, the findings from Table 5 are largely consistent with the broader literature, particularly in highlighting the importance of environmental awareness and the availability of alternative energy sources in reducing biomass consumption. While the non-significant impact of education and income deviates from some studies, it underscores the context-specific nature of energy choices, where factors like environmental awareness and household demographics may be more critical. These results support the need for a multifaceted approach to understanding and influencing household energy transitions, considering both socioeconomic and contextual factors.

While the ordered logit regression provided valuable insights into biomass consumption patterns, a deeper understanding of the factors influencing households' willingness to transition to alternative energy sources is necessary. To this end, a multinomial logit model was employed to examine the determinants of household energy choices. The results are presented in Table 6.

Table 6. Multinomial logistic regression

Variable	Neutral	Willing	Neutral	Willing	Neutral	Willing
	$\beta_{1/2}$	$\beta_{1/3}$	$\beta_{1/2}$	$\beta_{1/3}$	$\beta_{1/2}$	$\beta_{1/3}$
Environmental Awareness	-.17448 (.14161)	.2979999* (.1599568)	-.1459883 (.1450865)	.297282* (.1620001)	-.1506822 (.1455938)	.2974685 (.1623028)
Education Level	.09000** (.04101)	-.0044604 (.045265)	.0891495** (.0419439)	.0016523 (.0458751)	.0881228 (.0422109)	.0019335 (.0458885)
Income Level	.00001 (.00001)	.0000352** (.0000167)	.000014 (.0000136)	.0000345** (.0000169)	.0000151 (.0000137)	.0000342 (.0000169)
Household Age	.00057 (.01051)	-.0590437*** (.0132427)	-.0037599 (.0108687)	-.0618252*** (.0133869)	-.0024613 (.0109435)	-.0620983 (.0134754)
Household Size	.03877 (.05348)	-.0242338 (.0588244)	.0684123 (.0546571)	-.0030872 (.0601236)	.0663456 (.0548792)	-.0025311 (.0602432)
Alternative Energy Availability	-.49595* (.28419)	-.1944603 (.3316152)	-.6737909*** (.2950853)	-.3456993 (.3448552)	-.6917672 (.2960194)	-.3306609 (.3458359)
Occupation (Agriculture)			.1855876 (.314289)	.6157799* (.3362834)	.1839502 (.3154826)	.6142766 (.3361865)

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Occupation (Non-Agriculture)			1.152249** (.3071125)	.8894473** (.3717296)	1.146733 (.3082423)	.8912462 (.371933)
Cultural Influence					-.2582385 (.2633719)	.0462875 (.2872431)
Social Influence					-.2627535 (.1945867)	.0844509 (.2227407)
_cons	-1.8310** (.93009)	-.7389691 (1.09224)	-2.444628** (.9711083)	-1.22998 (1.107024)	-1.534287 (1.203106)	-1.466287 (1.371012)
R^2McFadden	0.104		0.127		0.130	
AIC	782.534		771.273		776.417	
BIC	838.379		843.074		864.174	
χ^2	87.730***		106.991***		109.847***	
Correctly Specified						
N	399		399		399	

Note: The estimated coefficients reflect the effect of explanatory variables on the log ratio of households' willingness to transition to alternative clean energy. Standard errors are shown in parentheses, with significance levels indicated by stars: *p < .10. **p < .05. ***p < .01. Dependent variable; willingness to transition (Not-Willing=1 (baseline); Neutral=2; Willing=3.

Table 6 present estimated results of Multinomial logit regression. Three outcome categories were considered: "Neutral," "Willing," and "Not Willing" with "Not Willing" as the reference category. The model compared "Neutral" households to "Not Willing" households, and subsequently, "Willing" households to "Not Willing" households. First, estimates of the coefficients for the baseline model (A) was presented (see Table 6; columns (1). Then the study examines whether Occupation affects households' energy choice (see Table 6; Model B). Model C of Table 6 (Columns (1) and (2) present separate regression including cultural and social influences.

As shown in column (1) to (6), Table 6, environmental awareness had insignificant impact on households being neutral about transitioning to cleaner energy compared to those not willing. Conversely, higher education levels increased the likelihood of a neutral stance compared to being unwilling at the 5% significance level. Every additional year of education leads to approximately 8.9% increase in the odds of neutrality. Income and age of the household head did not significantly influence the decision to be neutral compared to not willing. It is also notable that the coefficient on the household size was positive, but its effect on the household choice being neutral was not statistically significant. Interestingly, availability of alternative energy sources appeared to be in important factor, which reduced the likelihood of being neutral compared to not willing at the 5% significant level. While households engaged in Agricultural occupation did not seem to be neutral compared to not willing, while those engaged in non-agricultural occupation were significantly more likely to be neutral about transitioning to cleaner energy compared to those not willing, which is significant at the 1% level.

Comparing households willing to adopt clean energy alternatives to those unwilling, we found a positive association between environmental awareness and the likelihood of transitioning to cleaner energy sources. However, this relationship was only statistically significant at the 10% level. Education level did not significantly influence the likelihood of adopting clean energy alternatives. Conversely, higher income levels were significantly associated with a greater propensity to adopt cleaner energy sources. Specifically, a one-unit increase in household income was linked to a approximately 0.00345% higher likelihood of adopting clean energy. Older household heads were significantly less likely to adopt clean energy alternatives compared to younger counterparts. The coefficient for household age is

-0.0618252, indicating that, on average, the likelihood of adopting clean energy decreases by approximately 6.18% for each additional year of age. This effect is statistically significant at the 1% level. Conversely, household size and the availability of alternative energy sources did not significantly influence the likelihood of transitioning to cleaner energy. Agricultural households exhibited a tendency towards adopting clean energy, with a 61% increase in likelihood. Nevertheless, this finding is marginally significant at the 10% level, indicating a lower level of confidence in the result compared to the stronger association observed among non-agricultural households, which demonstrated an 88.9% increase in likelihood at the 5% significance level.

Given the complexities of multinomial logit models, coefficient estimates alone may not fully capture the impact of independent variables on the probability of each outcome category. To address this, Average Marginal Effects were evaluated. The results are presented in Table 7.

Table 7. Average Marginal Effects on Willingness to Transition to Alternative Clean Energy

Variable	Neutral Coefficient (Std. Err.)	Willing Coefficient (Std. Err.)
Environmental Awareness	-0.0482* (0.0251)	0.0545** (0.0217)
Education Level	0.0171** (0.0074)	-0.0058 (0.0064)
Income Level	0.00000037 (0.0000026)	0.00000424* (0.00000245)
Household Age	0.0034* (0.0019)	-0.0090*** (0.0017)
Household Size	0.0134 (0.0097)	-0.0051 (0.0084)
Alternative Energy Availability	-0.1068** (0.0509)	-0.0064 (0.0467)
Occupation (Agriculture)	-0.0057 (0.0562)	0.0799* (0.0465)
Occupation (Non-Agriculture)	0.1624*** (0.0512)	0.0558 (0.0494)

Table 7 presents the average marginal effects from a multinomial logit model. Columns (1) and (2) display the estimated effects on the probabilities of "Neutral" and "Willing" households, respectively, compared to the reference category (not willing). The results indicate that a one-unit increase in environmental awareness reduces the probability of being neutral relative to not willing by 4.8%, but this effect is not statistically significant. Conversely, education level enters the model with a negative coefficient and is significant. Each additional year of education increases the probability of being neutral compared to not willing by 0.71%, and this effect is statistically significant at the 5% level. Notably, household income does not appear to impact the likelihood of being neutral.

The marginal effect of household age on being neutral rather than not willing is 0.3%. This effect is, however, marginally statistically significant at the 10% significance level, suggesting older household heads might slightly increase the probability of being neutral compared to not willing. Alternative availability appears to be significantly important in reducing the probability of being neutral by about 10.7% compared to not willing at the 5% significance level. Households where the head is involved in agriculture do not seem to be neutral compared to not willing, but being in non-agricultural activities increases the probability of being neutral compared to not willing by about 16.2%, and this effect is statistically significant at the 1% level.

The results also indicate several factors influencing the likelihood of a household being "willing" compared to "not willing." A one-unit increase in environmental awareness significantly increases the probability of being willing by 5.45%. Surprisingly, education does not appear to significantly influence the likelihood of households' willingness to choose alternative energy sources. But income level income seems to show negligible effects. Conversely, each additional year of household age decreases the chances of being willing by 0.01%, and this effect is also statistically significant at the 1% level.

Household size and alternative availability, and occupation do not significantly influence the probability of a household falling into the "willing" category. However, being in agriculture seems to increase the probability of being willing compared to not willing by about 8%, but this effect is only marginally statistically significant at the 10% level. Being in non-agriculture is far from being willing compared to not willing.

The results presented in Table 7 offer several interesting insights, many of which align with the broader literature on household energy choices, while some findings deviate, highlighting the complexity and context-specific nature of these decisions. Firstly, the finding that environmental awareness reduces the probability of being neutral relative to not willing by 4.8%, albeit not statistically significant, aligns with the literature emphasizing the role of environmental awareness in influencing energy choices. Previous studies, such as those by Capareda (2011) and Orifah et al. (2019), have demonstrated that greater environmental awareness often drives households towards cleaner energy sources. Although the lack of statistical significance in this study may suggest other overriding factors, the direction of the effect remains consistent with existing research.

The statistically significant positive impact of education level on the probability of being neutral compared to not willing supports the notion that education plays a crucial role in shaping energy choices. The finding that each additional year of education increases the probability of being neutral by 0.71% aligns with Pandey and Chaubal (2011), who found that higher education levels are linked to greater awareness of environmental and health impacts, which could lead to more cautious decision-making processes, reflected in a neutral stance.

The marginal effect of household age on the probability of being neutral (0.3%), significant at the 10% level, suggests that older household heads may be slightly more likely to be neutral compared to not willing. This is consistent with Kuunibe et al. (2013), which indicates that older individuals might have accumulated more knowledge or experience that informs their energy choices, leading to a more moderate or neutral stance. The significant negative impact of alternative availability on the probability of being neutral by about 10.7% suggests that greater availability of alternative energy sources encourages households to move away from a neutral stance, likely towards willingness to adopt cleaner energy. This finding aligns with the Energy Stacking model (Hosier & Dowd, 1987; Schlag & Zuzarte, 2008; Kitole, Tibamanya & Sesabo, 2023), which emphasizes the importance of fuel availability in energy choice decisions.

The significant positive association between being involved in non-agricultural activities and the probability of being neutral compared to not willing (16.2%) highlights the influence of occupation on energy choices. This finding is consistent with the literature suggesting that non-agricultural households might have different energy needs and access levels, influencing their stance towards alternative energy (Hanna et al., 2016).

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

Regarding the willingness to adopt alternative energy sources, the positive and significant effect of environmental awareness (5.45%) corroborates findings by Capareda (2011) and Orifah et al. (2019), reinforcing the idea that environmental awareness significantly drives households towards cleaner energy adoption. However, the lack of significant influence of education on willingness contradicts some literature, such as Pandey and Chaubal (2011), which posits that higher education levels should promote cleaner energy choices. This discrepancy might be due to context-specific factors or other overriding variables not captured in this study.

The negligible effect of income on willingness is surprising, as it contrasts with traditional theories like the Energy Ladder model (Hosier & Dowd, 1987), which suggests that higher income levels should facilitate transitions to cleaner energy sources. This inconsistency highlights the complexity of energy choices, suggesting that factors beyond income, such as availability and awareness, play more crucial roles in this context. The negative and statistically significant effect of household age on the likelihood of being willing (0.01%) aligns with Kuunibe et al. (2013), suggesting that older household heads might be more conservative or set in their energy use habits, thus less willing to adopt new energy sources.

Finally, the lack of significant influence of household size, alternative availability, and occupation on willingness, except for a marginally significant positive effect of being in agriculture (8%), suggests that these factors might not be as crucial in determining willingness to adopt alternative energy in this specific context. This partially aligns with the literature indicating that while these factors are important, their influence can vary significantly based on local circumstances (Hanna et al., 2016).

In general, the results from Table 7 are generally consistent with the literature regarding the influence of environmental awareness and education on energy choices. However, some findings, such as the negligible impact of income and the mixed effects of household demographics and occupation, highlight the need for context-specific analysis to fully understand the determinants of household energy transitions. Furthermore, these findings align more closely with the Energy Stacking model, which emphasizes the simultaneous use of multiple fuel sources and the influence of various factors beyond income alone, rather than the Energy Ladder model, which suggests a linear progression in fuel types based on income.

Multinomial logit coefficients and average marginal effects offer complementary insights into factors influencing household energy choices. While both methods generally agree on the direction of effects for most variables, their magnitudes and statistical significance can vary. Environmental awareness consistently predicts a higher likelihood of adopting clean energy. Education also positively influences adoption, although its impact is more pronounced in the multinomial logit model.

Income and household age exhibit contrasting relationships across the models. Income positively predicts clean energy adoption in the multinomial logit model but shows negligible effects in the Average Marginal Effects model. Household age negatively influences adoption in the multinomial logit model, while the Average Marginal Effects suggest a weak, non-significant positive association. Household size and alternative energy availability appear to have limited impact on energy choices. Non-agricultural occupations are associated with both neutrality and willingness to adopt clean energy, while the role of agricultural occupations remains unclear.

The findings from the multinomial logit and Average Marginal Effects models provide valuable insights into the factors influencing household energy choices. While both models indicate that environmental awareness is a significant predictor of clean energy adoption, the impact of other variables, such as education, income, and age,

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

varies across the models. This highlights the complexity of household decision-making and the need for a nuanced understanding of the factors at play.

The results suggest that policies aimed at increasing environmental awareness and education, as well as expanding access to clean energy options, could be effective in promoting clean energy adoption. However, further research is needed to fully understand the role of income, age, and occupational factors in shaping household energy choices. To accelerate clean energy adoption, policymakers should prioritize comprehensive strategies that enhance environmental awareness, expand educational opportunities, and improve access to alternative energy sources. By investing in public education campaigns, supporting skill development, and fostering a conducive regulatory environment for renewable energy, governments can empower households to make informed energy choices. Tailored policies targeting specific demographics, such as non-agricultural households, can further optimize clean energy adoption rates. Continuous monitoring and evaluation of these initiatives are essential to ensure their effectiveness and to inform future policy adjustments.

5.0 CONCLUSION AND POLICY RECOMMENDATIONS

Understanding the factors influencing biomass consumption and the public's willingness to adopt cleaner energy sources is essential for developing effective sustainable energy policies. This study employed ordered logit and multinomial logit regression to examine these determinants. Our findings reveal a complex interplay between environmental factors, socioeconomic conditions, and household characteristics in shaping energy consumption patterns. Environmental consciousness emerged as a key driver of the transition from traditional biomass to cleaner energy sources. However, demographic factors such as household size and the age of the household head significantly influenced biomass use. Surprisingly, education and income levels did not significantly impact biomass consumption, challenging the traditional Energy Ladder model. Instead, these findings align more closely with the Energy Stacking model, suggesting that households often use a combination of energy sources based on factors like availability, affordability, and cultural practices. This implies that factors beyond economic status, such as accessibility and environmental concerns, may play a more crucial role in fuel choice. Interestingly, while income level did not significantly impact biomass consumption, it was a significant factor in adopting cleaner energy sources, suggesting a potential role for economic incentives in promoting clean energy transitions.

These findings hold significant policy implications. Given Adamawa State's ongoing efforts to address environmental concerns, addressing the challenges associated with biomass consumption and promoting clean energy adoption is crucial. Policymakers should enhance environmental awareness through comprehensive public campaigns. By increasing understanding of the environmental and health impacts of biomass, policymakers can create a more supportive environment for clean energy transitions. Expanding community access to clean energy technologies is also essential. Investing in the development and distribution of affordable and reliable clean energy options will empower households to make informed choices and reduce their reliance on biomass. Targeted interventions should address the specific needs of different population segments, particularly older households. These interventions might include education, financial incentives, or accessible technological solutions. To sustain progress, policies should leverage economic incentives to accelerate the adoption of clean energy technologies. Given the positive relationship between income and clean energy adoption, policies supporting financial incentives can encourage a wider range of households to invest in clean energy options. Finally, creating a supportive policy environment for fostering the development and deployment of clean energy solutions is essential. By implementing policies that reduce barriers to entry for clean energy

@A Publication of the Department of Economics, ADSU, Mubi. ISSN-Print: 2550-7869; ISSN-Online:3043-5323. Journal homepage: https://ajaefm.adsu.edu.ng

technologies and provide incentives for investment, governments can accelerate the transition to a sustainable energy future.

References

Adamu, M. B., Adamu, H., Ade, S. M., & Akeh, G. I. (2020). Household energy consumption in Nigeria: A review on the applicability of the energy ladder model. *Journal of applied sciences and environmental management*, *24*(2), 237-244.

Adeleke, A. T., Odesola, O. V., Hussayn, J. A., Odesola, M. M., & Odesola, O. (2022). Household poverty status and willingness to pay for renewable energy technologies: Evidence from Southwestern Nigeria. *Environmental Sciences Proceedings*, *15*(1), 3.

Afriyie, A. B., Oteng-Abayie, E. F., Frimpong, P. B., & Amanor, K. (2024). Households' preference and willingness to pay for alternative energy sources: a discrete choice experiment. *Sustainable Energy Research*, *11*(22), 1-18.

Bensch, G., Jeuland, M., & Peters, J. (2021). Efficient biomass cooking in Africa for climate change mitigation and development. *One Earth*, *4*(6), 879-890.

Campbell, B. M., Vermeulen, S. J., Mangono, J. J., & Mabugu, R. (2003). The energy transition in action: Urban domestic fuel choices in a changing Zimbabwe. *Energy Policy, 31*(6), 553–562.

Capareda, S. C. (2011). Biomass energy conversion. Sustainable growth and applications in renewable energy sources, (1), 19.

Dagnachew, A. G., Hof, A. F., Lucas, P. L., & van Vuuren, D. P. (2020). Scenario analysis for promoting clean cooking in Sub-Saharan Africa: Costs and benefits. *Energy*, *192*, 116641.

Elfaki, K. E., Handoyo, R. D., & Ibrahim, K. H. (2021). The Impact of industrialization, rade Openness, Financial Development, and Energy consumption on Economic Growth in Indonesia. *Economies*, 9(4), 174 https://doi.org/10.3390/economies9040174 [Crossref] [Web of Science ®], [Google Scholar

Ghebreyesus, T. A. (2024, May 14). *Who director-general's remarks at the summit on clean cooking in Africa – 14 may 2024*. World Health Organization. https://www.who.int/director-general/speeches/detail/who-director-general-s-remarks-at-the-summit-on-clean-cooking-in-africa---14-may-2024#:~:text=And%20around%20one%2Dquarter%20of,communities%20are%20the%20worst%20affected

Guerrero-Lemus, R., Shephard, L. E., Guerrero-Lemus, R., & Shephard, L. E. (2017). Biomass for heating and power production. *Low-Carbon Energy in Africa and Latin America: Renewable Technologies, Natural Gas and Nuclear Energy*, 121-148.

Hanna, R., Duflo, E., & Greenstone, M. (2016). Up in smoke: The influence of household behavior on the long-run impact of improved cooking stoves. *American Economic Journal: Economic Policy, 8*(1), 80–114.

Heltberg, R. (2004). Fuel switching: Evidence from eight developing countries. Energy *Economics, 26*, 869–887.

Hemstock, S. L., Charlesworth, M., & Singh, R. D. (2020). Household energy usage, indoor air pollution, and health. Good Health and Well-Being, 382-394.

Hosier, R. H., & Dowd, J. (1987). Household fuel choice in Zimbabwe: An empirical test of the energy ladder hypothesis. *Resources and Energy, 9*(4), 347–361.

Jacob, A., Johnson, K., Cohen, R., & Carlson, S. E. (2020). Incorporating natural ecosystems into global health and food security programmes. *Bulletin of the World Health Organization*, *98*(8), 576.

Jotaworn, S., Nitivattananon, V., Teparakul, O., Wongboontham, T., Sugiyama, M., Numata, M., & Alvarez, D. D. B. (2023). Households' Willingness to Pay for Renewable Energy Alternatives in Thailand. *Social Sciences*, *12*(634). 1-21'

Kitole, F. A., Tibamanya, F. Y., & Sesabo, J. K. (2023). Cooking energy choices in urban areas and its implications on poverty reduction. *International Journal of Sustainable Energy*, *42*(1), 474-489.

Kumar, P., Dover, R. E., Díaz-Valdés Iriarte, A., Rao, S., Garakani, R., Hadingham, S., ... & Yadama, G. N. (2020). Affordability, accessibility, and awareness in the adoption of liquefied petroleum gas: a case-control study in rural India. *Sustainability*, *12*(11), 4790.

Kuunibe, N., Issahaku, H., & Nkegbe, P. K. (2013). Wood based biomass fuel consumption in the Upper West Region of Ghana: Implications for environmental sustainability. Journal of Sustainable Development Studies, 3(2).

Madukwe, C. E. (2014). Domestic energy usage pattern of households in selected urban and rural communities of Enugu State. *Unpublished MSc. Thesis. Institute for Development Studies, Enugu, Nigeria*.

Mangeni, J. N., Menya, D., Mwitari, J., Shupler, M., Anderson de Cuevas, R., Sang, E., ... & Asante, K. P. (2023). Household cooking fuel choice and associated factors in a rural and peri-urban community in Western Kenya. *Energy & Environment*, 0958305X231185338.

McCullagh, P. (1980). Regression models for ordinal data. *Journal of the Royal Statistical Society: Series B (Methodological)*, 42(2), 109-142.

McFadden, D. (1974). "Conditional Logit Analysis of Qualitative Choice Behavior." In *Frontiers in Econometrics* (P. Zarembka, Ed.), Academic Press, New York, pp. 105-142.

McGuirk, G. B. (2014). Food expenditure measures to supplement net energy ratios for selected countries 1961-2011. https://core.ac.uk/download/322359160.pdf

Muhammad, F., Qayyum, A., Bawazir, A. A., Jan, M., & Ahmed, N. (2024). Assessing the Tri-Dimensional Nexus of Energy, Environment, and Economic Growth in Pakistan: An Empirical Study. *International Journal of Energy Economics and Policy*, *14*(4), 329-343.

Mustafa, S., Zhang, W., Sohail, M. T., Rana, S., & Long, Y. (2023). A moderated mediation model to predict the adoption intention of renewable wind energy in developing countries. *Plos one*, *18*(3), e0281963.

Nazir, M., & Tian, J. (2022). The influence of consumers' purchase intention factors on willingness to pay for renewable energy; mediating effect of attitude. *Frontiers in Energy Research*, *10*, 837007. 1-13.

Nnaji, C., Ukwueze, E., Chukwu, J. (2012). Determinants of Household Energy Choices for Cooking in Rural Areas: Evidence from Enugu State, Nigeria. Continental J. Social Sciences 5, 21414265. northern Cameroon. WIDER Working Paper Series 2014/038. 45.

Nnaji, M., Eze, A. A., Uzoma, C. C. & Nnaji, C. C. (2021). Addressing Household Cooking Fuel Options in Nigeria, IOP Conference Series, Earth and Environmental Science, 720.

Orifah, O. M., Ijeoma, M. C., Omokhudu, G. I., Ahungwa, G. T., & Muktar, B. G. (2019). Awareness of the environmental implications of the unsustainable use of biomass energy sources among rural households in Jigawa State, Nigeria. Acta Universitatis Sapientiae, Agriculture and Environment, 10(1), 39-51.

Pandey, V. L., & Chaubal, A. (2011). Comprehending household cooking energy choice. *Biomass and Energy, 35*, 4724–4731.

Penco, L., & Bruzzi, C. (2023). Individuals' Willingness to Become a Prosumer of Green Energy: An Explorative Study and Research Agenda. *Business for Sustainability, Volume II: Contextual Evolution and Elucidation*, 233-260.

Rafaj, P., Kiesewetter, G., Gül, T., Schöpp, W., Cofala, J., Klimont, Z., ... & Cozzi, L. (2018). Outlook for clean air in the context of sustainable development goals. *Global Environmental Change*, *53*, 1-11.

Rapu, C. S., Adenuga, A. O., Adenuga Kanya, W. J., Abeng, M. O., Golit, P. D., Hilili, M. J., Uba, I. A., & Ochu, E. R. (2015). Analysis of energy market condition in Nigeria. *Central Bank of Nigeria, Occasional Paper No. 55*. Retrieved September 19, 2023, from https://www.cbn.gov.ng/out/2017/rsd/analysis%20of%20energy.pdf

Ruppel, O. C., & Althusmann, B. (2016). Perspectives on energy security and renewable energies in Sub-Saharan Africa - Practical opportunities and regulatory challenges. https://core.ac.uk/download/83042609.pdf

Saleem, L., & Ulfat, I. (2024). Energy, Society and Sociodemographic Constraints Nexus: Development and Future Prospects. *Sir Syed University Research Journal of Engineering & Technology*, *14*(1), 07-11.

Schlag, N., & Zuzarte, F. (2008). Market barriers to clean cooking fuels in sub-Saharan Africa: a review of the literature. *Working Paper*, Stockholm: Stockholm Environment Institute. Retrieved Oct 18 2020 from https:// media manag er. sei. org/ docum ents/ Publi catio ns/ Clima te/ market_ barri ers_ clean_cooki ng_ fuels_ 21apr il. pdf.

Sumardjo, S., Firmansyah, A., & Dharmawan, L. (2023). Social Transformation in Peri-Urban Communities toward Food Sustainability and Achievement of SDGs in the Era of Disruption. *Sustainability*, *15*(13), 10678.

Tadele, H., & Kalyebara, B. (2023). Willingness to pay for green energy sources in the United Arab Emirates (UAE). *International Journal of Renewable Energy Development*, *12*(3), 528-540.1-23

Timilsina, G. R., & Malla, S. (2021). Clean cooking: Why is adoption slow despite large health and environmental benefits?. Economics of Energy & Environmental Policy, 10(1).

Varkey, A. M. (2023). *The Rural to Urban Transition in Developing Countries: Urbanisation and Peri-urban Land Markets*. Routledge.

Wesnawa, I. G. A., Sarmita, I. M., & Christiawan, P. I. (2023, January). Migrant Livelihood Challenges in Peri-Urban Area. In *Proceedings of the 4th International Conference on Law, Social Sciences, and Education, ICLSSE 2022, 28 October 2022, Singaraja, Bali, Indonesia*.

WHO (World Health Organization). Household Use of Solid Fuels and HighTemperature Frying/IARC Working Group on the Evaluation of Carcinogenic Risks to Humans (2016, Lyon, France). (2016). Available at: https://citeseerx.ist.psu.edu/docum

ACKNOWLEDGMENT

The research team wishes to acknowledge the financial support provided by the Tertiary Education Trust Fund (TETFund) through the Institutional Based Research (IBR) grant. The Grant Award number TEFT/DR&D/UNI/MUBI/RG/2023/VOL.1. Also worthy of recognition is the Adamawa State University and the Research and Innovation Directorate for their enormous support.