Sustainable Energy Research

RESEARCH Open Access

# Households' preference and willingness to pay for alternative energy sources: a discrete choice experiment

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## Abstract
As consumers play an increasingly active role in the energy market, understanding their preferences for renewable and non-renewable energy is essential for achieving Sustainable Development Goal 7. This study employs a labelled discrete choice experiment to investigate consumers' preferences and willingness to pay for solar PV panels, power generators, and biomass, considering service provider, service quality, and purchasing price. The survey was administered to 250 households in Kumasi, Ghana. This study finds that solar PV panels are the most preferred energy source, with the highest willingness to pay estimate. However, in cases where solar panels are not easily accessible, households turn to biomass as an alternative. Although there are similarities in choices, variations in preferences among consumers were identified. Furthermore, consumers value product or service quality but remain indifferent between foreign and domestic service providers. Based on these findings, policymakers are advised to engage in awareness campaigns and provide incentives such as subsidies and low-interest loans, to drive solar PV panel adoption among households. Energy developers should consider customized payment plans based on income levels to facilitate affordability. Additionally, recognizing the heterogeneity in preferences necessitates an inclusive policy approach that considers diverse consumer needs and addresses the energy access challenges faced by low-income households.

**Keywords** Consumer preferences, Renewable energy, Climate change, Choice experiment, Willingness to pay, Power supply

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## Introduction
Access to electricity is a requirement for long-term development and an overall improvement in the quality of life (Malchol & Rizk, 2013). Harnessing electricity for productive use has the potential to alleviate poverty in the long term by reducing domestic workload and freeing up time for other economic activities. A reliable electricity supply also boosts economic growth and contributes to a sustainable environment by reducing household dependence on fossil fuels (Kuunibe et al., 2013). According to The Fifth Assessment Report of the United Nations' Intergovernmental Panel on Climate Change (IPCC), emissions from fossil fuels are the primary cause of global warming and climate change. The United Nations, in their recent energy access report, has urged

countries, particularly developing countries, to transition to renewable energy to achieve climate-smart development (Kumi, 2017; United Nations Energy Access Report, 2021). Climate change and the adverse effects of carbon emissions on the environment have become a significant concern for most economies. Most developed economies have made substantial progress in transforming their existing energy market into a decarbonized one (IRENA, 2021; Energy Outlook Report, 2021; Agyekum et al., 2021; Aboagye et al., 2019; IEA, 2018).

However, countries in sub-Saharan Africa continue to be dominated by thermal power, with renewable energy generation accounting for a relatively small proportion (Blimpo et al., 2019). Even though developing countries are concerned with issues of environmental pollution and climate change, the aim to reduce poverty and improve individuals' welfare remains the primary priority. Access to electricity remains a challenge in Africa. In 2021, the World Bank Development Indicators (WDI) reported that 50.6 per cent of the population in sub-Saharan Africa had access to electricity. While this marks a slight improvement from the 47.1% access rate recorded in 2019, it falls short of the SDG target. As a result, policies are primarily focused on increasing access to electricity rather than reducing pollution caused by electricity generation. Furthermore, population growth, rapid urbanization, and the expansion of grid electricity have led to an increased demand for electricity in Sub-Saharan Africa (United Nations Energy Access Report, 2021; Ahlborg et al., 2015; Taale & Kyeremeh, 2016; Louw et al., 2008). The total power generated is inadequate to meet the rising electricity demand, resulting in an unstable power supply (Daggash et al., 2021). It is therefore vital for end-users to find an alternative source of power generation to mitigate the effect of frequent power outages. Fossil fuel-based energy sources such as power generators remain the most common alternative energy source in African households (Ibrahim et al., 2021). These power generators are not only costly to operate considering rising fuel prices but also emit greenhouse gases, which contribute to climate change.

Ensuring sustainable energy use requires consumers to switch to renewable energy sources such as biomass and solar PV panels. The 2021 report by the International Renewable Energy Agency highlights the significant contribution of renewable energy adoption to climate change adaptation and fostering innovative practices. In recent times, developing countries have devised policies to promote renewable energy development to address climate change and improve access to electricity (Kumar et al., 2010). Ghana, for example, implemented the Renewable Energy Master Plan (REMP) in 2019 to incorporate and increase the share of renewable sources into the national energy mix to ensure energy security and environmental sustainability. The policy also aims to increase private investment and local participation in the renewable energy industry (Renewable Energy Master Plan, 2019). Although this strategy will aid in regulating energy use, household consumers must also be actively engaged in the transition to a decarbonized energy system (Renewable Energy Master Plan, 2019; Kumi, 2017; Kochtcheeva, 2016; Bergmann et al., 2006). According to Curtin et al. (2018), encouraging citizen participation in the energy system is a way to gain societal support for energy transition, improve understanding of climate change, and raise awareness of available renewable energy sources.

To promote the adoption of renewable energy, energy developers must first understand consumer preferences and the various factors that influence their choice of energy products. Numerous studies (Kaenzig et al., 2013; Meried, 2021; Pyzalska, 2019; Sestino, 2018; Ndebele, 2020; Oseni, 2017; Wen et al., 2022; Menyeh, 2021; Siyaranamual et al., 2020 Rowlands et al., 2004; Almanzar & Ulimwengu, 2019; Ruokamo et al., 2019; Hanley & Czajkowski, 2020) have employed stated preference approaches such as contingent valuation and discrete choice experiments to examine consumer preferences. For example, Kaenzig et al. (2013) conducted a choice experiment to examine the effects of price, location of electricity generation, energy mix, monthly electricity bills, and service provider on consumer preference for electricity services in Germany. A total of 414 questionnaires were distributed to residential consumers during the survey. They find that home electricity users preferred a renewable energy mix of 15% biomass, 5% solar, 50% wind, and 30% hydro.

Similarly, Navrud et al. (2007) conducted a choice experiment in Norway to examine consumer preference for green and brown electricity. Results from the study indicated that residential consumers prefer renewable sources of electricity, such as wind power, over electricity imported from coal-fired power plants and domestic gas-fired power plants. Roe et al. (2001) conducted a survey to analyse consumer preference for different electricity services in the United States. The results indicated that consumers prefer electricity services that generate power from renewable sources. Similarly, a study by Meried (2021) revealed that residential consumers are willing to transition from fossil fuels to clean energy sources such as hydro and solar power to ensure a sustainable environment.

The studies cited in the previous discussion were conducted in developed countries boasting liberalized energy markets, where consumers enjoy the freedom to choose among various electricity service providers. However, the scenario takes a different turn in developing countries like Ghana, where a monopolized electricity market prevails, depriving consumers of the opportunity to select their preferred source of electricity (Sakah et al., 2017). This monopolistic structure in Ghana's electricity supply has brought forth higher electricity prices due to the absence of healthy competition. Moreover, it poses a potential obstacle to innovation and investment in the electricity sector, hindering progress in technological advancements and energy supply efficiency.

Despite these challenges, a cluster of studies (Faisal et al., 2013; Karakara et al., 2021; Kwakwa et al., 2013; Mensah et al., 2015) has delved into household energy consumption patterns in Ghana. These investigations specifically explored household preferences for cooking fuels, spanning from traditional and less environmentally friendly options like charcoal and wood to cleaner alternatives like liquefied petroleum gas (LPG). Shedding light on the subject, Heltberg (2005) highlighted the influence of various socioeconomic factors, including income, age, gender, educational level, location, and marital status, on household energy consumption. In their research, Karakara et al. (2021) harnessed data from the demographic and health survey (DHS) to delve into the factors impacting household preference for clean and dirty cooking fuels. The survey outcomes pointed to male-headed households exhibiting a higher likelihood of adopting clean cooking fuels compared to female-headed ones. Additionally, the study noted that household income had a positive influence on consumer preference for clean cooking fuel. Corroborating this perspective, Faisal et al. (2013) and Kwakwa et al. (2013) concurred that household income served as a primary determinant of household energy consumption, aligning with the energy ladder hypothesis. Going further, Kwakwa et al. (2013) conducted interviews with 207 households in Ghana to dissect the various factors influencing their choice of cooking fuel. The majority of households were found to rely on firewood and charcoal for cooking purposes. Through logistic regression, the survey results revealed that the employment and income levels of household heads significantly impacted their choice of cooking fuel. Echoing this theme, Mensah et al. (2015) relied on data from the Ghana standard living survey to scrutinize the effects of socioeconomic factors on household energy choice. Their findings unveiled that price and reliability of LPG supply significantly influenced the probability of households choosing clean energy fuels over fossil fuels.

In the Ghanaian context, there is a notable gap in the existing studies, as they do not explore the perspective of household choice concerning renewable energy as an alternative source of electricity. As far as our knowledge extends, there have been no studies specifically investigating consumer preference for alternative electricity sources in Ghana. The current studies on household energy consumption have primarily relied on data from the Ghana Living Standards Survey and the Demographic and Health Survey, which limits their scope to examining household energy choices solely based on socioeconomic factors. Relying solely on these factors may not fully capture the reality of consumer preferences, making it challenging to comprehend their true inclinations. Addressing this issue, Louviere (1982) emphasizes that a more comprehensive understanding of consumer preferences can be achieved through stated preference approaches, such as discrete choice experiments. By employing such methods, policymakers and energy developers can gain crucial insights into the various factors consumers consider when making their energy choices. Recognizing the significance of this understanding, we aim to contribute to the existing literature by conducting a labelled choice experiment. Through this approach, we intend to elicit and analyse consumer preferences for both renewable and non-renewable energy sources as potential alternative power options in Ghana.

In the context of a single electricity service provider in Ghana, it becomes imperative to examine consumers' willingness to pay (WTP) for an alternative source of power, particularly given the prevalent issues of inadequate and unreliable power supply. Understanding consumer WTP for renewable energy bears the potential to drive increased investments in sustainable energy solutions. Pyzalska (2019) highlights that various factor contribute to WTP for renewable energy, encompassing attributes of electricity service (energy source type, power supply reliability, outage duration, electricity bills, pricing, renewables share in energy mix, and service provider), socioeconomic factors (income levels, education, gender, age, marital status), and psychological factors (consumer awareness). In a study conducted by Nketiah et al. (2022) that explored individual WTP for renewable green electricity in Ghana, findings indicated that government involvement and individual awareness of the benefits of green energy significantly impact the willingness to pay for renewable green electricity. In a related study by Ayodele et al. (2021), which surveyed 400 respondents to assess their willingness to pay for electricity from renewable sources in Nigeria, the findings showed that the respondents were generally willing to pay an average of 5–10% more than the current cost of electricity.

While discrete choice experiments have been widely employed in the literature to gauge consumer willingness to pay for energy (e.g. Menyeh, 2021; Numata et al., 2021; Oseni, 2017; Wen et al., 2022; Kyeremeh et al., 2016), most of these studies have focused primarily on households' WTP for enhancements in the default electricity service and electricity generation from renewable sources. There is a paucity of empirical investigation attempting to unravel whether households would be amenable to paying for renewable energy as an alternative source of electricity as a backup in the events of power outages. Filling this research gap, our study aims to contribute to the limited literature on this subject by estimating how much households are willing to pay for renewable energy sources, such as biomass and solar PV panels, as alternative energy sources of power. Through this exploration, we seek to shed light on the crucial aspect of consumer acceptance and potential adoption of renewable energy options in Ghana's energy landscape.

Within this context, key research questions addressed in this paper are the following: Do consumers prefer a renewable or a non-renewable source of energy? What other factors will a consumer consider before choosing a particular alternative and how much will they be willing to pay for their preferred alternative? To answer these questions, we conducted a labelled choice experiment to examine how the various electricity service attributes (type of energy source, purchase price, service provider, and service quality) influence households' preferences and WTP for alternative electricity sources in Ghana. The remainder of the paper is structured as follows: Sect. "Data and Methodology" describes the choice of methodological approach, including the choice experiment design, selection of attributes and levels, and structure of the choice questionnaire. Sect. "Results" presents and discusses the survey and choice experiment results, including respondents' awareness of climate change and renewable energy, households' choices, and WTP. Sect. "Conclusion" provides a summary of the study findings. The final Sect. "Policy implication and limitations of the study" presents policy implications in line with the study's findings, limitations of the study, and suggestions for future studies.

## Data and methodology

### Description of study area, sample, and data collection

The survey was conducted in the Kumasi metropolis, which is located in the Ashanti Region of Ghana. The Ashanti Region is centrally located in the middle belt of Ghana. It lies between longitudes of 0.15W and 2.25W and latitudes of 5.50N and 7.46N. The Ashanti Region is the most populated region, with a population of 5,440,463 according to the 2020 census, accounting for 17.6% of Ghana's total population. The region shares boundaries with six of the sixteen political regions: the Bono, Bono East, and Ahafo regions in the north; the Eastern region in the east; the Central region in the south; and the Western region in the southwest. The Kumasi metropolis is the regional capital and the most populated district in the Ashanti Region. The city covers 254 square kilometres and encompasses ten sub-metropolitan areas, including Manhyia, Tafo, Suame, Asokwa, Oforikrom, Asawase, Bantama, Kwadaso, Nhyiaeso, and Subin. According to the 2020 population and housing census, the Kumasi metropolis has a population of 443,981, comprising 213,662 males and 230,319 females. Kumasi has attracted such a large population partly because it is the regional capital and the region's most commercialized centre. The metropolis is inhabited by a total of 137,068 households, with an average household size of 3. Over 98 per cent of the inhabitants have access to electricity, and of this number, nearly 75 per cent use prepaid meters.

The Kumasi metropolis comprises individuals from various socioeconomic backgrounds; as a result, we used a purposive sampling technique to select respondents for this survey. To be included in the sample, consumers were expected to be connected to the national grid. This was to ensure that the sampled units had experience with the frequent power outages and observed its effects and would be open to considering a backup option to ensure constant power supply. This study further targeted members of the middle class**.** The decision to focus on the middle class was based on the recognition that this segment of the population plays a crucial role in driving consumer demand and influencing market dynamics. The middle class often exhibits higher purchasing power and are more likely to have disposable income to invest in an alternative energy source. Analysing the preferences and decision-making patterns of the middle class can provide valuable insights into the potential for renewable energy adoption and its implications for a broader population.

The absolute method defines global middle-class individuals as earning between USD 10 and USD 100 per day in purchasing power parity terms. The minimal barrier for inclusion was set at USD 10. As a result, the lower band for survey inclusion was GHS 15,001–GHS 23,988 per annum. To ensure that everyone who responded to the survey was in the middle-income bracket, an initial income screening was performed. This study used primary data collected from households randomly selected from 6 communities (Manhyia, Tafo, Suame, Asokwa, Oforikrom, and Bantama) in the Kumasi metropolis. The data collection instrument was a paper-based questionnaire. A total of 250 paper-based questionnaires were administered face-to-face. Figure 1 shows the map of the study area showing the location (districts) of the sampled households.

### Choice of methodological approach

Lancaster's theory of value and McFadden's random utility theory are both used in choice experiments

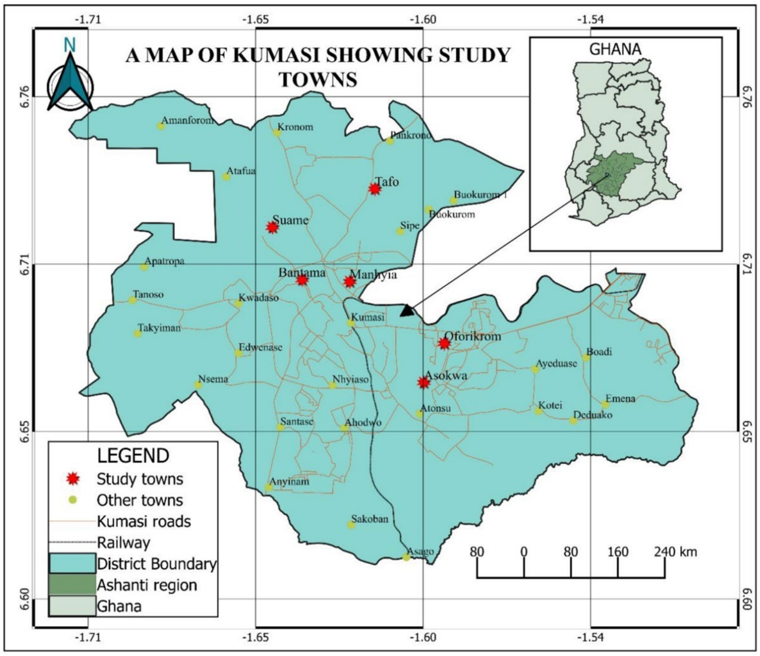


**Fig. 1** Study area showing the project sites

(McFadden, 1974). Individuals derive utility from the features of the good rather than from the commodity itself, according to Lancaster's characteristics theory of value. Lancaster's theory asserts that every good possesses unique characteristics, and its value is determined by the combination of these characteristics. Consequently, consumers make purchasing decisions based on the specific attributes of a product, as the utility they derive from it is derived from these qualities. McFadden's random utility theory further emphasizes that the utility an individual obtains from consuming a particular item is not directly observable, as it exists solely within the consumer's perception. However, expressed preference surveys can explain a considerable portion of this unobserved value. The remaining unexplained part of the consumer's utility is described as random according to this theory. The utility consumer "$i$" derives from choosing an alternative $j$ is given by the equation below:

$$U_{ij} = V_{ij} + \epsilon_{ij}, \tag{1}$$

where $U_{ij}$ is the utility individual $j$ derives from choosing alternative $i$ among various alternatives in a choice set. $V_{ij}$ is the observable component of the individual's utility subject to the various electricity service attributes (energy source, purchase price, service provider, and service quality). $\epsilon_{ij}$ is the unobservable or random component of the individual's utility. Several studies (Meried et al., 2021; Navrud et al., 2007) employed the multinomial logit model (MNL) to estimate household preferences for energy goods and services. In the MNL model, the probability of selecting a particular alternative is modelled as a function of explanatory variables using a logit function. Consider a hypothetical scenario where an individual faces a set of $J$ alternatives or choices. The MNL model assumes that the utility or attractiveness of each alternative depends on a set of explanatory variables. The utility ($U$) of alternative $j$ for individual $i$ can be represented as

$$U_{ij} = X_{ij}\beta_j, \tag{2}$$

where $U_{ij}$ is the utility of alternative $j$ for individual $i$, $X_{ij}$ represents the vector of explanatory variables for alternative $j$ and individual $i$, and $\beta_j$ is the vector of coefficients associated with the explanatory variables for alternative $j$. The probability that individual $i$ chooses alternative $j$ ($\Pr_{ij}$) can be obtained using the multinomial logit function:

$$\Pr_{ij} = \frac{\exp(U_{ij})}{\sum[\exp(U_{ik})]} \nabla k = 1, 2, \ldots, J. \tag{3}$$

In the above equation, the numerator represents the exponential of the utility of alternative $j$, and the denominator sums up the exponential of the utilities of all $J$ alternatives. By dividing the numerator by the denominator, we obtain the probability of choosing alternative $j$. The multinomial logit model is based on the assumption of independence of irrelevant variables

(IIA), which makes it unable to account for heterogeneity in respondents' preferences. Alternative models that relax the assumption of irrelevant variables are the mixed logit models, multinomial probit models, and latent class models. The mixed logit model (MXL) is an extension of the multinomial logit model that allows for heterogeneity or variation in preferences across individuals. In the MNL model, the coefficients ($\beta_j$) are assumed to be fixed and the same for all individuals. However, in the MXL model, the coefficients are allowed to vary randomly across individuals, capturing the heterogeneity in preferences. The MXL model incorporates random parameters or coefficients and models the distribution of these coefficients across the population. This allows for a more flexible representation of individual preferences and captures variations individual's choices (Meijer & Rouwendal, 2006; Hole, 2011). In this study, both the multinomial and mixed logit model are employed; however, the MXL model is chosen as the model of interest over the MNL model. We thus use the MNL to capture alternative viewpoint of evaluating consumer preferences (assuming a theoretical probability of homogeneous preferences) to test the results of the MXL estimation. In the context of MXL, an individual's utility is therefore specified as below:

$$U_{ij} = \beta_j' V_{ij} + \epsilon_{ij}, \tag{4}$$

where $U_{ij}$ is the utility individual $i$ derives from choosing alternative $j$. $\beta_j'$ is a vector of estimated coefficients that vary among respondents $V_{ij}$ a vector of the various electricity service attributes and $\epsilon_{ij}$ is the random component of the household's utility. The utility function has random taste parameters ($\beta_j'$) for each unit that is based on the values of the parameter $\theta$ of the underlying $f$ distribution $[f(\beta|\theta)]$. The outputs of mixed logit models present the degree of respondents' preferences and heterogeneity in preference captured in the standard deviation associated with each attribute coefficient. We estimated Eqs. (3) and (4) both in two ways. One with interaction terms (between service attributes and socio-demographic characteristics) and the other without interaction terms. The two models were tested using information statistics and best fit model was selected for analysis of household preferences (see Table 4).

Notwithstanding, we extend the analysis by also examining household's willingness to pay estimates. This investigation is necessary for two reasons: (1) to explore how much households' value their preferences and (2) to ascertain whether their WTP estimates are consistent with their preferences as the theory of rational choice suggests. WTP measures are a common objective of discrete choice models. Estimating respondents' WTP is essential for informing policy through the pricing of energy goods and services. The standard method for calculating WTP for an attribute is to divide the attribute coefficient by the price or cost attribute coefficient. As a result, the WTP for attribute $j$ is given as

$$\mathrm{WTP} = -\left(\frac{\beta_j}{\beta_m}\right), \tag{5}$$

where $\beta_j$ is the estimated coefficient for the $j$th attribute and $\beta_m$ is the estimated coefficient for the cost attribute. According to Tu et al. (2016), Eq. (5) gives the WTP for attributes in preference space. We initiate the willingness to pay computation within this preference space, as detailed in Table 6. However, this method yields a notably skewed WTP distribution. To address this concern, Hole and Kolstad (2012) suggest estimating the mixed logit model in the WTP space. In this approach, the model is reformulated to directly estimate the WTP distribution, with the coefficients representing the WTP measures. Rearranging and dividing Eq. (4) by $\kappa_i$, which is the scale parameter for the *ith* household, gives

$$U_{ij} = \lambda_i P_{ij} + \delta_i V_{ij} + \mu_{ij}, \tag{6}$$

where $\lambda_i = \beta_{mi}/\kappa_i$, $\delta_i = \beta_{ji}/\kappa_i$, and $\mu_{ij} = \beta_{ji}/\kappa_i$ gives the new error term which is an IID extreme distributed with variance, $\pi^2/6$. Equation 6 can further be rearranged to demonstrate a household utility in WTP space, such that

$$U_{ij} = \lambda_i \left[P_{ij} + \gamma_i V_{ij}\right] + \mu_{ij}, \tag{7}$$

where $\gamma_i$ is the WTP parameter $\left[-\beta_j/\beta_m\right]$. One significant advantage of estimating in the WTP space is the ability to specify the WTP distribution. Importantly, Eq. (7) yields more realistic estimates of consumers' willingness to pay (Hole and Kolstad, 2012). Due to this favourable characteristic, we rely on the MXL model in the WTP space for inference. We employed the maximum simulated likelihood approach, utilizing the MIXLOGITWTP syntax in Stata 17 for execution. The MIXLOGITWTP command was executed with 2000 Halton draws and 20 burns. We employed two alternative mixed logit models (uncorrelated and correlated), to compute households WTPs in both the preference space and the WTP space (see Table 6). In the uncorrelated model we assume a normally distributed WTP coefficients for all the alternative specific regressors but a log-normally distributed coefficients for the price. However, in the correlated WTP model we controlled for correlations among the attributes. Specifically, we controlled for the possibility that the attributes and their levels are not completely independent from each other.

We further conducted a heterogeneity test and a robustness analysis of the WTP estimates using the latent class model. The latent class model also gives the opportunity to thoroughly examine consumer preference heterogeneities. The latent class model is used to capture subpopulation dynamics in household preferences of renewable energy sources. As suggested by Tu et al (2016) and Antwi-Adjei et al. (2021) the latent class model assumes that there is an underlying unobserved attribute that defines the preferences of consumers into mutually exclusive and exhaustive classes. Thus, the latent class model assumes that respondents make decisions based on some observable characteristics and latent factors that are unknown to the analyst but could have an impact on respondents' preferences, as illustrated by Greene et al. (2005). For instance, assume that sample of consumers can be divided into $K$ classes of subpopulations with different values of taste parameters, $\delta_k = (\delta_1, \delta_2, \delta_3 \ldots \delta_K)$; then the probability that a consumer $j$ selected at random from the population will belong to class $k$ is given by $\rho_{jk}$, where $\rho_{jk} \epsilon [0,1]$ and $\sum_{k=1}^{K} \rho_{jk} = 1$; such that the probability of consumer $j$ of belonging to class $k$ fixed on observable individual characteristics $\omega_j$ is given by

$$\rho_{jk}(\theta) = \frac{exp\left(\theta_k \omega_j\right)}{\sum_{K}^{k=1} exp\left(\theta_k \omega_j\right)}, \tag{8}$$

where $\theta = \left(\theta_1, \ldots \theta_{k-1}\right)$ are the class membership parameters (Tu et al., 2016). Given this class membership probability, then the resultant probability of consumer $j$ selecting an alternative energy source $v$ from a choice set of $H$ alternatives given that the individual faced $C$ choice situations is given by

$$\rho_{vjc}^{k}\left(v|\beta^k\right) = \frac{\exp\left(\beta X_{vjc}\right)}{\sum_{h}^{h=1} \exp\left(\beta X_{hjc}\right)}. \tag{9}$$

According to Tu et al (2016), given that the membership of individual belonging to class $k$ is unknown, the unconditional probability for individual $j$ choosing alternative $h$ is then given by

$$L_j\left(h_{j1}, \ldots h_{jC_j}, |\beta_1, \ldots \beta_K\right) = \sum_{k=1}^{K} \rho_{jk} \left(\prod_{c=1}^{C} \rho_{jhc}\left(h_{jc}|\beta_k\right)\right). \tag{10}$$

The latent class choice model was estimated using Stata lclogitml2 syntax, which utilises optimization methods for maximum likelihood estimation. The classification of various classes was determined by taking into account respondents' socio-demographic, their knowledge of renewable energy, and their awareness of climate change.

### Choice experiment design

The initial step in the design of a discrete choice experiment involves the meticulous selection of attributes and their corresponding levels. This study focused on determining the attributes and levels relevant to electricity services through a comprehensive approach comprising a literature review, market research, focus group interviews, and a pre-test survey. The sample for the focus group consisted of household heads residing in Kumasi, who were in charge of making energy-related and financial decisions. Following an extensive literature review and market research, we conducted focus group interviews to gain valuable insights into consumer perspectives and attitudes towards choosing alternative energy sources. The findings of the focus group discussions revealed that consumer choices in the context of electricity services were influenced by several factors, including the type of energy source, purchase price, service provider, and service quality. Consequently, the attribute "energy source" was identified as a crucial factor to examine consumer preferences between renewable and non-renewable energy sources. Specific levels were assigned to the attribute "energy source" to reflect renewable energy sources, including solar PV panels and biomass, as well as non-renewable energy sources such as power generators. In choice experiments, price attributes play a crucial role in estimating consumers' willingness to pay (WTP) for their preferred energy source. The price of different energy sources is a significant determinant that consumers consider when making choices. To gather relevant data, a market research study was conducted, involving consultations with reputable energy providers, namely Takoradi Renewable Power Company Limited, Solar Franerix Limited, Phoenix Power Limited, Dyson Solar Limited, and Ased Generator Company Limited. These firms were selected as they are registered and certified by the Energy Commission of Ghana. The aim of the research was to determine the price ranges and available payment plans offered by these providers for solar PV panels, power generators, and biomass.

During the market research phase, it was revealed that the price range for the three energy sources intended for household use varied between GHS 30,000 and GHS 45,000, with payments typically spread over a period of 5 years. Our focus group discussions indicated that participants expressed concerns regarding the substantial upfront cost associated with the energy sources, but they demonstrated willingness to consider payments by instalment. Consequently, the attribute "Purchase price" was structured to encompass a 5-year payment plan, aligning with the prevailing practice of energy companies, where individuals make monthly payments towards their preferred energy choice over the specified time period. Drawing insights from both the focus group discussions and the data acquired through market research, we selected the cost levels GHS 475, GHS 625, and GHS 775 for the attribute "Purchase price".

The inclusion of the attribute "service provider" in this study aimed to investigate consumers' preferences between domestic (Ghanaian) and foreign firms. It is worth noting that Ghana currently has a sole state-owned electricity provider. However, the existing power generation capacity is insufficient to meet the growing electricity demand, leading to an unstable power supply and frequent power outages. Consequently, end-users are compelled to seek alternative power generation sources to mitigate the impact of these outages. In this regard, private entities serve as providers of alternative energy sources in the country. The Energy Commission of Ghana has set forth a vision to attract increased foreign direct investment in renewable energy. Considering the relatively low adoption of domestic energy firms that offer alternative energy services, it becomes crucial to examine consumer preferences for foreign firms.

The frequent power outages raise concerns about service quality. According to Parasuraman et al. (1985), service quality refers to the discrepancy between a consumer's perception of a company's service and their expectations regarding that service. In this study, we assessed service quality based on the quality of inputs utilized in production, reliability (the firm's ability to deliver promised services accurately), and responsiveness (the firm's promptness in assisting customers). Three levels were designated for the attribute "Service quality": low, moderate, and high. In the context of this study, service quality was categorized as "low" if the service provider employed substandard materials, failed to ensure uninterrupted power supply, and disregarded customer complaints. Service quality was classified as "moderate" when the service provider utilized standard materials, guaranteed continuous power supply, but did not adequately address customer complaints. Lastly, service quality was deemed "high" when the service provider employed high-quality materials, ensured uninterrupted power supply, and promptly responded to customer complaints. Overall, four attributes pertaining to electricity services were chosen for the discrete choice experiment: (1) energy source, (2) purchasing price, (3) service provider, and (4) service quality. Table 1 provides a comprehensive overview of the selected attributes along with their corresponding levels.

### Design and structure of choice questionnaire

The subsequent step, as outlined by Hoyos (2010), following the selection of attributes and their corresponding levels, involves the creation of choice sets that offer individuals options to choose from. The third and final steps are the development of questionnaires and the selection of an appropriate sampling strategy. In this study, an efficient design consisting of 40 choice sets was generated using the "*dcreate*" package in Stata 17. In the construction of our efficient design, the decision to utilize random priors was informed by a preliminary analysis based on a pilot survey and estimates derived from a prior sample of 500 individuals residing in the same study area. The careful derivation of random priors involved an in-depth analysis of data from the prior sample, guiding the distribution of the priors. The selected normal distribution aligns with the characteristics of our data and the nature of the variables under consideration. This methodological approach ensures a robust integration of prior information into our study design. Regarding the number of draws, we utilized 2000 draws. This count was chosen to strike a balance between computational efficiency and capturing the inherent variability present in the distribution. Sensitivity analyses were conducted to validate the robustness of our results across different draw counts. To mitigate the cognitive burden on respondents, the 40 choice sets were subsequently distributed across five blocks, with each block containing eight choice sets. To ensure random assignment, respondents were allocated randomly to one of the five blocks. As a result, each participant answered eight choice scenarios, thereby limiting their cognitive burden (Louviere et al., 2000; Hensher et al., 2015). Each choice set contained four alternatives, including an opt-out option representing those that were not interested in choosing an alternative energy source. This was to ensure that the survey was as realistic and

**Table 1** Selected attributes and associated levels

| Attributes | Description | Levels |
|---|---|---|
| Type of energy source | This represents the alternative sources of electricity including renewable and non-renewable energy | Solar PV panels, Power generators, Biomass |
| Purchase price | This represents how much a consumer is willing to spend to purchase his/her preferred alternative | GHS 475, GHS 625, GHS 775 |
| Service provider | This refers to the origin of the energy developer | Domestic firm, foreign firm |
| Service quality | This measures the quality of service being provided by the energy developer | Low, moderate, high |

**Table 2** Example of a choice set in the labelled choice experiment

| Choice task 1 | Power generators | Biomass | Solar PV panels | None |
|---|---|---|---|---|
| Purchase price | GHS775 | GHS475 | GHS 625 | |
| Service quality | High | Moderate | Low | |
| Service provider | Foreign firm | Domestic firm | Foreign firm | |
| I CHOOSE | [..] | [..] | [..] | [..] |

practical as a consumer would behave in the market in the real world. The overall paper-based questionnaire consisted of three parts. The first part of the questionnaire collected respondents' demographic information such as gender, age, location, household size, occupation, educational level, income, housing status, and marital status. The second part of the questionnaire collected energy-related information like respondents' source of power during power outages, meter ownership, monthly electricity bill, and respondents' awareness of climate change and renewable energy. The third and final part was the main choice experiment, where respondents were presented with 8 choice sets. The complete questionnaire was piloted with a small sample of 15 respondents to measure cognitive burden and clarity. This led to some minor corrections before the final survey was administered in person. The selected attributes and their levels were explained to respondents before the choice survey was administered.

In addition to undergoing training on effectively communicating these attributes and levels in both English and the local dialect, Twi, field officers were specifically instructed to thoroughly explain each attribute to every respondent. This explanation included the provision of pictured illustrations depicting each attribute and its corresponding levels. Moreover, prior to data collection, consensus was reached among the research team on the semantics, precise local examples, and definitions for each attribute and level. These measures were implemented to ensure that respondents fully comprehended the attributes presented to them, thus minimizing potential biases in the experiment's presentation. Table 2 represents a sample choice set that was presented to respondents.

## Results

### Descriptive statistics of sampled households

We report the descriptive statistics of respondents' sociodemographic characteristics. 245 complete responses out of 250 questionnaires were obtained, representing a response rate of 98%. Each respondent was presented with eight choice sets, and each choice set had four alternatives resulting in 7,840 choice observations in total for analysis. Out of the 245 respondents, 156 identified as male, while 89 were females representing 64% and 36%, respectively. 78% of respondents were married. 57% of respondents were homeowners. The sampled households had an average household size of 4.8 persons, with a minimum and maximum of 1 and 15 persons, respectively. The majority of the survey respondents were aged between 25 and 44 years representing an active work population, representing 71%. The majority of the sampled respondents (83%) reported having formal education. The occupational classification employed in the survey was adopted from the Ghana Living Standard Survey (GLSS) classification. The majority of survey respondents, thus more than 53% of the total sample, identified as professionals. Finally, 66% of the sampled respondents are in the middle-income bracket (with income earned ranging between GHS 15000 and GHS 23998 annually), while 24% of the respondents reported a earning a higher level of income ranging between GHS 24000 and GHS 59988 annually.

### Respondents' energy-related information

It was a requirement for all households to have access to electricity to be included in the survey. This was to ensure that they had experience with the frequent power outages and would be open to consider a backup option to ensure constant power supply. Hence, 245 households, representing 100% of the sample, had access to electricity and were connected to the national grid. The average monthly electricity bill of sample households was GHS 158, with the minimum and maximum monthly electricity bills being GHS 30 and GHS 1000, respectively. Table 3 provides a summary of households' alternative

**Table 3** Alternative sources of light used by respondents during power outages

| Type of alternative source | Number of respondents | Per cent |
|---|---|---|
| Power generators | 27 | 11.02 |
| Solar PV panels | 5 | 2.04 |
| Biomass | 2 | 0.82 |
| Rechargeable lamp | 50 | 20.41 |
| Solar lamp | 27 | 11.02 |
| Battery lamp | 84 | 34.29 |
| Candles | 7 | 2.86 |
| Mobile phones | 34 | 13.88 |
| None | 9 | 3.67 |
| Total | 245 | 100.00 |

sources of light during power outages. Sampled households spent an average of GHS 22 monthly on their alternative energy source. 74% of the sampled respondents also reported using separate meters over shared meters. In Ghana, shared meters are usually used in compound houses; however, due to common disagreements over the power usage and payment, many households are shifting from shared meters system to separate meters. Lamps were the most used alternative source of lighting among sample households. About 65% of sample households used battery-powered lamps, solar lamps, and rechargeable lamps to provide light for their households during power outages. With regard to alternative energy sources that can help households meet their basic needs aside from lighting, about 11% of sampled households had power generators as an alternative source of lighting and about 2% of the sample households had solar PV panels. The least used alternative was biomass, accounting for less than 1%.

#### Respondents' knowledge of renewable energy and climate change

Firstly, respondents were asked whether they knew what renewable energy was. About 95.51% of the total sample responded "Yes". Secondly, respondents were asked if there was enough information to convince them to adopt renewable energy; 63.67% of the respondents answered No. Only 46.94% of the total sample knew of existing energy companies in Ghana that were in charge of installing renewable energy technologies such as solar PV panels and biomass. Thirdly, respondents were presented with four renewable energy sources (solar energy, wind energy, biomass, and hydro energy) and asked to tick the ones they are familiar with. Results shown in Fig. 2 show that about 85% of the survey respondents were most familiar with hydro energy. This finding is no surprise since hydro was the dominant source of power generation in Ghana until the early 2000s. The next most familiar renewable energy source was solar energy. About 11% of the total survey respondents were familiar with solar energy. Lastly, respondents were asked if they were concerned about climate change. The majority of the respondents (98%) answered "Yes".

#### Estimated results

The discrete choice experiment aimed to investigate household preference and WTP for alternative sources of energy and their attributes. The findings are presented in Table 4, which includes parameter estimates from the MNL and MXL models (in preference space). The results of the Hausman test indicate that we cannot accept the Independence from Irrelevant Alternatives (IIA) assumption at a 5% significance level. Consequently, the MXL estimates are considered more reliable than the MNL estimates (Prob $>$ Chi$^2 = 0.008$). To conduct our analysis, we estimated two models: one without interaction terms (Model 3) and another with interactive terms (Model 4). The information statistics favour the mixed logit model without interaction terms over the latter. Therefore, our main focus was on the mixed logit model without interactions (Model 3). The alternative specific constants for solar PV panels, power generators, and biomass are all positive and significant, indicating a positive preference for all energy sources. However, when ranking the coefficients, solar PV panels show the strongest preference ($\beta = 4.020$), followed by biomass ($\beta = 3.132$), and power generators as the least preferred ($\beta = 2.359$). This implies that, on average, respondents prefer renewable energy sources over non-renewable ones. The standard deviations also reflect preference heterogeneity among

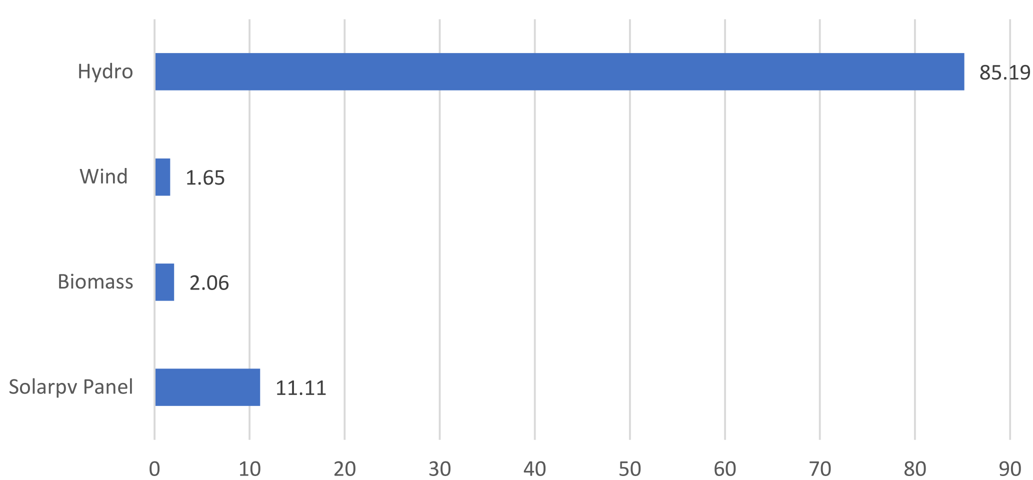


**Fig. 2** Respondents' familiarity with renewable energy sources (*N* = 245)

**Table 4** Parameter estimates for the MNL and MXL model

| FIXED | MNL | | MXL | |
|---|---|---|---|---|
| | Model 1 | Model 2 | Model 3 | Model 4 |
| ASC_Solar PV Panels | 10.324 (2.288)*** | 10.476 (2.521)*** | 4.020 (0.244)*** | 4.067 (0.245)*** |
| ASC_Power generators | 7.020 (1.911)*** | 7.143 (2.131)*** | 2.359 (0.225)*** | 2.315 (0.226)*** |
| ASC_Biomass | 7.907 (1.971)*** | 8.018 (2.166)*** | 3.132 (0.230)*** | 3.277 (0.230)*** |
| Service quality (Base: Moderate) | | | | |
| Low service quality | – 1.575 (0.292)*** | – 1.540 (0.296)*** | – 2.051 (0.083)*** | – 2.029 (0.084)*** |
| High service quality | 0.537 (0.131)*** | 0.573 (0.142)*** | 0.392 (0.061)*** | 0.389 (0.062)*** |
| Foreign service provider | 0.223 (0.139) | 0.225 (0.147) | 0.116 (0.165) | 0.167 (0.266) |
| Purchase price | – 0.007 (0.001)*** | 0.007 (0.001)*** | – 0.004 (0.001)*** | – 0.004 (– 0.001)*** |
| Gender_Female x Low Service quality | | 0.153 (0.339) | | 0.141 (0.171) |
| Gender_Female x High Service quality | | 0.131 (0.236)* | | 0.203 (0.115)* |
| Gender_Female x Foreign Service provider | | – 0.220 (0.249) | | – 0.068 (0.126) |
| Income_High x Low Service quality | | – 0.313 (0.150)** | | – 0.413 (0.149)** |
| Income _High x High Service quality | | – 0.268 (0.230) | | – 0.080 (0.108) |
| Income _High x Foreign Service provider | | – 0.213 (0.262) | | – 0.041 (0.108) |
| Renting x Low Service quality | | 0.239 (0.161) | | 0.249 (0.165) |
| Renting x High Service quality | | 0.144 (0.109) | | 0.149 (0.122) |
| Renting x Foreign Service provider | | – 0.019 (0.112) | | – 0.031 (0.121) |
| *Std. dev. of random parameters (MXL model)* | | | | |
| Purchase price | | | 0.004 (0.001)*** | 0.044 (0.001)*** |
| Solar PV panels | | | 1.262 (0.210) *** | 1.873 (0.247)*** |
| Power generators | | | 2.019 (0.189)*** | 1.544 (0.126)*** |
| Biomass | | | – 0.044 (0.144) | 0.138 (0.134) |
| Service quality (base: moderate) | | | | |
| Low service quality | | | 1.416 (0.099)*** | – 0.903 (0.083)*** |
| High service quality | | | – 0.216 (0.105)*** | – 0.373 (0.161)** |
| Foreign service provider | | | – 0.116 (0.078) | 0.071 (0.065) |
| Diagnostic test | | | | |
| Observations | 7840 | 7840 | 7840 | 7840 |
| Hausman test | | | 26.09*** | |
| AIC | 3707.012 | 3713.749 | 3833.843 | 3837.836 |
| BIC | 3762.748 | 3811.287 | 3889.579 | 3956.275 |
| Log-likelihood | – 1845.506 | – 1842.8744 | – 1908.059 | – 1901.918 |
| Prob > $Chi^2$ | 0.000 | 0.000 | 0.000 | 0.000 |

Standard errors are in parentheses

$*p < 0.1$

$**p < 0.05$

$***p < 0.01$

**Table 5** Summary statistics of respondent preferences

| | Nos. of times selected | Percent | Nos. of respondents |
|---|---|---|---|
| Solar PV panel | 1035 | 53 | 129 |
| Power generator | 316 | 16 | 40 |
| Biomass | 488 | 25 | 61 |
| None | 121 | 6 | 15 |
| Total | 1960 | 100 | 245 |

respondents. The standard deviation for the purchase price is significant, indicating that there exists an unobserved heterogeneity of preferences among respondents. Table 5 provides a summary statistic of preferred options based on the 7840 choices made by 245 respondents. The results reveal that 53% of the sampled population most preferred solar energy as their top choice of energy source. Additionally, approximately 25% of the respondents demonstrated a preference for biomass. When

**Table 6** WTP estimates with mixed logit model in WTP space

| Variable | WTP space | | | | Preference space | | | |
|---|---|---|---|---|---|---|---|---|
| | Uncorrelated | | Correlated | | Uncorrelated | | Correlated | |
| **Random parameters** | **Mean** | **S. E.** | **Mean** | **S. E.** | **Mean** | **S. E.** | **Mean** | **S. E.** |
| ASC_Solar PV panels | 902.63*** | 64.04 | 908.71*** | 63.73 | 1005.02*** | 87.36 | 998.32*** | 67.08 |
| ASC_Power generators | 502.08*** | 50.73 | 518.07*** | 45.80 | 587.39*** | 61.12 | 586.54*** | 44.62 |
| ASC_ Biomass | 735.72*** | 54.30 | 746.67*** | 54.84 | 783.01*** | 80.12 | 776.09*** | 67.08 |
| Service quality (Base: Moderate) | | | | | | | | |
| Low service quality | − 300.14*** | 82.77 | − 356.77*** | 96.06 | − 312.82** | 106.36 | − 308.06*** | 92.56 |
| High service quality | 164.06** | 26.48 | 163.51*** | 25.70 | 98.11*** | 35.01 | 100.64*** | 38.90 |
| Foreign Service provider | 12.38 | 36.11 | 8.56 | 33.65 | 29.09 | 42.65 | 25.34 | 36.41 |
| Std. dev. of random parameters | | | | | | | | |
| ASC_Solar PV panels | 268.18*** | 62.53 | 253.82*** | 63.99 | | | | |
| ASC_Power generators | 397.18*** | 116.64 | 398.61*** | 145.40 | | | | |
| ASC_ Biomass | − 73.60 | 68.37 | − 3.81 | 124.17 | | | | |
| Service quality (Base: Moderate) | | | | | | | | |
| Low Service quality | 924.13*** | 238.57 | 724.74*** | 288.51 | | | | |
| High Service quality | − 36.68 | 134.79 | − 63.11 | 148.78 | | | | |
| Foreign Service provider | − 16.02 | 80.59 | 1.87 | 71.44 | | | | |
| Diagnostic Test | | | | | | | | |
| Observations | 7840 | | 7840 | | 7840 | | 7840 | |
| Log-Likelihood | −1797.97 | | −1711.20 | | − 1908.059 | | − 1887.594 | |
| Prob > Chi2 | 0.000 | | 0.000 | | 0.000 | | 0.000 | |

# of draws = 2000, burns = 20 * p < 0.05; ** $p < 0.1$; ***$p < 0.01$; No. of respondents = 245

considering cumulative percentages, it becomes evident that around 88% of the population prefers renewable energy sources. Only 6% of the respondents selected the opt-out energy option, while 16% showed a preference for power generators as an alternative non-renewable energy source. These findings align with previous studies like Kaezing et al. (2013), Navrud et al. (2007), and Meried (2021), which also reported a greater preference for renewable energy. As anticipated, the estimated coefficient for the purchase price is negative and significant, indicating that, on average, households are hesitant to choose alternative energy sources that require a higher purchase price. Interestingly, the results suggest that the type of service provider of renewable energy does not significantly impact respondents' preference. The negative coefficient associated with "low service quality" indicates that, on average, respondents do not prefer energy service providers that produce energy products with inferior materials, do not guarantee continuous power supply, and do not respond to customer complaints. On the other hand, the positive coefficient associated with "high service quality" suggests that, on average, respondents strongly prefer energy developers that use high-quality materials, guarantee continuous power supply, and promptly respond to customer complaints.

Subsequent to the Table 4 results which suggest that the model without interaction best fits the data than the model with interactions, we proceed with further analysis (i.e. examination of household willingness to pay) using the MXL models without interactive terms. Table 6 presents the estimates of willingness to pay (WTP) obtained from the mixed logit model, analysed in preference and WTP space assuming all the random variables are either correlated or uncorrelated. Upon comparing the results from all approaches, we find that all attributes share the same direction, and their absolute values are quite similar. However, a notable difference lies in the "Standard Error" columns, where the standard errors of the mean marginal WTP, estimated by the MXL model in preference space, are larger than those from the MXL model in WTP space. Smaller standard error indicates more precise measurements and reduced uncertainty.

Furthermore, the analysis of Willingness-to-Pay (WTP) space models highlights the impact of allowing full correlation between coefficients. The simulated log-likelihood at convergence for the Mixed Logit (MXL) model in preference space is − 1908.059 (for uncorrelated model) and − 1887.594 (for the correlated model). Transitioning to the MXL model in WTP space demonstrated an improvement, with values of − 1797.97 for the uncorrelated model and − 1711.20 for the correlated model. This shift from − 1908.059 to − 1797.97 indicates an improvement in the model's performance in the WTP space. The increase in log-likelihood values [from − 1797.97 for the uncorrelated model and − 1711.20 for the correlated model for MXL model in WTP pace] underscored the significance of incorporating full correlation between coefficients in enhancing the model's fit to the data in the WTP context. The estimated means have the same signs and orders of magnitude across the models. As a result of this comparison, we conveniently relied on the WTP results obtained from the MXL model in WTP space (with full correlation) for further discussion, as we considered it as more efficient. This observation aligns with the findings of previous studies conducted by Tu et al. (2016), Hensher (2006) and Sonnier et al. (2007).

The estimated coefficients for the various energy sources and the attribute levels reflect the respondents' preferences and how much they are willing to pay. As shown in Table 6, the WTP estimate is positive and significant for all the alternative energy sources. The result shows that generally, households are willing to pay more for solar energy (approx. GH₵909) as compared to biomass (approx. GH₵ 745) and power generators (approx. GH₵ 518), respectively. Regarding the impact of service attributes on households' willingness to pay, the findings indicate that, on average, respondents are willing to pay approximately GH₵ 357 less for an alternative energy source that does not ensure a constant power supply. However, they are willing to pay approximately GH₵ 164 more for an alternative energy source with high service quality compared to one with moderate service quality. It can also be concluded that, on average, respondents are willing to pay more for renewable energy sources provided the provider that offers high-quality services to consumers. According to the WTP estimates, respondents are indifferent regarding the source of the power supply. Thus, using the 5-year payment plan system, it can be estimated that consumers are willing to spend between GH₵ 33,120 and GH₵ 64,380 to acquire solar PV panel to power electricity in their homes. For biomass-powered electricity, computations suggest that respondents on average are willing to spend between GH₵ 23,280 and GH₵ GH₵54,540 over a 5-year period to acquire it as an alternative energy source. In terms of power generator, respondents are willing to spend between GH₵ 9660 and GH₵ 40,920.

#### Latent class model

The estimated coefficients' standard deviation in the mixed logit model reflects preference heterogeneity among respondents, indicating that individuals within the surveyed population have diverse inclinations towards the analysed attributes. The significant standard deviation for price points to the presence of unobserved heterogeneity in preferences, meaning that underlying factors influence how individuals perceive and value the price attribute concerning the alternative energy source. However, the standard deviation does not provide specific insights into the nature of the preference distribution within the subpopulation. Further analysis is needed to explore and understand the subpopulation's preference distribution, potentially identifying distinct preference clusters and gaining deeper insights into the factors driving these variations. To gain such understanding of the complex dynamics at play in consumer preferences for alternative energy sources, we applied the latent class model to explore heterogeneities in preferences and to test the results of the MXL results. When estimating a latent class model, the efficient number of classes is determined using the Bayesian Information Criterion (BIC) and Akaike Information Criterion (AIC) values. The best class is the one with the lowest information criteria values. Given the AIC and BIC values, a three-class model was deemed adequate in this investigation. The findings from the three-class latent model are presented in Table 7. Class 2 is the largest group, comprising 43.6% of the sample population, followed by class 1 with 35.6%, and class 3 representing 20.8%. An examination of the determinants influencing class membership reveals that class 1 affiliation is primarily influenced by awareness of climate change, familiarity with renewable energy, and access to market information on renewable energy. Conversely, socio-demographic variables such as gender, educational attainment, household size, age, income, and housing status are significant predictors of class 2 membership. For class 3, both socioeconomic indicators and environmental concerns play pivotal roles in determining membership.

With reference to the preference analysis, similar to the findings from the mixed logit model, the estimated coefficients for variables such as service quality, purchase price, and alternative energy sources are significant across all classes. The latent class parameter estimates confirm the mixed logit result regarding the ranking of consumer preferences, with a strong preference for renewable energy and a lesser preference for non-renewable energy. However, the latent class results reveal notable differences in preferences among the three subpopulations. For instance, members of class 2 and class 3 show the strongest preference for solar PV panels. However, members of class 1 have a strong preference for Biomass. Additionally, members of class 1 have a strong preference for foreign service providers, while members of classes 2 and 3 are indifferent about the origin of the service provider. Class 2 members are likely to

**Table 7** Parameter estimates for the latent class model

| **Class membership** | **Class 1** | | **Class 2** | | **Class 3 (Reference class)** | |
|---|---|---|---|---|---|---|
| | **dy/dx** | **Std. error** | **dy/dx** | **Std. error** | **dy/dx** | **Std. error** |
| Gender (Ref: Male) | 0.109 | 0.145 | – 0.179** | 0.076 | – 0.473** | 0.166 |
| Education level (Ref: Lower) | – 0.008 | 0.113 | – 0.134*** | 0.050 | 0.136*** | 0.015 |
| Household size (Ref: HH size ≤ 4) | 0.804*** | 0.159 | – 0.131*** | 0.088 | – 0.297*** | 0.117 |
| Age (Ref: young age) | | | | | | |
| 1. Middle age | – 0.085 | 0.118 | 0.142** | 0.064 | 0.092 | 0.143 |
| 2. Old age | 0.349* | 0.201 | 0.572** | 0.285 | – 0.124 | 0.099 |
| Marital status (Ref: Single) | 0.480*** | 0.075 | – 0.001 | 0.002 | 0.154 | 0.101 |
| Income level (Ref: Low) | | | | | | |
| 1. Middle income | – 0.086 | 0.084 | – 0.142 | 0.388 | 0.205*** | 0.042 |
| 2. High income | 0.025 | 0.062 | 0.411** | 0.255 | 0.507** | 0.181 |
| Housing status (Ref: Renting) | – 0.009 | 0.066 | – 0.326* | 0.181 | 0.306*** | 0.119 |
| Awareness of climate change | 0.605*** | 0.245 | – 0.309 | 0.202 | 0.618*** | 0.181 |
| Knowledge of renewable energy | 0.311** | 0.126 | 0.503 | 0.699 | 0.717* | 0.402 |
| Concerned about climate change | 0.151** | 0.070 | 0.269*** | 0.081 | 0.264*** | 0.081 |
| Access to information | – 0.249*** | 0.101 | – 0.163* | 0.092 | 0.359*** | 0.119 |

| **Preference estimates** | **Class 1** | **Class 2** | **Class 3** |
|---|---|---|---|
| | **Coef. (Std. error)** | **Coef. (Std. error)** | **Coef. (Std. error)** |
| ASC_Solar PV panels | 3.674 (0.412)*** | 4.474 (0.764)*** | 6.459 (1.073)*** |
| ASC_Power generators | 3.330 (0.357)*** | – 1.788 (0.841)** | 6.003 (1.065)*** |
| ASC_Biomass | 4.020 (0.392)*** | – 1.044 (0.017)*** | 5.129 (1.099)*** |
| Service quality (Base: Moderate) | | | |
| Low service quality | – 2.432 (0.290)*** | – 3.290 (0.384)*** | – 0.208 (0.150)*** |
| High service quality | 0.879 (0.124)*** | 1.061 (0.326)*** | 0.075 (0.018)*** |
| Foreign service provider | 0.330 (0.137)*** | – 0.099 (0.276) | 0.063 (0.113) |
| Price | – 0.007 (0.001)*** | – 0.004 (0.001)*** | – 0.003 (0.001)*** |
| *Class share* | 0.356 | 0.436 | 0.208 |
| *Observations* | | 7840 | |
| *Log-Likelihood* | | – 1880.575 | |
| *AIC* | | 3827.149 | |
| *BIC* | | 4057.06 | |

*$p < 0.05$; **$p < 0.1$; ***$p < 0.01$

purchase renewable energy generated by solar PV panels and prefer high-quality services. On the other hand, they have a negative preference for biomass and power generators, indicating a need for compensation or incentives to choose these options. Despite these differences, a common characteristic among all three latent classes is that their utility decreases with low service quality but improves with a high-quality energy source.

Members of class 1 can be considered staunch renewable energy enthusiasts compared to members of class 2. Even though members of class 2 have a positive preference for solar PV panels, they cannot be classified as staunch renewable energy enthusiasts because they will require compensation to use biomass. Notwithstanding, the evidence suggest that respondents may not have enough knowledge about all renewable energy sources and their benefits, particularly members of class 2. Consumers who have appropriate information of present renewable energy technology, as well as the effectiveness of renewable energy, are more inclined to adopt green energy, according to Irfan et al. (2021). Furthermore, members of class 1 are more likely to be worried about climate change, global warming, and other environmental issues, as suggested by the distribution of preferences from the latent class groups. Consumers have become more interested and devoted to fixing environmental concerns as worldwide knowledge of climate change and other environmental challenges have grown. Consumers that have a good attitude towards environmental concerns and the promotion of a sustainable environment are more inclined to use renewable energy. A policy implication that can be gleaned from this result is that policymakers can design targeted incentive programs, subsidies, or tax benefits coupled with educational campaigns to encourage adoption. In marketing renewable energy technologies, developers can prioritize the importance of sustainable energy sources in mitigating climate change and protecting the environment.

## Conclusion

This study sought to examine consumers' preferences and WTP for alternative energy sources in Ghana. Specifically, a labelled choice experiment was conducted to examine households' preference for solar PV panels, biomass, and power generators taking into consideration the purchase price, service quality, and service provider. It is evident from the mixed logit results that households on average prefer renewable energy to non-renewable energy. Consumers' willingness to adopt renewable energy is significant in the transition towards sustainable energy use and a decarbonized energy system. Jabeen et al. (2019) also reported that consumers with positive attitudes towards addressing environmental issues such as climate change are more likely to adopt renewable energy. Solar PV panels, in particular, are the most preferred renewable energy source among consumers and it is also associated with the highest WTP estimates. Solar energy is widely accepted among consumers, and the majority of respondents expressed confidence in solar power during the survey. Notwithstanding, the results from the mixed logit model suggest that households are more likely to choose biomass when solar PV panels are not readily available. This could be explained by the existing demand for biomass energy for cooking (Akpalu et al., 2011).

Purchase price was identified to be significant factor determining consumers' preferences. Consumers on average shy away from an alternative energy source that has a higher purchase price. It is important to note that renewable energy technologies are capital intensive; hence, consumers take into consideration the cost associated with adopting green energy technologies. The high cost associated with green energy technologies is as a result of high interest rates demanded by lenders due to the high risk associated with renewable energy projects (Muangmee et al., 2021). Several studies (Hansla et al., 2008; Kiprop et al., 2019; Nakai et al., 2022; Wall et al., 2021; Makki & Mosly, 2020) have reported a negative relationship between cost and consumer adoption of renewable electricity. According to Makki and Mosly (2020), the cost of renewable energy technologies relative to conventional fossil fuels remains high despite the consistent reduction in the cost of renewable energy technologies. The study further reported a negative impact of the cost of green energy technologies on consumers' willingness to adopt renewable energy. According to the Kiprop et al. (2019), developing countries may face major challenges in transitioning to a decarbonized energy system due to the negative impact of cost on consumer willingness to adopt renewable energy technologies. Kiprop et al. (2019) proposed that developing countries must subsidize renewable energy technologies in order to increase their adoption. In terms of service quality, consumers on average do not prefer low-quality services as it tends to reduce their utility. On the other hand, the positive coefficient associated with "high service quality" indicates that consumers on average have a strong preference for energy developers that use high-quality materials, guarantee continuous power supply, and promptly respond to customer complaints. Consumers are also indifferent between foreign energy service providers and domestic service providers.

## Policy implication and limitations of the study

This study uncovers consumers' strong preference for solar PV panels, indicating a potential customer base for existing solar energy developers. To capitalize on this preference, energy developers should provide consumers with adequate information to convince them of the benefits of purchasing solar PV panels. Furthermore, promoting and incentivizing the adoption of solar PV panels among households through measures like subsidies, tax benefits, and low-interest loans is crucial. Analysing the pricing structures for renewable energy sources and ensuring competitiveness compared to non-renewable sources will also encourage consumer uptake of renewable energy. The survey revealed that a significant percentage of respondents were unaware of existing renewable companies, and many lacked sufficient information to consider renewable energy options. Addressing this lack of knowledge through awareness campaigns that emphasize the environmental, economic, and health benefits of renewable energy will be instrumental in driving adoption. Biomass emerged as the second-best alternative after solar PV panels in the study, yet the renewable energy market remains predominantly dominated by solar energy technologies. To increase accessibility, efforts should focus on improving the availability of solar panels in both rural and urban areas by expanding distribution networks and streamlining importation processes. For regions where solar panels may not be feasible, promoting biomass as an alternative energy source, through investments in improved biomass technologies like efficient stoves or biogas digesters, presents a viable option. To achieve a comprehensive renewable energy development, energy policies should encompass training programs for local energy developers in biomass electricity generation technologies, thereby fostering adoption of not only solar PV panels but also biomass. The willingness-to-pay (WTP) estimates obtained from the study can serve as a basis for constructing an optimal energy investment plan for consumers. The findings indicate that consumers are willing to pay varying amounts for solar PV panels, necessitating the design of payment instalment plans tailored to individual income levels. Collaboration between banks and renewable energy companies to offer instalment plans (green energy plans) can facilitate consumer adoption.

Regarding service providers, this study revealed that consumers prioritize high-quality service over the identity of the provider. To attract consumers and encourage local content in the energy sector, energy policies should focus on developing the local renewable energy industry. The Renewable Energy Master Plan implemented by the Ghanaian government aims to stimulate local content and participation in the renewable energy industry. This includes initiatives to enhance the skills and technical expertise of local energy developers. Additionally, providing a stable and supportive system for domestic energy developers, such as substantial tax reductions and import duty exemptions for renewable energy-related equipment, will enable them to offer affordable renewable energy products to consumers. Collaborations between government entities and private companies can play a pivotal role in expanding renewable energy infrastructure and services. Encouraging domestic firms to invest in renewable energy projects while allowing foreign companies to participate fosters a competitive and dynamic market. Furthermore, enacting and enforcing policies that promote renewable energy deployment, like feed-in tariffs, renewable portfolio standards, and net metering, create an enabling environment for the growth of renewable energy. Lastly, given the existence of preference heterogeneity among respondents, energy developers must engage consumers to better understand their diverse needs and motivations to attract them towards adopting renewable energy. Ensuring inclusivity by considering the needs of low-income households and marginalized communities is vital. Implementing inclusive policies and financial models will ultimately enable broader access to renewable energy for all citizens.

The scope of this study was limited to only the demand side of the energy market in Ghana, with a particular focus on consumer preferences. Future studies can focus on the supply side of the energy market to address supply-side constraints limiting renewable energy development in the country. Researchers can consider relevant issues of availability, accessibility, and development of renewable energy (technology). Also, this study focused on household preference and WTP for alternative energy sources. For further research, studies can conduct a survey to examine preferences and willingness to pay among firms and small-scale enterprises.

## Appendix

See Table 8.

**Table 8** Description of socio-demographic variables used in the mixed logit regression

| Variable | Description | Classification | Mean | Freq. |
|---|---|---|---|---|
| Gender | Dummy | Male (base) | 0.363 | 89 |
| | | Female | 0.637 | 156 |
| Educational level | Dummy | Lower (at least a Bachelor's degree) | 0.829 | 203 |
| | | Higher (above Bachelor's degree) | 0.171 | 42 |
| Household size | Dummy | Small (HH $\leq$ 4) | 0.453 | 111 |
| | | Large (HH > 4) | 0.547 | 134 |
| Age | Categorical | Young (18 to 34 years) | 0.229 | 56 |
| | | Middle aged (35 to 64 years) | 0.694 | 170 |
| | | Old- aged (65 years and above) | 0.078 | 19 |
| Housing status | Dummy | Renting | 0.429 | 105 |
| | | Owning (base) | 0.571 | 140 |
| Household annual Income levels | Categorical | Middle—GHS 15000–GHS 23998 (base) | 0.224 | 55 |
| | | High- (GHS 24000–GHS59988) | 0.776 | 190 |
| Marital status | Dummy | Single (base) | 0.250 | 61 |
| | | Married | 0.750 | 184 |

## Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s40807-024-00117-z.

Supplementary Material 1.

### Author contributions

AAB made substantial contribution to the conceptualization, data acquisition and analysis, and draft of the manuscript. EFOA was instrumental in the conceptualization and supervision of the work and made relevant input in the revision of the manuscript. PFB played the role of a reviewer of the work and was instrumental in the revised version of the manuscript. KA analysed the data and interpretation of results; assisted in drafting the manuscript; and was also instrumental in the study design.

### Data availability

Data will be made available upon request.

## Declarations

### Competing interests

The authors declare no competing interests.

Received: 23 February 2024 Accepted: 8 June 2024
Published online: 20 June 2024

### References

Aboagye, S., Ibrahim, A., & Ngatched, T. M. (2019). Energy efficient user association, power, and flow control in millimeter wave backhaul heterogeneous networks. *IEEE Open Journal of the Communications Society, 1*, 41–59.

Agyekum, E. B., Ali, E. B., & Kumar, N. M. (2021). Clean energies for Ghana—An empirical study on the level of social acceptance of renewable energy development and utilization. *Sustainability, 13*(6), 3114. https://doi.org/10.3390/su13063114

Ahlborg, H., Boräng, F., Jagers, S. C., & Söderholm, P. (2015). Provision of electricity to African households: The importance of democracy and institutional quality. *Energy Policy, 87*, 125–135. https://doi.org/10.1016/j.enpol.2015.09.002

Akpalu, W., Dasmani, I., & Aglobitse, P. B. (2011). Demand for cooking fuels in a developing country: To what extent do taste and preferences matter? *Energy Policy, 39*(10), 6525–6531. https://doi.org/10.1016/j.enpol.2011.07.054

Almanzar, M., & Ulimwengu, J. (2019). Willingness to pay for improved electricity services in senegal: households and businesses estimates using contingent valuation surveys with multiple bids. International Food Policy Research Institute 2019. https://assets.mcc.gov/content/uploads/paper-willingness-to-pay-for-improved-electricity-servicesin-senegal.pdf

Antwi-Agyei, P., Wiafe, E. A., Amanor, K., Baffour-Ata, F., & Codjoe, S. N. A. (2021). Determinants of choice of climate change adaptation practices by smallholder pineapple farmers in the semi-deciduous forest zone of Ghana. *Environmental and Sustainability Indicators, 12*, 100140. https://doi.org/10.1016/j.indic.2021.100140

Ayodele, T. R., Ogunjuyigbe, A. S. O., Ajayi, O. D., Yusuff, A. A., & Mosetlhe, T. C. (2021). Willingness to pay for green electricity derived from renewable energy sources in Nigeria. *Renewable and Sustainable Energy Reviews, 148*, 111279.

Bergmann, A., Hanley, N., & Wright, R. (2006). Valuing the attributes of renewable energy investments. *Energy Policy, 34*(9), 1004–1014. https://doi.org/10.1016/j.enpol.2004.08.035

Blimpo, M. P., & Cosgrove-Davies, M. (2019). *Electricity access in Sub-Saharan Africa: Uptake, reliability, and complementary factors for economic impact*. World Bank Publications.

Curtin, J., McInerney, C., & Johannsdottir, L. (2018). How can financial incentives promote local ownership of onshore wind and solar projects? Case study evidence from Germany, Denmark, the UK and Ontario. *Local Economy, 33*(1), 40–62.

Daggash, H. A., & Mac Dowell, N. (2021). Delivering low-carbon electricity systems in sub-Saharan Africa: Insights from Nigeria. *Energy & Environmental Science, 14*(7), 4018–4037.

Energy Outlook Report. (2021).

Faisal, W. A., Brew-Hammond, A., & Osei, E. E. (2013). Relationships between energy use and income levels for households in Ghana. *European Scientific Journal, 9*(6), 233–245.

Greene, W. H., Hensher, D. A., & Rose, J. M. (2005). Using classical simulation-based estimators to estimate individual WTP values. In R. Scarpa & A. Alberini (Eds.), *Applications of simulation methods in environmental and resource economics* (pp. 17–33). Berlin/Heidelberg: Springer-Verlag.

Hanley N, Czajkowski M. (2020). The role of stated preference valuation methods in understanding choices and informing policy. *Review of Environmental Economics and Policy*, pp. 248–266. https://www.journals.uchicago.edu/doi/10.1093/reep/rez005

Hansla, A., Gamble, A., Juliusson, A., & Gärling, T. (2008). Psychological determinants of attitude towards and willingness to pay for green electricity. *Energy Policy, 36*(2), 768–774. https://doi.org/10.1016/j.enpol.2007.10.027

Hensher, D. A. (2006). Revealing differences in willingness to pay due to the dimensionality of stated choice designs: an initial assessment. *Environmental and Resource Economics*, *34*(1), 7–44.

Hensher, D. A., Ho, C., & Mulley, C. (2015). Identifying preferences for public transport investments under a constrained budget. *Transportation Research Part a: Policy and Practice, 72*, 27–46.

Heltberg, R., (2005). Factors determining household fuel choice in Guatemala. Environment and development economics, *Cambridge University Press*, *10*(3), 337–361. https://doi.org/10.1017/S1355770X04001858

Hole, A. R. (2011). Estimation of willingness to pay in preference space vs. willingness to pay space. *Danish Choice Modelling Day, Odense, December*, *8*.

Hole, A. R., & Kolstad, J. R. (2012). Mixed logit estimation of willingness to pay distributions: a comparison of models in preference and WTP space using data from a health-related choice experiment. *Empirical Economics*, *42*, 445–469.

Hoyos, D. (2010). The state of the art of environmental valuation with discrete choice experiments. *Ecologicaleconomics, 69*(8), 1595–1603. https://doi.org/10.1016/j.ecolecon.2010.04.011

Ibrahim, I. D., Hamam, Y., Alayli, Y., Jamiru, T., Sadiku, E. R., Kupolati, W. K., et al. (2021). A review on Africa energy supply through renewable energy production: Nigeria, Cameroon, Ghana and South Africa as a case study. *Energy Strategy Reviews, 38*, 100740.

IEA. (2018). World energy Outlook 2018. Paris: IEA. https://doi.org/10.1787/weo2018-en

IRENA. (2021). Bracing for climate impact: Renewables as a climate change adaptation strategy, International Renewable Energy Agency, Abu Dhabi.

Irfan, M., Hao, Y., Ikram, M., Wu, H., Akram, R., & Rauf, A. (2021). Assessment of the public acceptance and utilization of renewable energy in Pakistan. *Sustainable Production and Consumption, 27*, 312–324. https://doi.org/10.1016/j.spc.2020.10.031

Jabeen, G., Yan, Q., Ahmad, M., Fatima, N., & Qamar, S. (2019). Consumers' intention-based influence factors of renewable power generation technology utilization: A structural equation modeling approach. *Journal of Cleaner Production, 237*, 117737. https://doi.org/10.1016/j.jclepro.2019.117737

Kaenzig, J., Heinzle, S. L., & Wüstenhagen, R. (2013). Whatever the customer wants, the customer gets? Exploring the gap between consumer preferences and default electricity products in Germany. *Energy Policy, 53*, 311–322. https://doi.org/10.1016/j.enpol.2012.10.061

Karakara, A. A., Osabuohien, E. S., & Asongu, S. (2021). Domestic energy consumption in Ghana: Deprivation versus likelihood of access. *Management of Environmental Quality: An International Journal, 32*(4), 804–821. https://doi.org/10.1108/MEQ-11-2020-0247

Kiprop, E., Matsui, K., & Maundu, N. (2019). The role of household consumers in adopting renewable energy technologies in Kenya. *Environments, 6*(8), 95. https://doi.org/10.3390/environments6080095

Kochtcheeva, L. V. (2016). Renewable energy: global challenges. *E-International Relations*. https://www.e-ir.info/2016/05/27/renewable-energy-global-challenges/

Kumar, A., Kumar, K., Kaushik, N., Sharma, S., & Mishra, S. (2010). Renewable energy in India: current status and future potentials. *Renewable and Sustainable Energy Reviews, 14*(8), 2434–2442.
Kumi, E. N. (2017). *The electricity situation in Ghana: challenges and opportunities* (p. 30). Washington, DC: Center for Global Development. https://www.cgdev.org/publication/electricity-situation-ghana-challenges-and-opportunities
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).
Kwakwa, P. A., Wiafe, E. D., & Alhassan, H. (2013). Households energy choice in Ghana. *Journal of Empirical Economics, 1*(3), 96–103.
Louviere, J. J., Hensher, D. A., & Swait, J. D. (2000). *Stated choice methods: Analysis and applications*. Cambridge University Press.
Louviere, J. J. (1982). An experimental approach for integrating conjoint and functional measurement with discrete choice theory, working, *Institute of Urban and Regional Research*, The University of Iowa, Paper No. 56.
Louw, K., Conradie, B., Howells, M., & Dekenah, M. (2008). Determinants of electricity demand for newly electrified low-income African households. *Energy Policy, 36*(8), 2812–2818. https://doi.org/10.1016/j.enpol.2008.02.032
Machol B., & Rizk, S. (2013). Economic value of US fossil fuel electricity health impacts. *Environment International, 52*, 75–80. https://doi.org/10.1016/j.envint.2012.03.003
Makki, A. A., & Mosly, I. (2020). Factors affecting public willingness to adopt renewable energy technologies: an exploratory analysis. *Sustainability, 12*(3), 845. https://doi.org/10.3390/su12030845
McFadden, D. (1974). The measurement of urban travel demand. *Journal of Public Economics, 3*(4), 303–328. https://doi.org/10.1016/0047-2727(74)90003-6
Meijer, E., & Rouwendal, J. (2006). Measuring welfare effects in models with random coefficients. *Journal of Applied Econometrics, 21*(2), 227–244.
Mensah, J. T., & Adu, G. (2015). An empirical analysis of household energy choice in Ghana. *Renewable and Sustainable Energy Reviews, 51*, 1402–1411. https://doi.org/10.1016/j.rser.2015.07.050
Menyeh, B. O. (2021). Financing electricity access in Africa: a choice experiment study of household investor preferences for renewable energy investments in Ghana. *Renewable and Sustainable Energy Reviews, 146*, 111132. https://doi.org/10.1016/j.rser.2021.111132
Meried, E. W. (2021). Rural household preferences in transition from traditional to renewable energy sources: the applicability of the energy ladder hypothesis in North Gondar Zone. *Heliyon, 7*(11), e08418. https://doi.org/10.1016/j.heliyon.2021.e08418
Meried, E. W. (2021). Rural household preferences in transition from traditional to renewable energy sources: the applicability of the energy ladder hypothesis in North Gondar Zone. *Heliyon*, *7*(11).
Muangmee, C., Dacko-Pikiewicz, Z., Meekaewkunchorn, N., Kassakorn, N., & Khalid, B. (2021). Green entrepreneurial orientation and green innovation in small and medium-sized enterprises (SMEs). *Social Sciences, 10*(4), 136. https://doi.org/10.3390/socsci10040136
Nakai, M., Ravago, M. L. V., Miyaoka, Y., Saito, K., & Arimura, T. H. (2022). Tokyo Center for Economic Research. https://www.tcer.or.jp/wp/pdf/e166.pdf
Navrud, S., & Bråten, K. G. (2007). Consumers' preferences for green and brown electricity: a choice modelling approach. *Revue D'économie Politique, 117*(5), 795–811.
Ndebele, T. (2020). Assessing the potential for consumer-driven renewable energy development in deregulated electricity markets dominated by renewables. *Energy Policy, 136*, 111057. https://doi.org/10.1016/j.enpol.2019.111057
Nketiah, E., Song, H., Adu-Gyamfi, G., Obuobi, B., Adjei, M., & Cudjoe, D. (2022). Does government involvement and awareness of benefit affect Ghanaian's willingness to pay for renewable green electricity? *Renewable Energy, 197*, 683–694.
Numata, M., Sugiyama, M., Swe, W., & del Barrio Alvarez, D. (2021). Willingness to pay for renewable energy in Myanmar: energy source preference. *Energies, 14*(5), 1505. https://doi.org/10.3390/en14051505
Oseni, M. O. (2017). Self-generation and households' WILLINGNESS TO PAYfor reliable electricity service in Nigeria. *The Energy Journal*. https://doi.org/10.5547/01956574.38.4.mose
Parasuraman, A., Zeithaml, V. A., & Berry, L. L. (1985). A conceptual model of service quality and its implications for future research. *Journal of marketing*, *49*(4), 41–50.
Pyzalska-Kowalska, A. (2019). Do consumers want to pay for green electricity? a case study from Poland. *Sustainability, 11*(5), 1310. https://doi.org/10.3390/su11051310
Renewable Energy Master Plan. (2019).
Roe, B., Teisl, M. F., Levy, A., & Russell, M. (2001). US consumers' willingness to pay for green electricity. *Energy Policy, 29*(11), 917–925. https://doi.org/10.1016/S0301-4215(01)000064.
Rowlands, I. H., Parker, P., & Scott, D. (2004). Consumer behaviour in restructured electricity markets. J Consum Behav: *an International Research Review*, *3*(3), 272–283.
Ruokamo, E., Kopsakangas-Savolainen, M., Meriläinen, T., & Svento, R. (2019). Towards flexible energy demand—Preferences for dynamic contracts, services and emissions reductions. *Energy Economics, 84*, 104522. https://doi.org/10.1016/j.eneco.2019.104522
Sakah, M., Diawuo, F. A., Katzenbach, R., & Gyamfi, S. (2017). Towards a sustainable electrification in Ghana: a review of renewable energy deployment policies. *Renewable and Sustainable Energy Reviews, 79*, 544–557.
Sestino, A. (2018). review about consumers' perception on renewable energy market. Available at SSRN 3220528. https://doi.org/10.2139/ssrn.3220528
Siyaranamual, M., Amalia, M., Yusuf, A., & Alisjahbana, A. (2020). Consumers' willingness to pay for electricity service attributes: a discrete choice experiment in urban Indonesia. *Energy Reports, 6*, 562–571. https://doi.org/10.1016/j.egyr.2020.02.018
Sonnier G, Ainslie A,  Otter T. (2007).Sonnier, G., Ainslie, A., & Otter, T. (2007). Heterogeneity distributions of willingness-to-pay in choice models. *Quantitative Marketing and Economics*, *5*, 313–331.https://doi.org/10.1007/s11129-007-9024-6
Taale, F., & Kyeremeh, C. (2016). Households′ willingness to pay for reliable electricity services in Ghana. *Renewable and Sustainable Energy Reviews, 62*, 280–288. https://doi.org/10.1016/j.rser.2016.04.046
Tu, G., Abildtrup, J., & Garcia, S. (2016). Preferences for urban green spaces and peri-urban forests: an analysis of stated residential choices. *Landscape and Urban Planning, 148*, 120–131. https://doi.org/10.1016/j.landurbplan.2015.12.013
United Nations Energy Access Report, 2021. https://openknowledge.worldbank.org/entities/publication/70d430a1-0e78-5613-8447-f61454fcf317 Accessed 19 Oct 2022.
Wall, W. P., Khalid, B., Urbański, M., & Kot, M. (2021). Factors influencing consumer's adoption of renewable energy. *Energies, 14*(17), 5420. https://doi.org/10.3390/en14175420
Wen, C., Lovett, J. C., Rianawati, E., Arsanti, T. R., Suryani, S., Pandarangga, A., & Sagala, S. (2022). Household willingness to pay for improving electricity services in Sumba Island, Indonesia: a choice experiment under a multi-tier framework. *Energy Research & Social Science, 88*, 102503. https://doi.org/10.1016/j.erss.2022.102503

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