sustainability

MDPI

Article

Incorporating Elicited Preferences for Equality into Electricity System Planning Modeling

Charles Van-Hein Sackey [1], Destenie Nock [1,2,*], Christine Cao [1], Daniel Armanios [3] and Alex Davis [1]

[1] Department of Engineering & Public Policy, Carnegie Mellon University, Pittsburgh, PA 15213, USA; cvanhein@andrew.cmu.edu (C.V.-H.S.); shenglun@andrew.cmu.edu (C.C.)
[2] Department of Civil & Environmental Engineering, Carnegie Mellon University, Pittsburgh, PA 15213, USA
[3] Saïd Business School, University of Oxford, Oxford OX1 3AZ, UK; daniel.armanios@sbs.ox.ac.uk
* Correspondence: dnock@andrew.cmu.edu

Abstract: Sustainable Development Goal 7 of the United Nations is to achieve universal access to clean, modern and affordable electricity by 2030. However, 600 million people in sub-Saharan Africa (SSA) currently do not have access to electricity. As a result of this energy inequality, countries in SSA need to plan electricity systems that provide access in an equitable manner. The research question we explore in this paper is how integrating elicited preferences for equality into an electricity system planning model affects investment decisions regarding technology deployment. Our novel contribution is proposing a framework in the form of a discrete choice experiment and a statistical estimation model to determine decision makers' preferences for equality. In our study, we find that higher preferences for equality result in an increased deployment of solar diesel mini-grids. These hybrid mini-grids, in turn, drive the carbon emissions intensity of the electricity system fourfold. As such, there is a need for stakeholders in Africa's energy sector to consider the potential divergence between a carbon-minimizing electrification strategy and equitable electrification.

Keywords: electricity system planning; energy justice; discrete choice experiment; equality

check for updates

Citation: Van-Hein Sackey, C.; Nock, D.; Cao, C.; Armanios, D.; Davis, A. Incorporating Elicited Preferences for Equality into Electricity System Planning Modeling. *Sustainability* **2023**, *15*, 16351. https://doi.org/10.3390/su152316351

Academic Editor: Mohamed A. Mohamed

Received: 9 September 2023
Revised: 15 November 2023
Accepted: 16 November 2023
Published: 27 November 2023

1. Introduction

As of 2022, there are roughly 800 million people without access to electricity worldwide. Of these 800 million people, two-thirds reside in sub-Saharan Africa (SSA) [1]. As such, it has become pertinent for researchers to investigate pathways to achieve 100% electrification (i.e., universal electrification) in sub-Saharan Africa. Research shows that access to electricity is strongly correlated with economic growth in rural areas [2] and the rate at which economic growth follows urbanization [3]. This will depend on appliance adoption and dwelling type [4], which subsequently affects demand growth [4]. That being said, a study in Nigeria identified the nexus between electrification and urbanization as being tied to development. This correlation is the guiding principle behind United Nations Sustainable Development Goal Seven, which aims to achieve universal "access to affordable, reliable, sustainable and modern energy for all" [2]. To achieve universal electrification, just electricity system planning will be necessary to ensure that people have access to the quality and quantity of electricity they need. Research has shown that the preferences and priorities of stakeholders in the energy sector in SSA are crucial to increasing access to electricity in a just manner [3].

Instead of taking a purely economic-growth-oriented perspective, we create an approach to integrate energy justice into the electrification process. In their review, Jenkins et al. defined three energy justice dimensions—distributional, recognition, and procedural [4]. Distributional justice aims to provide resources to people in the amount proportional to their need. Recognition justice aims to include marginalized groups in society in the decision-making process. Procedural justice deals with engaging all stakeholders in the decision-making process. Most countries in SSA lack energy-just policy frameworks for electrification decision making (i.e., legal or policy environments that encourage the implementation of one or more of the dimensions of energy justice). An assessment of renewable energy policy in African countries identified that only 9 of 34 countries had both procedural and recognition justice built into their policy framework. Only South Africa had all three tenets of energy justice represented in their policy framework [5]. To close this gap in procedural and recognition justice, energy systems researchers should better center stakeholder engagement in their analysis and optimization of electricity systems in SSA.

There are a multitude of methods to engage stakeholders [6]. One research study engaged a variety of stakeholders in the energy sector in Ghana [7]. Baker et al. [7] educated stakeholders about value-focused thinking, interviewed stakeholders, and provided a questionnaire to the stakeholders to capture their priorities. The authors identified that the priorities of community leaders representing end-users differed widely from those of policymakers and international development organizations. Specifically, community leaders did not prioritize environmental sustainability although they acknowledged its importance when asked. Specifically, Baker et al. found that stakeholders in Ghana faced a key tradeoff between cost and reliability: on one hand, cost reduction via subsidies would alleviate the energy burden of citizens, but on the other hand, the resulting decrease in revenue would compromise the reliability of service due to the lack of finances to maintain the electricity system [7].

Another study used a game to empirically illustrate how decision makers can make "selfish" high-impact decisions affecting large groups [8]. A different study looked at the tie between engaging stakeholders on the perceived value of the Sustainable Development Goals [6]. Engaging stakeholders can help identify the important tradeoffs that electricity system planners ought to consider in the formulation and implementation of these systems [9].

The study by Wang et al. showed that study participants in Nepal preferred a more politically feasible and affordable electricity system than an increased renewable generation portfolio. Another study showed that preferences for equality among decision makers may change depending on the individual's perceived role in allocating a given resource [10]. In the case of electricity as a resource, it can be inferred from the study by Li et al. that stakeholders in the sector who may be more involved in planning (i.e., policymakers, generation, transmission and distribution companies, and international funders) will have preferences that would differ from those of their counterparts less involved in the planning process (i.e., end-users). The novelty of our paper lies in our creation of a framework that determines stakeholders' preferences for equality and integrates those preferences into an electricity planning model.

Beyond incorporating stakeholder preferences for equality, there are two main methods of estimating population preferences: (i.) stated preference; (ii.) revealed preferences. In the first method, stakeholders (i.e., decision makers) are provided with direct questions asking about choices they would hypothetically make. Atkinson et al. used a stated preference approach by issuing a survey on the aversion to risk and inequality [11]. In a revealed preference study, researchers engage stakeholders in an experiment or simulation, in which they make a series of decisions to purchase certain goods based on different price and income levels [8]. One contribution of our study is that we use a discrete choice experiment (a form of stated preference) to capture decision makers' preferences for equality based on the choices they make. We then integrate this preference into an optimization model that determines where to make generation and transmission investments. A stated preference approach is appropriate in our experiment since we are not examining individuals' willingness to pay at various income levels, which would have required a revealed preference study.

Despite the need for incorporating stakeholder perspectives and preferences in electricity planning, the existing research on electricity system planning often misses how the preferences of decision makers impact infrastructure planning for electrification. These system planning models often use least-cost approaches to optimize generation and transmission investments in a national electrification plan. For example, in two SSA-based studies, the focus and findings were around the investment needed to provide adequate access [12], or how differences in demand drive different optimal systems (i.e., low demand: standalone photovoltaics and diesel generators vs. high demand: grid and mini-grid systems) [13]. Kemausuor et al. used a decision support tool to explore the cost of different electricity supply options in unelectrified communities in Ghana [14]. Ohiare used a spatial electricity planning model to identify the least-cost supply option for electrification in Nigeria [15]. Azimoh et al. used a cost-based model to determine the viability of a hybrid mini-grid as a generation source for rural communities in South Africa [16]. Moner-Girona et al. developed a spatial electrification model to comprehensively review the energy infrastructure in Kenya [17]. Trotter et al. developed a multi-objective optimization tool to determine the tradeoffs involved in achieving equal levels of access and prioritizing electrification in urban areas in Uganda [18]. Even more problematic, research has also shown that this disproportionate focus on least-cost methods in electricity system planning has led to energy policymakers investing in infrastructure that is actually socially and environmentally inequitable [3].

Overall then, and as recent reviews of rural electrification models have concurred [19], there is still need for the development of tools that consider other objectives, such as equity and reliability, in the electricity planning literature for SSA. While there are some exceptions that have incorporated equity, these studies do not adequately take into account stakeholders' aversion to inequality (i.e., [18]), or only measure preferences for equity by proxy (via representative preferences) rather than directly. Our paper takes these analyses further by investigating stakeholder preference for energy equality using a discrete choice experiment and directly evaluating how those equality preferences impact technology deployment and electricity system configuration. We ask the following: how do the elicited preferences for equality among decision makers inform electricity system modeling and technology deployment? Building on prior work [20], we elicit stakeholders' aversion to inequality using a discrete choice experiment, and integrate those preferences into an electricity system planning model. Our work fits into the literature (as shown in Table 1) by filling in the gap between studies that use least-cost approaches to electricity system planning and research that has qualitatively shown the need for energy justice when planning electricity systems.

Table 1. Key literature highlighting our study's novel contribution.

Study	Method	Finding	Limitation of Previous Work	Our Contribution
Mentis et al., 2017 [13]	Geospatial least-cost optimization	Rural electrification in SSA requires deployment of standalone systems.	Limited focus on rural areas and does not include preferences for equality.	We expand this work to consider not just least-cost models in a rural area, but integrate equality preferences into a national electrification model.
Korkovelos et al., 2019 [21]	Geospatial least-cost optimization	Off-grid PV is optimal for electrifying most of Malawi.	Solely using least-cost models does not capture different preferences for equality among stakeholders.	We build on this work to consider how evolving preferences of potential stakeholders may lead to different national electrification plans.

Table 1. *Cont.*

Study	Method	Finding	Limitation of Previous Work	Our Contribution
Conteh et al., 2021 [22]	Genetic algorithm used to minimize the loss of power supply probability and cost of energy	Analysis of hybrid grid-connected renewable power generation for sustainable electricity supply in Sierra Leone.	Focuses on optimizing reliability, economic, and sustainability, but misses the equality considerations driving the universal development goals within the continent.	Our model includes an adjustable reliability constraint and combines this with assessments of renewable power generation deployment.
Jenkins et al., 2016 [4]	Qualitative review	Energy justice is a useful framework for providing access to unelectrified societies.	Although this review paper discusses the importance of providing access it misses, it does not provide a framework for integrating preferences into electrification models.	We detail a framework for eliciting preferences for equality from decision makers and then integrating those preferences into electricity system planning models.
Tarekegne, 2020 [3]	Qualitative analysis	Emphasis on techno-economic approaches has resulted in locally ineffective energy infrastructure.	Misses how different preferences for equality from decision makers may diverge from the least-cost solutions.	We survey a population of future engineers and evaluate how their equality preferences will lead to different power system build outs.
Baker et al., 2021 [7]	Value-focused thinking for aligning stakeholder priorities	Stakeholder engagement is necessary for developing effective energy system models.	The team surveyed stakeholders to determine their values and objectives for the power system, but did not integrate these objectives into an electricity system model.	We develop a discrete choice survey, elicit people's actual equality preferences, and integrate those into an energy optimization model to highlight how these preferences translate to generation and transmission investments.
Our study	Discrete choice + benefit-maximization model	Higher preferences for equality result in deployment of solar–diesel hybrid minigrids.	-	We present a novel framework for eliciting preferences of decision makers and integrating these into electrification models.

Our main contributions to the literature are as follows: (1) We present a novel framework for eliciting preferences of decision makers and integrating these into electrification models. (2) We highlight how including the preferences of decision makers and stakeholders may diverge from the least-cost solution, which highlights an inherent gap in studies that only use the least-cost objective. (3) The framework for surveying decision-maker preferences (using discrete choice) and tying that to infrastructure investments can be used to understand why models and implementation in practice do not always align.

2. Methods

To determine decision makers' preferences for equality, we (1) deployed a discrete choice experiment, (2) statistically estimated decision makers' individual preferences for equality, and (3) integrated those preferences into the maximize energy access (MEA) model to determine the optimal capacity investment strategy. A discrete choice experiment is an experiment designed to infer the preferences of decision makers from their selections made in a series of choice sets (i.e., set of possible options). The participants of our experiment were mostly engineering graduate students. Globally, studies have shown that decisions in the energy sector are highly influenced by professionals with engineering graduate or undergraduate degrees [23]. Geng et al. investigated how the Chinese industry and government has invested in higher education to address problems in the industry and research [24]. We fully acknowledge that such a sample of engineering graduate students poses significant limitations on our work given that they are not representative of African decision makers. Our novel contribution to the literature is in proposing a framework that can be used to elicit preferences of decision makers and integrate these preferences into an electricity system planning model. Furthermore, given the influence of foreign stakeholders in SSA's energy sector (the World Bank, USAID, etc.), our sample of engineering graduate students may provide some insight into the perspectives of stakeholders from developed countries when making decisions about SSA's energy sector. Although, due to financial and time constraints, we were not able to replicate this experiment for engineering graduate students in SSA, future work should prioritize sampling from decision makers in SSA. Thus, in this paper, we use the term "decision makers" to refer to the sample of students who participated in this experiment and the stakeholders whose perspectives they may represent. Figure 1 outlines the methods used to integrate elicited decision makers' aversion to inequality into an electricity system planning model. Table 2 details each variable and parameter used in our methods.

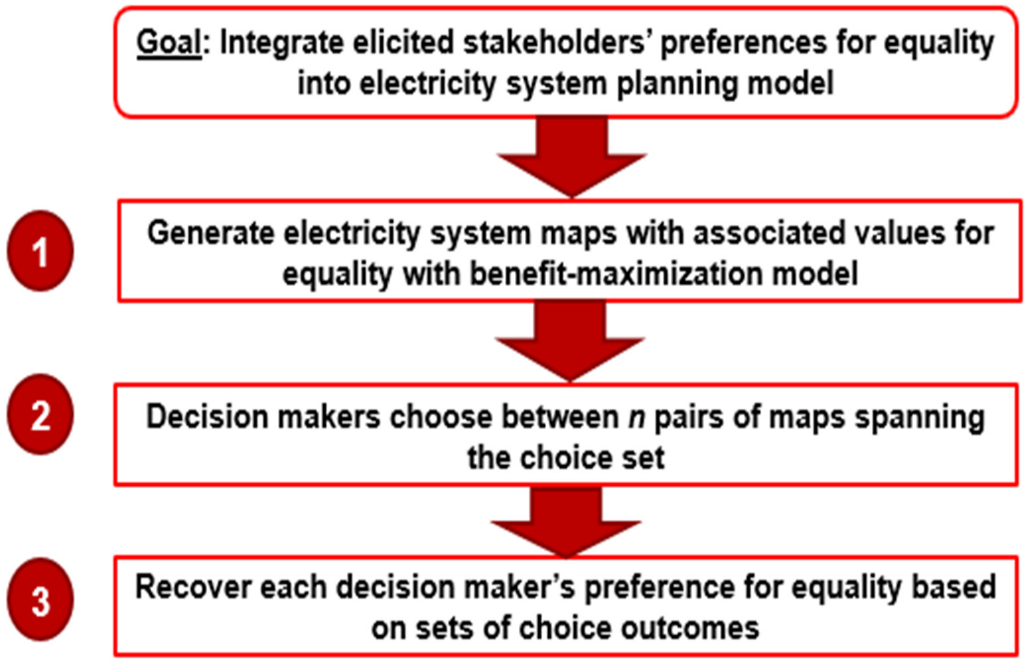

Figure 1. Summary of methods used to integrate decision makers' aversion to inequality into an electricity system planning model.

A discrete choice experiment is an experiment designed to infer the preferences of decision makers based on the choices they make from hypothetical alternatives, which consist of different attributes or characteristics. A choice set is the collection of alternatives a decision maker must select from. We define the variables used in our methods in Table 2.

Table 2. Description of variables and parameters used in methods.

Symbol	Description	Units
a	Indicator for map A	-
α	Equality preference parameter	-
b	Indicator for map B	-
B	Budget	USD/year
c	choice outcome	-
C	Set of choice outcomes	-
$C^{T,L}$	Annualized cost for low-voltage transmission line	USD/km-year
$C^{T,H}$	Annualized cost for high-voltage transmission line	USD/km-year
$C_k{}^F$	Annualized fixed cost for generation technology k	USD/MW-year
$C_k{}^V$	Variable cost for generation technology k	USD/MWh
$d_{i,j}$	Length of transmission line from node i to node j	km
E	Set of possible transmission edges	-
$f_{i,j}$	Average annual power flow from node i to node j	MWh
g_i	Total generation in node i	MWh
$g_{i,k}$	Generation by technology k in node i	MWh
$G_{i,k}$	Capacity of generation technology k installed at node i	MW
p_i	Population at node i	ppl
p	Vector of total population in all nodes i in I	-
P(a > b)	Probability of choosing Map A over Map B	-
ρ_i	Per-capita electricity consumption in node i	MWh/ppl [1]
s	Scale factor for utility functions	-
U	Utility function	-
$v_{i,j}{}^L$ and $v_{i,j}{}^H$	Indicator for high- or low-voltage transmission line between nodes i and j	-
x_i	Electricity consumption at node i	MWh
x	Vector of electricity consumption in all nodes i in I	-
y_c	Set of choice outcomes	-

[1] In the experiment, participants were shown per-capita electricity consumption in units of kWh/ppl in each node.

2.1. MEA Model

We generated the decision makers' choice set using the Maximize Energy Access (MEA) model. The MEA model is a benefit-maximization model that develops a country's electrification plan by maximizing the utility of a stakeholder, U (Equation (1)). The stakeholder's utility for a graphic location is assumed to be a function of the per-capita electricity consumption and population and is represented using an iso-elastic utility function.

$$U(x,p)_{max} = \sum_{i \in I} u(x_i, p_i) \ = \sum_{i \in I} p_i \frac{\left(\rho_i^{1-\alpha} - 1\right)}{1-\alpha} \tag{1}$$

where x_i is the electricity consumption at node i in the given country, p_i is the population at node i, and ρ_i is the per-capita electricity consumption at node i. We use an equality parameter, α, which ranges from zero to one, to model stakeholders' preferences for equality. In economics literature, this term is referred to as the inequality aversion parameter with regard to income [25]. Thus, in the utility function expressed in Equation (1), α represents a stakeholder's aversion to inequality (i.e., their preference for equality). An alpha value closer to zero indicates a linear aversion to inequality, i.e., a decision maker perceives equal value from increased electricity consumption, regardless of whether a node had a lower or higher initial level of consumption. On the other hand, an alpha closer to one indicates that the decision maker perceives more value from increased electricity consumption in nodes with lower initial consumption values and less value from increased electricity consumption in nodes with higher initial consumption values [20]. The country was broken down into nodes that represent locations where electricity would be consumed.

Equations (2)–(4) represent key constraints of the MEA electricity generation capacity optimization model. Equation (2) ensures that the fixed and variable costs associated with generation and transmission infrastructure are within a specified budget constraint, which we fixed at USD 15 million for this paper. Equation (3) is an energy balance for the electricity system to ensure that electricity generated at a node, transmitted from a node, and transmitted to another node balances with the electricity consumed in that node. Equation (4) ensures that the sum of each generator's capacity at a node constrains the total generation at a node.

$$\sum\nolimits_{(i,j) \in E} \left(C^{T,L} d_{i,j} v_{i,j}^{L} + C^{T,H} d_{i,j} v_{i,j}^{H} \right) + \sum\nolimits_{i \in I,\ k \in K} \left(C_k^F G_{i,k} + C_k^V g_{i,k} \right) \le B \tag{2}$$

$$x_i \le \ g_i + \sum_{(j,i) \in E} f_{j,i} - \sum_{(i,j) \in E} f_{i,j} \quad \forall\, i \in I,\ (i,j) \in E \tag{3}$$

$$g_i \le \sum_{i \in I,\ k \in K} g_{i,k} \ \ \forall\ i \in I,\ k \in K \tag{4}$$

For further documentation on the MEA model, and the full set of the constraints, refer to [20]. We used the MEA model to generate a series of maps (i.e., optimal electricity system plans) corresponding to different values of inequality aversion, alpha (ranging from low inequality aversion, 0.1, to high inequality aversion, 0.9), for use in the discrete choice experiment. We used Liberia as our case study for electricity system planning in low-access countries in sub-Saharan Africa in this experiment due to the country's low electrification rate (currently 28%) [26], and the ease of seeing differences in generation allocation decisions in the survey. We set the budget constraint at USD 15 million based on data from Liberia's energy sector [27] and on existing literature that performed sensitivity analysis on various budget levels for the country's electrification [20].

Having determined the optimal electricity system plan using the MEA model, we used the carbon emissions factors found in Table 3 to determine the total carbon emissions from each electricity system plan.

Table 3. Carbon emission factors for generation sources used in MEA model.

Generation Source	Carbon Emissions Factor (gCO_2eq/kWh)	Water Consumption Factor (L/MWh)	Source
Hydro	7	4491	Klein & Whalley [28]
PV (Photovoltaic)-Diesel Minigrid	413	11.5	Sovacool, [29]; Klein & Whalley [28]
Solar Home System	41	23	Schloemer et al., [30]
Oil	768	1893	Klein & Whalley [28]

2.2. Discrete Choice Experiment

In the discrete choice experiment, we generated nine maps corresponding to the nine alpha values and then had experimental participants make pairwise comparisons between these electrification plans, yielding X choice sets (9-choose-2). The values of alpha were hidden from decision makers to estimate each decision maker's true preference for equality since the literature indicates that there tends to be some difference between individuals' stated preference and their true preference [31].

Figure 2 shows an example of the pairwise comparison decision makers had to make in the survey. In the introduction to the survey, we explained the difference between an electricity system plan that provides more individuals with baseline access to electricity consumption (i.e., Tier 1) and one that increases electricity consumption via the usage of higher-end appliances (i.e., Tier 3) in nodes with higher population densities. Table 4 shows the per-capita consumption of electricity associated with each tier according to [32].

Table 4. Tiers of electricity access and corresponding per-capita consumption.

Level of Access	Consumption per Capita per Year (kWh/person/year)	Appliances Electrified
Tier 1	8	Light bulbs, radio, phone charging
Tier 3	167	Tier 1 + Washing machine, air cooler, food processor

Figure 2a shows the population density at each node in the country. Figure 2b,c show examples of two maps serving as a choice set presented to each decision maker. Consistent with the literature on preference elicitation, the introductory section of the survey explained key concepts about the electricity planning maps and contained knowledge check questions to ensure that decision makers understood the choices provided [33]. Prior to deploying the survey, we issued the survey to test users (consisting of students, faculty, and non-academics), whom we interviewed to ensure that the attributes in each choice set and information in the survey were shown in a manner that allowed a user to understand how to make choices based on the attributes and information provided in the survey. Based on existing literature on the stated preference elicitation, we included "rational check" questions in the survey, in which one map corresponded to a remarkably higher inequality aversion, alpha value (i.e., it clearly dominated the other map), to determine if decision makers were consistent in their responses [34].

We determined that a discrete choice experiment would be appropriate for our study because its use of hypothetical alternatives allows researchers to replicate scenarios in which decision makers would have to engage with tradeoffs based on the defining attributes and characteristics of each alternative [35]. Generally, discrete choice models are suitable for experiments in which the outcome variable can have a countable number of values (i.e., a discrete variable) [36]. Since decision makers in the energy sector often make choices from a discrete set of alternatives (e.g., whether to invest in a power plant or not), a discrete choice experiment would be useful in eliciting the underlying preferences guiding their decision making. While the preference for equality variable, α, is continuous by definition, the choice that a decision maker has to consider regarding electricity infrastructure is discrete in nature (e.g., the choice to build a thermal power plant versus a solar photovoltaic (PV) mini-grid). Thus, by observing the choices of decision makers in the discrete choice experiment, we can determine how their preferences impact technology deployment in electricity system planning.

One limitation of discrete choice experiments is that by using hypothetical alternatives instead of real-world options, the choices that decision makers make may not be useful for modeling their behavior in a real-world scenario. As a result, in this paper, we address this limitation by using the MEA model, which uses real-world economic and power systems data and constraints, to create alternatives that are technically and economically feasible in a given country. As displayed in Figure 2, our experiment required decision makers to choose from a given Map A or Map B.

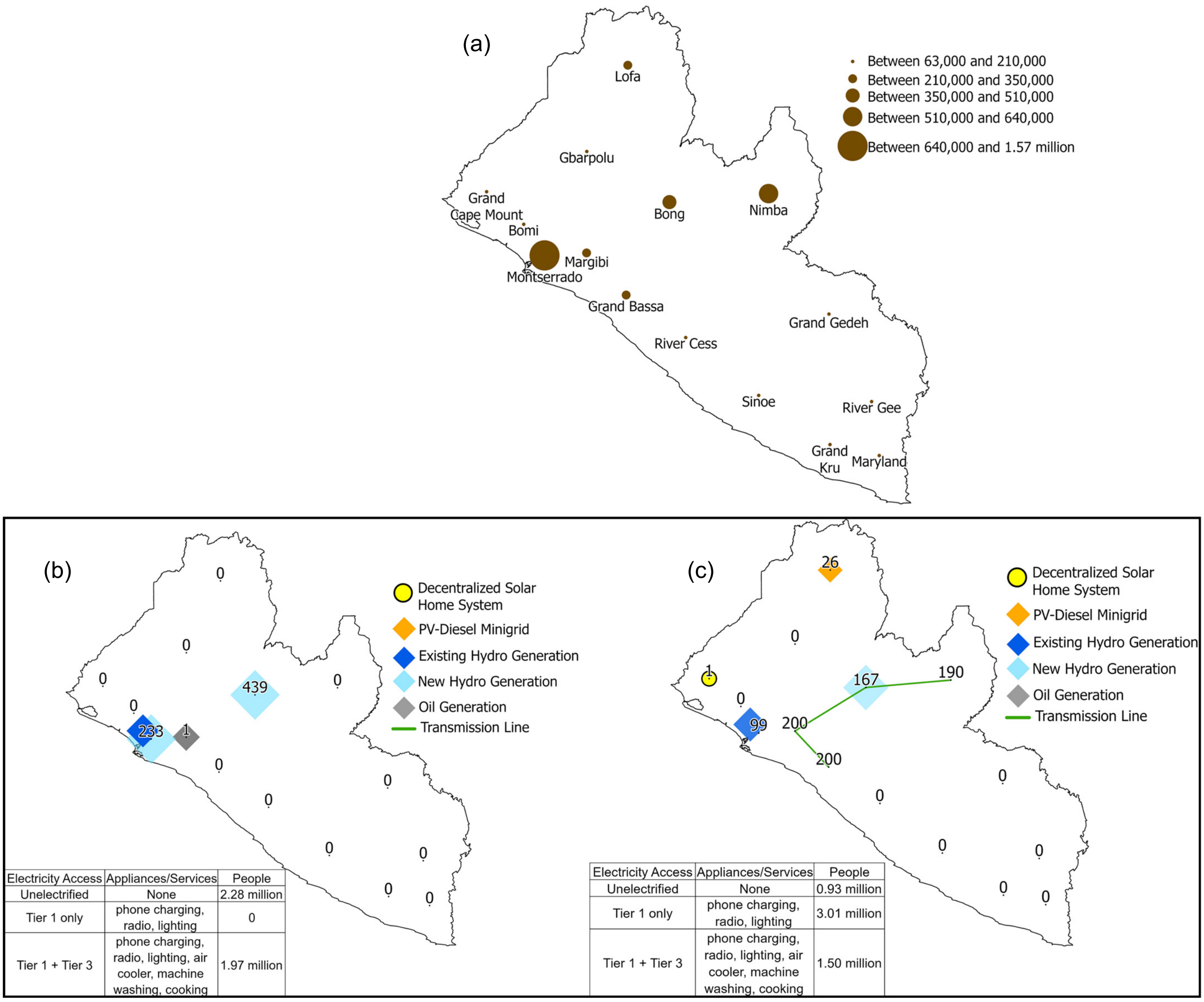

Figure 2. In each survey question, we showed a (**a**) population density map, and two maps (**b**,**c**), referred to as "a given Map A and Map B" in this paper, to the decision maker, as shown in the figure. The respondent had to choose between the two maps (**b**,**c**), which were generated from the MEA model using two distinct values of alpha. The table in the bottom-left corner of each map shows the population that would have access to Tier 1 or Tier 3 level of electricity consumption.

2.3. Statistical Estimation of Preference Parameter

Given the selections made in each choice set (i.e., the choice outcome of either Map A or Map B), we recovered each decision maker's preference for equality using a statistical estimation model. The estimation model, binary logit model, determines the inequality aversion parameter value (i.e., alpha) that maximizes the Bernoulli likelihood. A binary logit model is a regression model that has a binary dependent variable, in this case, the decision maker's choice between Map A and Map B. We used a binary logit model because the decision makers in our experiment will be choosing between two maps—a binary choice, which can be described by a Bernoulli probability distribution. A key assumption for the binary logit model is that the utility that a decision maker derives from each alternative (i.e., Map A and Map B) is independent of each other. More specifically, the aspects of the decision maker's utility for one option that is unobserved are independent of the unobserved factors for the other option [36].

Thus, for a given set of binary choice outcomes, maximizing the Bernoulli log-likelihood function estimates the choice probability that was likely used to generate the set of choice outcomes. Equation (5) shows the overall objective function used to determine the estimate of a decision maker's preference for equality (i.e., alpha).

$$max : \log\left(\prod_{c=1}^{36} P(a > b)^{y_c} \times (1 - P(a > b))^{1-y_c}\right) \tag{5}$$

Given the optimal choice probability derived from maximizing the log-likelihood function, we estimate the true alpha used to make the set of choice outcomes for a given decision maker. Since choice probability, expressed in Equation (6), is a function of alpha by means of the utility function, we are able to determine the value of alpha that was most likely used to generate the set of choice outcomes (i.e., y_c).

$$P(a > b) = \frac{e^{u(x_a,\, p_a) - u(x_b,\, p_b)}}{\left(1 + e^{u(x_a,\, p_a) - u(x_b,\, p_b)}\right)} = \frac{e^{u(x_a,\, p_a)}}{e^{u(x_a,\, p_a)} + e^{u(x_b,\, p_b)}} \tag{6}$$

2.4. Text Aggregation Method

We also identify factors feeding into the decisions maker's choices using a simple text aggregation on the qualitative question: "What is the most important factor in your decisions about which power system to build?" The initial level of processing involved simplifying each statement to a set of the most important words by removing punctuation; making all characters lowercase; correcting spelling errors; and removing common, meaningless words. Removed words include articles, prepositions, being verbs, and conjunctions; additionally, words that are common in context were removed, such as "electricity", "energy", or "power". Among the remaining words, those in a list of important words, such as "equality", "access", "equity", "renewable", and "population", were first prioritized. If these were absent, the longest words were prioritized. The majority of responses were thus analyzed. The remaining responses were analyzed based on a heuristic connecting common phrases with related priorities; for example, responses about "maximizing" the "number of people" with electricity were categorized with "access". The premise of this categorization was that responses seeking a larger "number" or "amount" of people with electricity were categorized with access, while those seeking a "more" "equally" "distributed" system were categorized with equality. If a response did not fulfill any of these criteria, as was the case for two to three responses in each dataset, the most important word(s) were manually deduced. All responses were manually checked against their selected words to ensure reasonability. The aggregated list of words from all essays was sorted by frequency and by categorization with their respective responses for analysis.

2.5. Uncertainty Analysis

Finally, we account for uncertainty in our statistical estimation process using a bootstrapping process. Bootstrapping is a process of deriving the variance of a parameter estimated by developing a simulation dataset, which is created by sampling values of the input parameters with replacements. In our experiment, we reconstructed each respondent's choice dataset by sampling with the replacement 36 times (i.e., the number of choices each respondent made) and then repeated the process 1000 times to quantify the uncertainty of the statistical estimation process more robustly. Due to computational constraints, we limited our repetitions to 1000, which allowed for sufficient variability given our question sample size of 36.

2.6. Limitations

To integrate the elicited preferences from decision makers into the electricity planning model, we made some key assumptions. In discrete choice theory, one can decompose the utility of a decision maker into observed and unobserved factors. Given that in the MEA model, we use an iso-elastic utility function for the decision maker, we assume that the iso-elastic utility function adequately captures the behavior of our decision makers, such that those unobserved factors are random and uncorrelated [36]. Also, by using the binary logit model, we inherently assume that the utility that a decision maker derives from each alternative (i.e., Map A and Map B) is independent of one another, and that the unobserved factors in the utility function are identically distributed. The literature on discrete choice models indicates that the independence assumption underlying the logit model tends to be inconsistent when dealing with substitution choices [36]. Since our experiment does not require decision makers to make a choice in place of another (i.e., substitution), the use of the logit model is appropriate in this case.

In addition to resource and time constraints, of the approximately 110 students who participated in this study, only 54 participants fully completed the survey for the experiment in a coherent manner. As such, there is a need to incentivize experiment participants to complete the study in a coherent manner in future iterations of this study.

Also, since we did not collect specific nationality data in the experiment, we were not able to group the sample by country of origin. Thus, future work would need to sample decision makers enrolled in institutions in developing countries to understand how their preferences may differ from their counterparts in US institutions. Such work may infer the influence of different education systems on preferences for equality among decision makers.

Furthermore, the electricity system planning model used (i.e., the MEA model) did not consider an entirely solar PV mini-grid as an electricity supply option. While the literature on cost analysis of solar PV mini-grids in sub-Saharan Africa suggests that energy storage technology for solar mini-grids may be too expensive to allow mini-grid operators to recover costs in some countries [34], future work ought to consider increasing the array of electricity supply options in system planning models [18,37,38].

3. Results and Discussion

In this section, we present our results for recovering a decision maker's preference for energy equality and how integrating these preferences into electrification planning in low-income/developing countries impacts the electrification plan. First, we show the results of the discrete choice experiment, specifically the distribution of preferences for equality and corresponding electricity system plans. Then, we discuss the results of the simple text aggregation on the qualitative data collected from the experiment. Lastly, we provide the results of our bootstrapping uncertainty analysis.

3.1. Elicited Preferences and Electricity System Plans

In total, 54 participants responded to the survey, 94% of which were engineering graduate students. Using the statistical estimation model, we estimated each decision maker's alpha value. Figure 3 shows the distribution of alpha values recovered from the discrete choice experiment.

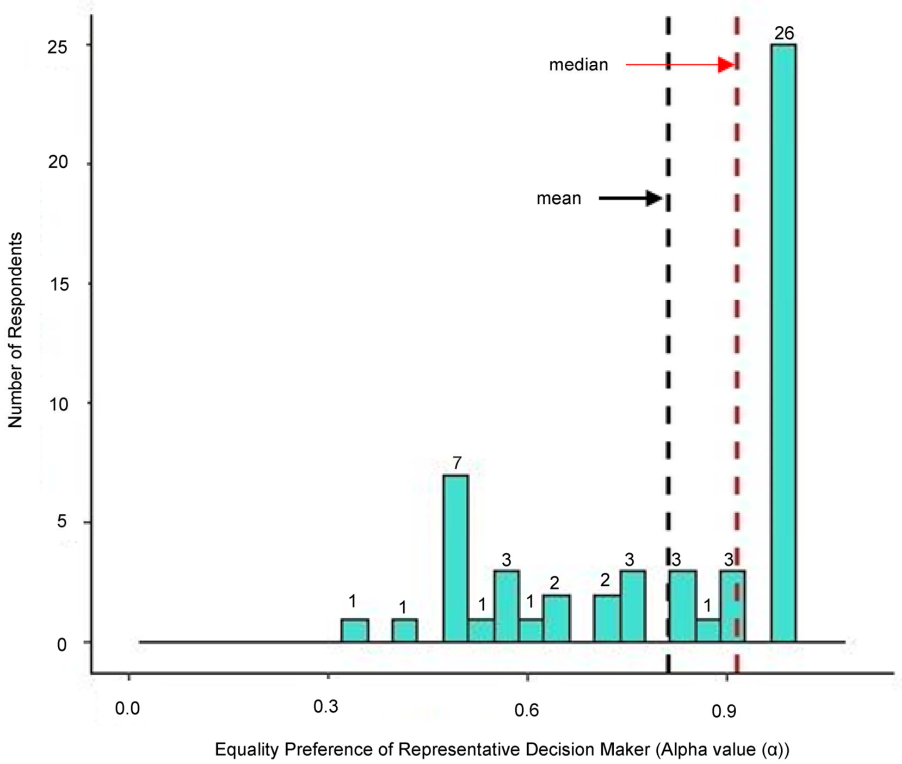

Figure 3. Distribution of alpha values recovered from discrete choice experiment. An alpha value closer to zero indicates that a decision maker perceives equal value from increased electricity consumption, regardless of whether a node had a lower or higher initial level of consumption. An alpha closer to one indicates that the decision maker perceives more value from increased electricity consumption in nodes with lower initial consumption values and less value from increased electricity consumption in nodes with higher initial consumption.

We observed that our sample had relatively high preferences for equality. Specifically, we had an average alpha value of 0.81 and a median value of 0.91. It is important to note that since the recovered alpha values were not normally distributed, we showed the median as a summary statistic in addition to the mean. The sample had a standard deviation of 0.21 (variance was 0.04). The range of alpha recovered was 0.34 to 0.99. Given the mean of 0.81 and the standard deviation, it is evident that the sample is relatively left-skewed (toward 0.99). The relatively high value of the average preference for equality is consistent with the literature on inequality aversion, which suggests that decision makers in developed countries tend to have a lower inequality aversion (or higher equality preferences) than their counterparts from developing countries [11]. In Section 3.4, we delve into the correlation between demographics and the recovered preferences for equality.

The estimated preferences for equality were fed back into the electricity system planning model to determine how they might influence the optimal electricity system plan. In Figure 4, we show the system plans corresponding to the minimum, 10th percentile, 25th percentile, 50th percentile, median, and maximum of the estimated alpha values (i.e., 0.34, 0.5, 0.6, 0.81, 0.91, and 0.99, respectively). As a reference point, we show the electricity system plan corresponding to the lowest value of alpha (i.e., 0.1) in Figure 4a, which is the equivalent of a least-cost electrification plan (since the decision maker would have a linear aversion to inequality). In Figure 4b–g, we observe that all decision makers diverged from the least-cost electrification plan. Table 5 shows the range in per-capita electricity consumption for each value of alpha represented in Figure 4. Our finding contributes to the literature on electricity system planning because it shows that energy decision makers may tend to deviate from least-cost electrification plans based on preferences. As such, there is a need for a paradigm shift from least-cost models to models that combine decision science with optimization in its methods such as that proposed here.

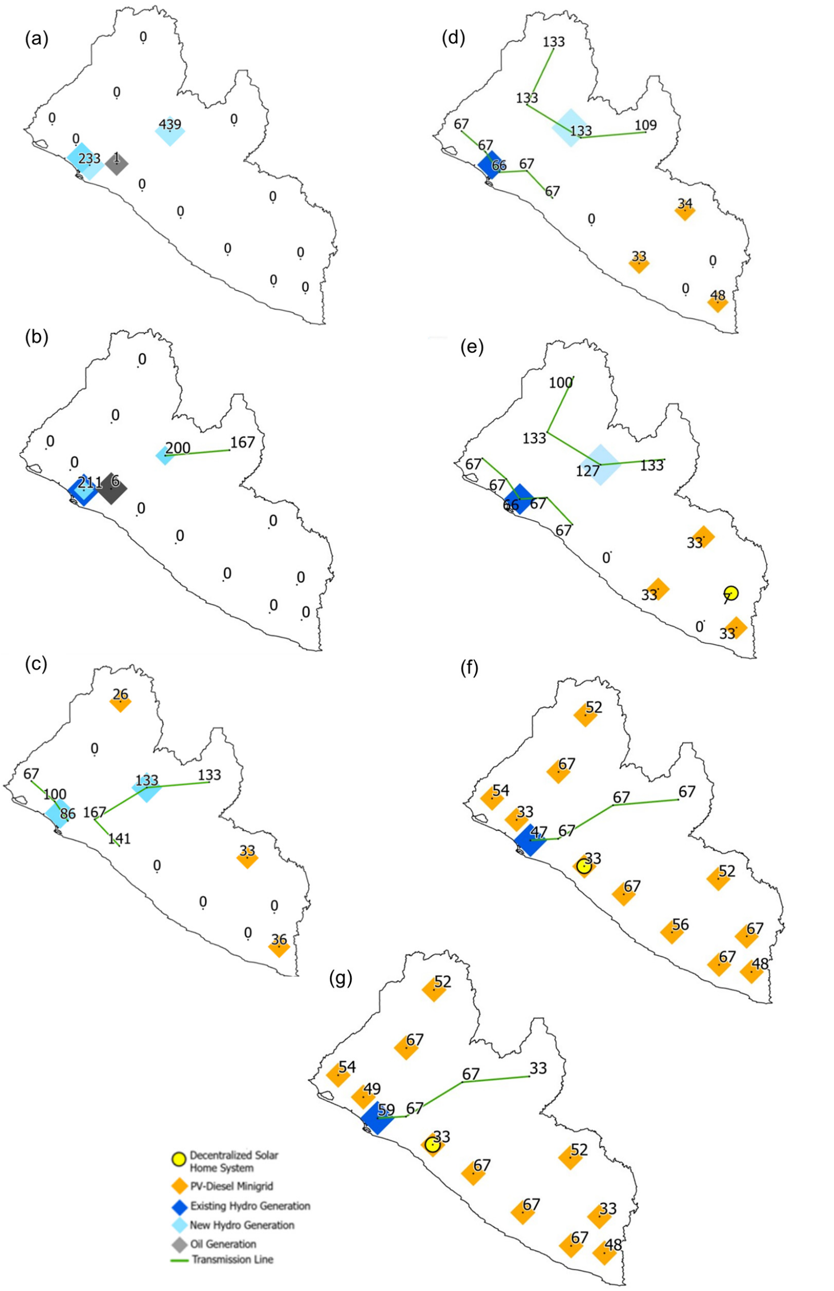

Figure 4. Distribution summary of optimal electricity system plan corresponding to estimated alpha (α) values of (**a**) $\alpha = 0.1$ (least-cost equivalent), (**b**) $\alpha = 0.34$ (minimum), (**c**) $\alpha = 0.5$ (10th percentile, n = 1), (**d**) $\alpha = 0.60$ (25th percentile, n = 13), (**e**) $\alpha = 0.81$ (50th percentile, n = 8), (**f**) $\alpha = 0.91$ (median, n = 5), and (**g**) $\alpha = 0.99$ (maximum). We note that subplots (**f**,**g**) look similar following rounding of the per-capita electricity consumption in each node to two decimal places. This signifies that a decision maker does not need to have the maximum preference for equality to electrify the entire country.

In the results illustrated in Figure 4, we observe an increased deployment of PV-diesel mini-grids in rural parts of the country (i.e., remote areas farther from the urban hub electrified by hydro generation). The increased use of diesel increased per-MWh carbon emissions from the electricity system. In Section 3.2, we discuss the specific demand and carbon emissions impact resulting from these electricity system plans.

Table 5. Minimum and maximum per-capita electricity consumption for each map generated using the alpha values from Figure 4.

Alpha Value	Minimum–Maximum per-Capita Electricity Consumption (kWh/pp)
0.1	0–439
0.34	0–211
0.5	0–167
0.6	0–133
0.81	0–133
0.91	33–67
0.99	33–67

3.2. Impact Evaluation

Given the various generation systems being deployed in the electricity system plans, we evaluated the impact of these preference-based electricity systems on total electricity demand/consumption, water consumption intensity, and carbon emissions intensity. One of our major findings was that while the total electricity demand and water consumption intensity of the electricity system decreased, the total carbon emissions intensity increased with increasing preference for equality. In Figure 5, we show the trends in total demand, water intensity, and carbon emission intensity for alpha values 0.34 (minimum alpha recovered), 0.5 (10th percentile), 0.6 (25th percentile), 0.81 (mean), 0.91 (median), and 0.99 (maximum). In Figure 5a, we observe that the total consumption of electricity in the country decreases from 0.34 to 0.6, stabilizes from 0.6 to 0.81, and then declines from 0.81 to 0.91. Due to the MEA model being a mixed-integer program, in all three trends in Figure 5, there is no difference in values from an alpha value of 0.91 to 0.99. Based on the trend in Figure 5a, we find that between the decision maker with an alpha value of 0.34 and that with a value of 0.91, there will be a two-times decrease in total electricity consumed in the country. However, the lower difference in alpha between 0.5 and 0.81 suggests that decision makers with such preferences for equality would plan systems with the same national consumption of electricity but distributed differently (per Figure 4). Hence, the concept of distribution justice will also be key to such decision makers as they would essentially be deciding where each electron would be consumed and by whom.

In Figure 5b, we see that the water consumption intensity between alpha values of 0.81 and 0.91 decreases by about 1.5 times, whereas there is a less-than-5% difference in water intensity between alpha values of 0.34 and 0.81. The initial drop in water intensity from 0.34 to 0.5 is due to the removal of the oil plant (water intensity factor of 1893 L/MWh) as the preference for equality increases. Given that in place of the oil plant, the node is being powered by a hydro plant via the transmission line, water intensity drops because the singular hydro plant serves more nodes, and therefore it is serving more demand than that for the oil plant (i.e., the use of water is now serving more demand and thus driving down the intensity).

In Figure 5c, we observe that the carbon emissions intensity between alpha values of 0.81 and 0.91 increases by fourfold. The increased carbon emissions are primarily driven by the increased deployment of PV-diesel mini-grids to serve rural nodes where electricity consumption is lower than in their urban counterparts. This finding is particularly relevant to the conversation of just transitions in sub-Saharan Africa because we show that in the case of Liberia, a carbon-emissions-minimizing electricity system significantly diverges from the most distributionally just electricity system. Moreover, given the apparent differences in preference elasticities in carbon emissions and electricity consumption, future research may consider examining those elasticities (i.e., how incremental changes in electricity consumption change carbon emissions) by using a larger sample size to determine exactly where tradeoffs would occur. Thus, future work would need to consider the tradeoffs that decision makers may make between preferences for equality and aversion to carbon emissions.

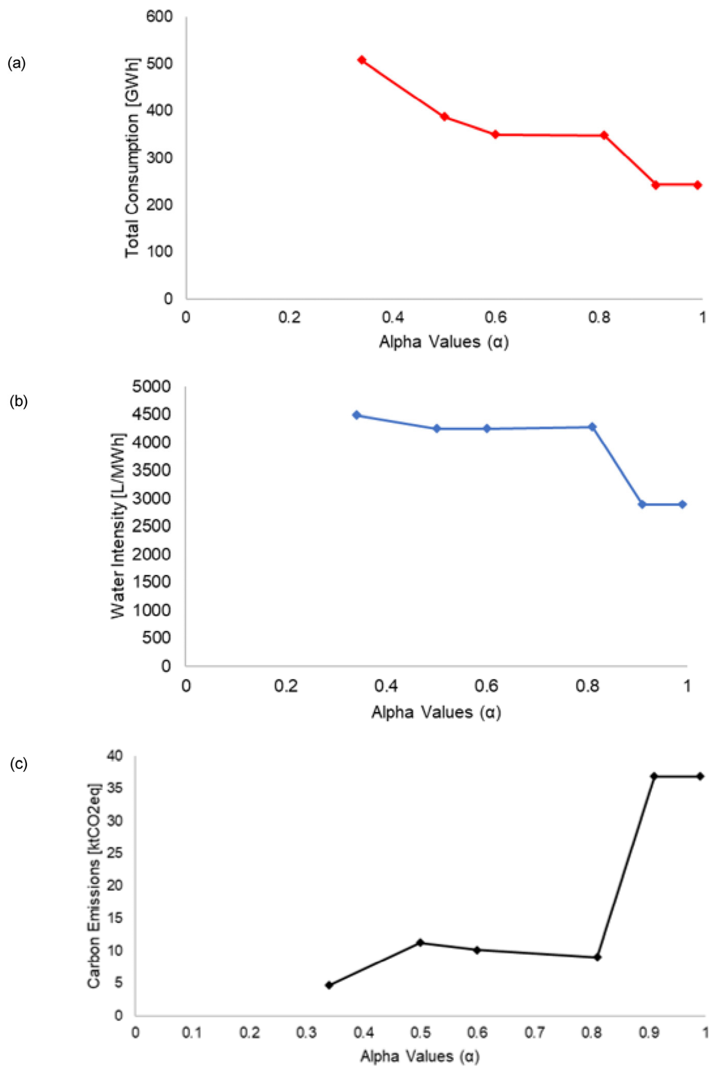

Figure 5. We observe that (**a**) total electricity consumption and (**b**) water intensity generally decrease with increasing values of alpha, whereas (**c**) carbon emissions increase with increasing values of alpha (α). Here, alpha represents the recovered equality preference of the decision maker.

3.3. Results of Text Aggregation

Additionally, we performed a simple text aggregation on the decision makers' responses to determine which factors influenced their choice outcomes. Figure 6 shows the word cloud illustrating the text analysis. We found that most decision makers tended to choose maps that would provide the most access to electricity consumption in the country. Given that a higher amount of access corresponds to a higher preference in equality, the text aggregation qualitatively validates the high preference for equality (with a median alpha of 0.91) identified in our experiment. The relatively high preference for equality observed in our results aligns with the existing literature on equality preferences. In a study of the relationship between risk aversion, intertemporal substitution, and inequality aversion regarding climate change, researchers found that respondents from developed countries had relatively high preferences for equality [39]. As such, our future work would comprise replicating this experiment in a country in sub-Saharan Africa to determine how their preferences for equality compare with those of their counterparts from the United States, and how those preferences may result in a different optimal capacity expansion plan.

Figure 6. A word cloud that shows the most frequently used factors by decision makers when choosing between electricity system plans in our experiment.

3.4. Demographic Breakdown of Results

We further inspected the demographic breakdown of our results to explore how identity may have influenced decision makers' preferences for equality. The relatively high preference for equality observed in our results may be due to the demographic of people we sampled for this experiment. Approximately 94% of the decision makers (i.e., experiment participants) in our sample were engineering graduate students. To reiterate, we acknowledge that they are not representative of African decision makers in SSA's energy sector. However, our work contributes to the literature by providing a framework for researchers to elicit preferences among stakeholders and to integrate those preferences into electricity planning models. Further, the perspectives of these engineering graduate students in a private university in the United States may provide insights into preferences of decision makers from developed countries who make investment allocation decisions for SSA's energy sector, like the World Bank.

As illustrated in Figure 7a, we observed similar preferences between decision makers who were citizens of the United States and those who were of other nationalities. However, there was a wider range of alpha among non-US citizens, with a minimum alpha of 0.34, a median of 0.81, and a maximum of 0.99 as compared to US citizens who had a minimum alpha of 0.43, a median of 0.93, and a maximum of 0.99. While about 60% of our sample were non-US citizens, it must be noted that their enrollment in an engineering graduate program at a private institution may indicate a tendency to maximize social benefit from infrastructure development.

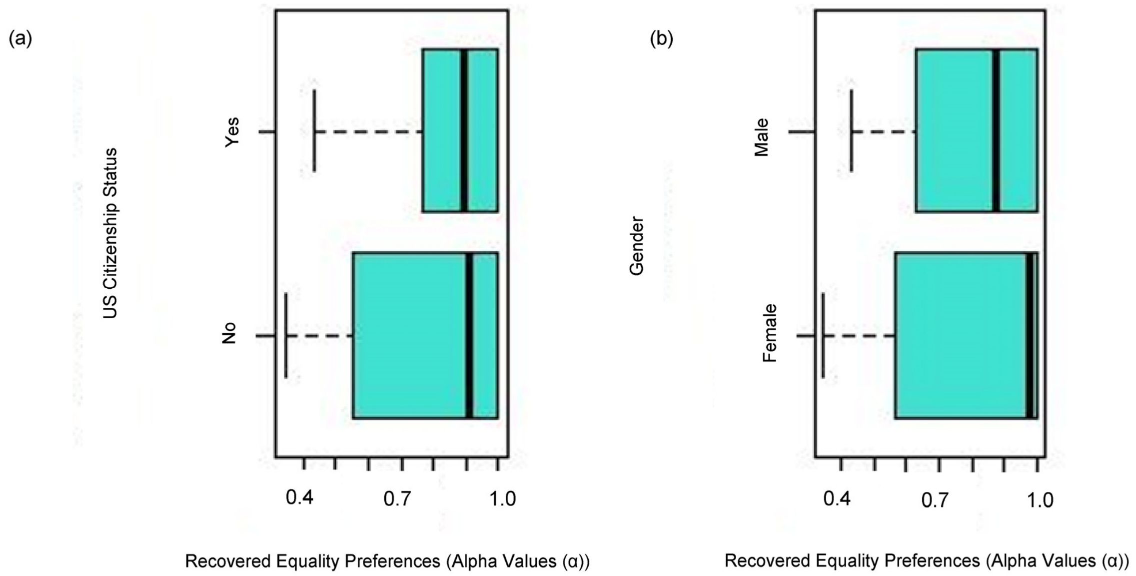

Figure 7. Results from our sample indicate that (**a**) non-US citizens (n = 32; median = 0.81) had preferences for equality similar to those of US citizens (n = 21; median = 0.93) on average. Also, (**b**) female (n = 21; median = 0.98) decision makers have higher preferences for equality than their male counterparts (n = 31; median = 0.86).

Given that the existing literature suggests that female decision makers tend to be more focused on the welfare of their community than their male counterparts in decision-making [40–42], we decided to compare preferences for equality between male and female decision makers. Of all decision makers, 60% were male participants and 40% were female participants. In Figure 7b, we observed that female decision makers had a median alpha value of 0.97, while their male counterparts had a lower median alpha value of 0.87. It must also be noted that there was a wider range in preferences among female decision makers than those of males, with female decision makers having a range of 0.66 (alpha variance = 0.05) and male decision makers having a range of 0.57 (alpha variance = 0.04). We note that there was one respondent who identified as non-binary, but we exclude their response from Figure 7 due to the small sample size. Since these results are an aggregation of the point estimate of each decision maker's preference for equality, we evaluate the uncertainty associated with the statistical estimation process in Section 3.5.

3.5. Uncertainty Analysis

To determine the uncertainty associated with our statistical estimation model, we performed a bootstrapping analysis using the choice sets of each decision maker in the experiment. In Figure 8, we show the results of our bootstrapping, which was carried out by sampling choice sets with replacements 36 times to reconstruct the original dataset, and then repeating the process 1000 times. Each box plot in the figure represents an individual survey respondent's bootstrapped preference for equality. Their original survey responses were sampled with replacements 36 times to construct the bootstrapped dataset, on which the statistical estimation process was performed to obtain the alpha value. This process was repeated 1000 times for each individual, and the range of recovered alpha on each bootstrapped dataset is visualized in Figure 8. For some individuals, the uncertainty range on their recovered alpha values shows that they have a dominantly high preference for equality. However, some individuals, typically those with lower equality preferences, demonstrate a large uncertainty range. The uncertainty likely comes from the individual not displaying a strong transitive preference for a certain level of equality. For example, suppose the following maps have decreasing equality (i.e., decreasing alpha values) in the following order: Map A1 > Map B1 > Map A2 > Map B2. If Student 1 chose Map A2 over Map B1 in Question 1 of the survey, and then chose Map A1 over Map B1 in Question 2, then Student 1 did not have a strong transitive preference for equality, since their choice in Question 1 indicates a lower preference for equality (Map A2 over B1), but then they chose Map A1 over Map B1, which corresponds to a higher preference for equality.

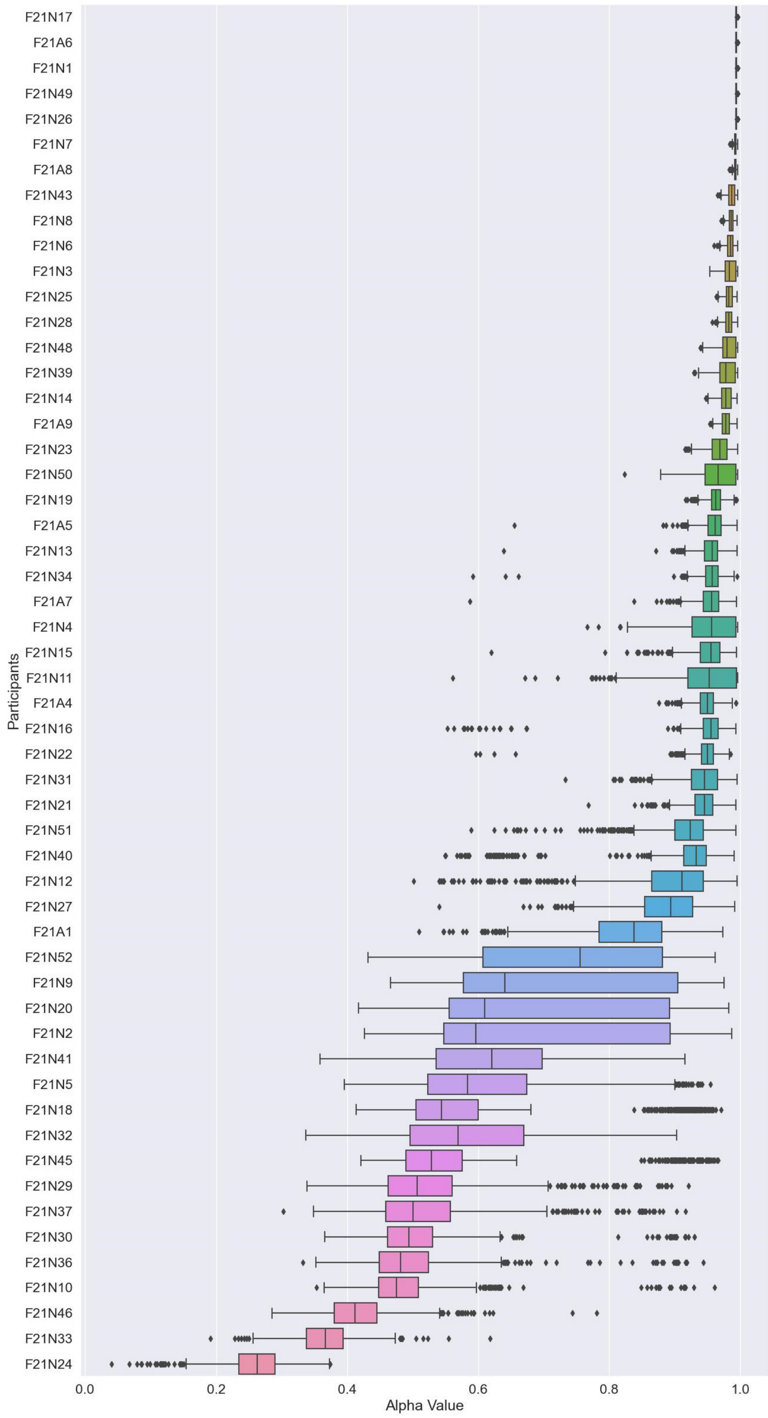

Figure 8. Uncertainty analysis of parameter recovery model. In this boxplot, we observe that the individual mean alpha values in this bootstrapping analysis (1000 runs) correspond to the relatively high median equality preference (alpha value) observed in Figure 2.

4. Conclusions

In this paper, we determined how to integrate elicited preferences for equality from decision makers into an electricity system planning model. Our specific contribution is highlighting how to elicit decision-maker preferences and then integrate these preferences into electrification and infrastructure deployment models. There is evidence that the mixed-methods approach (e.g., engaging stakeholders and quantitative analysis) is important to developing successful implementation and deployment strategies for electrification [43]. Our framework can assist with tackling the energy deficiency in countries within the African continent [22] through engaging with stakeholders to identify how their preferences for equality can impact the deployment of centralized and decentralized infrastructure within a country. This is very important in places that are currently working to expand their electricity infrastructure and have large levels of unmet energy demand [41].

Using a discrete choice experiment, we demonstrated that higher preferences for equality would require an increased deployment of decentralized systems, specifically PV-diesel hybrid mini-grids. The increased carbon emissions from the use of diesel for electricity generation suggests that there may be tradeoffs between preferences for equality and aversion to carbon emissions that decision makers may consider when planning electricity infrastructure. As such, future work ought to incorporate an aversion to carbon emissions in the utility function specification to further examine how these tradeoffs are being made by decision makers. Additionally, we found that female decision makers have higher preferences for equality than their male counterparts when making infrastructure investment decisions. Our finding regarding the role gender may play in preferences for equality further validates efforts to achieve gender parity and increase inclusivity among decision makers in the energy sector.

By integrating these elicited preferences into an electricity system planning model, we have demonstrated that future research regarding electrification in sub-Saharan Africa needs to move beyond the least-cost paradigm and explore how preferences among decision makers (and the values underlying these preferences) may influence the electrification pathway of countries in the sub-continent. This is crucial for thinking through how decision makers will electrify the residential sector, as well as productive uses of energy, such as agriculture [42]. Without understanding how decision-maker preferences influence infrastructure deployment, there is the risk that certain communities will be left out of the energy transition, and inequalities will widen during the development process [43].

Author Contributions: Conceptualization, C.V.-H.S., D.N., D.A. and A.D.; Methodology, C.V.-H.S., D.N., C.C. and A.D.; Software, C.V.-H.S.; Formal analysis, C.V.-H.S. and C.C.; Data curation, C.C.; Writing—original draft, C.V.-H.S. and C.C.; Writing—review & editing, D.N., D.A. and A.D.; Visualization, C.V.-H.S. and C.C.; Supervision, D.N.; Project administration, D.N.; Funding acquisition, D.N., D.A. and A.D. All authors have read and agreed to the published version of the manuscript.

Funding: This work has been supported by the National Science Foundation (NSF) (Grant Number: 2121730).

Institutional Review Board Statement: Ethical review and approval were waived for this study because any disclosure of the human subjects' responses outside the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation per IRB policy.

Informed Consent Statement: Informed consent was obtained from all the participants.

Data Availability Statement: The data presented in this study are available on request from the corresponding author. The data are not publicly available due to the need for the authors to protect the identity and information of study participants.

Acknowledgments: The authors would like to acknowledge the technical insights of Baruch Fischhoff at Carnegie Mellon University for providing feedback regarding the design of the discrete choice experiment.

Conflicts of Interest: The authors declare no conflict of interest.

References

1. IEA. Africa Energy Outlook 2022—Analysis. Available online: https://www.iea.org/reports/africa-energy-outlook-2022 (accessed on 6 December 2022).
2. IEA. Access to Electricity–SDG7: Data and Projections—Analysis. Available online: https://www.iea.org/reports/sdg7-data-and-projections/access-to-electricity (accessed on 7 December 2021).
3. Tarekegne, B. Just electrification: Imagining the justice dimensions of energy access and addressing energy poverty. *Energy Res. Soc. Sci.* **2020**, *70*, 101639. [CrossRef]
4. Jenkins, K.; McCauley, D.; Heffron, R.; Stephan, H.; Rehner, R. Energy justice: A conceptual review. *Energy Res. Soc. Sci.* **2016**, *11*, 174–182. [CrossRef]
5. Müller, F.; Claar, S.; Neumann, M.; Elsner, C. Is green a Pan-African colour? Mapping African renewable energy policies and transitions in 34 countries. *Energy Res. Soc. Sci.* **2020**, *68*, 101551. [CrossRef]
6. Di Lucia, L.; Slade, R.; Khan, J. Decision-making fitness of methods to understand Sustainable Development Goal interactions. *Nat. Sustain.* **2022**, *5*, 131–138. [CrossRef]
7. Baker, E.; Nock, D.; Levin, T.; Atarah, S.A.; Afful-Dadzie, A.; Dodoo-Arhin, D.; Ndikumana, L.; Shittu, E.; Muchapondwa, E.; Sackey, C.V.-H. Who is marginalized in energy justice? Amplifying community leader perspectives of energy transitions in Ghana. *Energy Res. Soc. Sci.* **2021**, *73*, 101933. [CrossRef]
8. Alós-Ferrer, C.; García-Segarra, J.; Ritschel, A. Generous with individuals and selfish to the masses. *Nat. Hum. Behav.* **2022**, *6*, 88–96. [CrossRef]
9. Wang, X.; Reardon, L.; To, L.S. Visualizing Nepal's electricity supply resilience from a whole-systems perspective: A participatory approach. *Energy Res. Soc. Sci.* **2022**, *85*, 102409. [CrossRef]
10. Li, O.; Xu, F.; Wang, L. Advantageous Inequity Aversion Does Not Always Exist: The Role of Determining Allocations Modulates Preferences for Advantageous Inequity. *Front. Psychol.* **2018**, *9*, 749. [CrossRef]
11. Atkinson, G.; Dietz, S.; Helgeson, J.; Hepburn, C.; Sælen, H. Siblings, Not Triplets: Social Preferences for Risk, Inequality and Time in Discounting Climate Change. *Economics* **2009**, *3*, 2009–2026. [CrossRef]
12. Falchetta, G.; Hafner, M.; Tagliapietra, S. Pathways to 100% Electrification in East Africa by 2030. *Energy J.* **2020**, *41*, 255–290. [CrossRef]
13. Mentis, D.; Howells, M.; Rogner, H.; Korkovelos, A.; Arderne, C.; Zepeda, E.; Siyal, S.; Taliotis, C.; Bazilian, M.; de Roo, A.; et al. Lighting the World: The first application of an open source, spatial electrification tool (OnSSET) on Sub-Saharan Africa. *Environ. Res. Lett.* **2017**, *12*, 085003. [CrossRef]
14. Kemausuor, F.; Adkins, E.; Adu-Poku, I.; Brew-Hammond, A.; Modi, V. Electrification planning using Network Planner tool: The case of Ghana. *Energy Sustain. Dev.* **2014**, *19*, 92–101. [CrossRef]
15. Ohiare, S. Expanding electricity access to all in Nigeria: A spatial planning and cost analysis. *Energy Sustain. Soc.* **2015**, *5*, 8. [CrossRef]
16. Azimoh, C.L.; Klintenberg, P.; Wallin, F.; Karlsson, B.; Mbohwa, C. Electricity for development: Mini-grid solution for rural electrification in South Africa. *Energy Convers. Manag.* **2016**, *110*, 268–277. [CrossRef]
17. Moner-Girona, M.; Bódis, K.; Morrissey, J.; Kougias, I.; Hankins, M.; Huld, T.; Szabó, S. Decentralized rural electrification in Kenya: Speeding up universal energy access. *Energy Sustain. Dev.* **2019**, *52*, 128–146. [CrossRef]
18. Trotter, P.A.; Cooper, N.J.; Wilson, P.R. A multi-criteria, long-term energy planning optimisation model with integrated on-grid and off-grid electrification—The case of Uganda. *Appl. Energy* **2019**, *243*, 288–312. [CrossRef]
19. Akbas, B.; Kocaman, A.S.; Nock, D.; Trotter, P.A. Rural electrification: An overview of optimization methods. *Renew. Sustain. Energy Rev.* **2021**, *156*, 111935. [CrossRef]
20. Nock, D.; Levin, T.; Baker, E. Changing the policy paradigm: A benefit maximization approach to electricity planning in developing countries. *Appl. Energy* **2020**, *264*, 114583. [CrossRef]
21. Korkovelos, A.; Khavari, B.; Sahlberg, A.; Howells, M.; Arderne, C. The Role of Open Access Data in Geospatial Electrification Planning and the Achievement of SDG7. An OnSSET-Based Case Study for Malawi. *Energies* **2019**, *12*, 1395. [CrossRef]
22. Conteh, F.; Takahashi, H.; Hemeida, A.M.; Krishnan, N.; Mikhaylov, A.; Senjyu, T. Analysis of Hybrid Grid-Connected Renewable Power Generation for Sustainable Electricity Supply in Sierra Leone. *Sustainability* **2021**, *13*, 11435. [CrossRef]
23. Stanek, E.K.; Tompkins, C.J. Power Engineering Education as Viewed from University Administration. *IEEE Trans. Power Syst.* **1987**, *2*, 226–231. [CrossRef]
24. Geng, H.; Zheng, Z.; Yang, G. Education and Research Activities of Electrical Engineering in China's University and Industry. In Proceedings of the 2015 IEEE Power & Energy Society General Meeting, Denver, CO, USA, 26–30 July 2015; pp. 1–5.
25. Atkinson, A.B. On the measurement of inequality. *J. Econ. Theory* **1970**, *2*, 244–263. [CrossRef]
26. World Bank Access to Electricity (% of Population)—Liberia | Data. Available online: https://data.worldbank.org/indicator/EG.ELC.ACCS.ZS?locations=LR (accessed on 31 October 2022).
27. Modi, V.; Adkins, E.; Carbajal, J.; Sherpa, S. *Liberia Power Sector Capacity Building and Energy Master Planning Final Report, Phase 4: National Electrification Master Plan*; Columbia University: New York, NY, USA, 2014.
28. Wardman, M. A Comparison of Revealed Preference and Stated Preference Models of Travel Behaviour. *J. Transp. Econ. Policy* **1988**, *22*, 71–91.

29. Sustainable Energy for All. *Chapter 2: Universal Access to Modern Energy Services*; United Nations: New York, NY, USA, 2013. Available online: https://www.seforall.org/sites/default/files/l/2013/09/7-gtf_ch2.pdf (accessed on 13 December 2020).
30. Fischhoff, B. Chapter 18 Cognitive Processes in Stated Preference Methods. In *Handbook of Environmental Economics*; Elsevier: Amsterdam, The Netherlands, 2005; Volume 2, pp. 937–968. ISBN 978-0-444-51145-4.
31. Grayek, E.; Yang, Y.; Fischhoff, B.; Schifferdecker, K.E.; Woloshin, S.; Kerlikowske, K.; Miglioretti, D.L.; Tosteson, A.N.A. A Procedure for Eliciting Women's Preferences for Breast Cancer Screening Frequency. *Med. Decis. Mak.* **2022**, *42*, 783–794. [CrossRef]
32. Sergi, B.; Azevedo, I.; Xia, T.; Davis, A.; Xu, J. Support for Emissions Reductions Based on Immediate and Long-term Pollution Exposure in China. *Ecol. Econ.* **2019**, *158*, 26–33. [CrossRef]
33. Train, K. *Discrete Choice Methods with Simulation*; Cambridge University Press: Cambridge, UK, 2002. Available online: https://eml.berkeley.edu/books/choice2.html (accessed on 28 October 2022).
34. African Minigrid Developers Association; Economic Consulting Associates. *Benchmarking Africa's Minigrids*; African Minigrid Developers Association: Nairobi, Kenya, 2020. Available online: https://africamda.org/wp-content/uploads/2021/08/AMDA-Benchmarking-2020-.pdf (accessed on 16 December 2021).
35. Falchetta, G.; Stevanato, N.; Moner-Girona, M.; Mazzoni, D.; Colombo, E.; Hafner, M. *M-LED: Multi-Sectoral Latent Electricity Demand Assessment for Energy Access Planning*; Social Science Research Network: Rochester, NY, USA, 2020. [CrossRef]
36. Dietz, S.; Atkinson, G. The Equity-Efficiency Trade-off in Environmental Policy: Evidence from Stated Preferences. *Land. Econ.* **2010**, *86*, 423–443. [CrossRef]
37. Andreoni, J.; Vesterlund, L. Which is the Fair Sex? Gender Differences in Altruism. *Q. J. Econ.* **2001**, *116*, 293–312. [CrossRef]
38. Kamas, L.; Preston, A.; Baum, S. Altruism in individual and joint-giving decisions: What's gender got to do with it? *Fem. Econ.* **2008**, *14*, 23–50. [CrossRef]
39. Brañas-Garza, P.; Capraro, V.; Rascón-Ramírez, E. Gender differences in altruism on Mechanical Turk: Expectations and actual behaviour. *Econ. Lett.* **2018**, *170*, 19–23. [CrossRef]
40. Eras-Almeida, A.A.; Fernández, M.; Eisman, J.; Martín, J.G.; Caamaño, E.; Egido-Aguilera, M.A. Lessons Learned from Rural Electrification Experiences with Third Generation Solar Home Systems in Latin America: Case Studies in Peru, Mexico, and Bolivia. *Sustainability* **2019**, *11*, 7139. [CrossRef]
41. Sackey, C.V.-H.; Todd, L.; Destenie, N. Latent Demand for Electricity in Sub-Saharan Africa: A Review. *Environ. Res. Infrastruct. Sustain.* **2022**, *2*, 022002. [CrossRef]
42. Sackey, C.V.-H.; Nock, D. The need for agricultural productive uses in the national electrification plan of sub-Saharan African countries—A call to action for Ethiopia. *Environ. Res. Infrastruct. Sustain.* **2022**, *2*, 023001. [CrossRef]
43. Lewis, E.; Sophie, M.; Jaclyn, Y. Do Disability Inequalities Grow with Development? Evidence from 40 Coun-tries. *Sustainability* **2022**, *14*, 5110. [CrossRef]