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RESEARCH PAPER

An OOHB-DC Survey for Estimating Willingness to Pay of Residual Consumers to Avoid Power Outage by Using PSO

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Abstract
In the face of insufficient energy production in power systems, load shedding in residential areas has become unavoidable. This study evaluates the willingness to pay (WTP) among households in Kerman, Iran, to prevent power outages. A survey of 800 households was conducted in May 2021 using a one-and-one-half-bound dichotomous choice (OOHB-DC) approach, integrated with a spike model to address zero WTP responses. The questionnaire was designed to clearly communicate the study's purpose, ensuring meaningful responses. Particle swarm optimization (PSO) was employed to estimate model parameters. Findings indicate that the average monthly WTP per household is 92,886 Rials (USD 0.37), with an annual aggregate value of 972 billion Rials (USD 3.89 million). These results, which are statistically significant, suggest that substantial investments are needed by utility providers to maintain reliable power supply in residential areas.
Keywords: OOHB-DC Survey, Particle Swarm Optimization, Residual Consumers, Willingness to Pay.
JEL Classification: C51, G53, R21.

1. Introduction
Electricity is an essential component of modern life, underpinning critical services such as healthcare, transportation, and communication infrastructure. Power outages disrupt these services, affecting societal well-being. Due to limited energy generation, load shedding is often necessary to protect equipment and stabilize grid voltage. To minimize disruption, utility companies must prioritize outages for customers with lower willingness to pay (WTP), thereby reducing economic and

social impacts. Understanding consumer preferences and behaviors is therefore critical for effective power management.

Two primary methods for assessing WTP are the choice experiment (CE) and contingent valuation method (CVM). In CE, goods or services are defined by their attributes, and respondents rank or select preferred options, allowing WTP to be inferred indirectly (Speckemeier et al., 2021). Conversely, CVM simulates a hypothetical market where respondents state their maximum WTP for non-market goods under specific conditions. CVM approaches include iterative bidding (IB), payment card (PC), dichotomous choice (DC), and open-ended (OE) formats (Tian et al., 2011).

In IB, respondents are offered an initial bid, which is adjusted based on their responses until their WTP is determined (Randall et al., 1974). The PC method, introduced by Carson et al. (1984), asks respondents to select their maximum WTP from a list of values (Venkatachalam, 2004). OE formats allow respondents to freely state their WTP without guidance. DC methods include single-bounded (SB-DC), double-bounded (DB-DC), and one-and-one-half-bounded (OOHB-DC) approaches. SB-DC involves a simple yes/no response to a bid, while DB-DC uses two sequential questions to refine WTP estimates, yielding four outcomes. OOHB-DC, discussed later, generates six outcomes, offering a balance of simplicity and precision (Bateman et al., 2001; Cooper et al., 2002).

Despite their strengths, DC methods face challenges like starting point bias and inconsistency (Arrow et al., 1993). OOHB-DC mitigates some of these issues, making it a preferred choice, as endorsed by NOAA (Ready et al., 2001). Additionally, zero WTP responses can skew results, but the spike model, proposed by Kriström (1997), addresses this by incorporating zero responses into the likelihood function.

Prior research employing choice experiments (CE) has focused on ranking attributes to determine respondents' willingness to pay (WTP) for reliable electricity. For example, Hensher et al. (2014) explored household preferences for avoiding disruptions in residential power supply, using CE to identify preferences and estimate a mean WTP of USD 23 to prevent brief outages. Similarly, Morrissey et al. (2018) applied a CE approach to assess the economic impact of power cuts in northwest England, finding that households were willing to pay an average of £7.37 to avoid outages during weekdays. Carlsson and Martinsson (2008) conducted a CE survey among Swedish households, revealing that WTP for reducing outages increased with outage duration and were higher for disruptions during weekends or winter months, based on random parameter logit analysis.

In contrast, studies using contingent valuation methods (CVM) have directly estimated outage costs. Reichl et al. (2013) developed a CVM model to quantify economic losses from power interruptions, calculating an average value of lost load at €17.1 per kWh for Austrian households and non-households during a 1-hour outage on a summer workday morning. Woo et al. (2014) utilized a CVM survey with ordered logit analysis to assess residential outage costs in Hong Kong, estimating an average WTP of USD 45 for a 1-hour outage. Ozbafli and Jenkins (2015) investigated WTP for improved electricity services in North Cyprus, using payment ladder CVM data from 350 interviews, finding households willing to pay a 13.8% increase in their monthly electricity bill to avoid outages. Kim et al. (2017) surveyed 1,000 households in South Korea with a CVM approach, determining a mean monthly WTP of KRW 1,522 (USD 1.41) to prevent power interruptions.

A study involving 871 online participants in Vietnam was carried out from April to August 2022 to assess preferences using a cross-sectional approach. A questionnaire employing a discrete choice experiment (DCE) framework was created and distributed via snowball sampling, with data analyzed conjointly on the Qualtrics platform. The study explored factors such as prior COVID-19 infection and vaccination, health conditions, willingness to vaccinate, willingness to pay, and additional variables (Bach Xuan Tran, 2022).

This study employs a contingent valuation approach utilizing a one-and-one-half-bound dichotomous choice (OOHB-DC) survey, integrated with a spike model to address zero willingness-to-pay (WTP) responses. Additionally, we apply particle swarm optimization (PSO) as a novel technique for parameter estimation in this domain. To enhance the survey's validity, the questionnaire was designed to clearly explain power outage impacts and ensure respondents understood the context, making responses reliable and meaningful. A hypothetical payment scenario was created to elicit bids from participants. The OOHB-DC spike model was used to derive WTP values. Notably, due to the COVID-19 pandemic, interviews were conducted via telephone.

2. Methodology

As highlighted in prior research, the OOHB-DC format offers notable benefits for WTP estimation. This section outlines a method combining an OOHB-DC survey with a spike model to determine the average WTP among residential consumers.

2.1 DC Survey

The OOHB-DC approach, developed by Cooper et al. (2002), employs a questionnaire with two bids: a lower bid (B_L) and a higher bid (B_H). The interviewer randomly presents B_L first to half of the participants and B_H first to the other half. If a participant accepts B_L, B_H is then offered; if B_L is rejected, no further questions are posed. Similarly, if B_H is accepted when offered first, no additional questions follow, but if B_H is rejected, B_L is proposed. This format often results in numerous zero WTP responses. To address these, Kriström (1997) introduced the spike model for the OOHB-DC framework. In this model, participants who reject B_L or both B_H and B_L are asked if they are willing to pay any amount. A positive response indicates a WTP between zero and B_L, while a negative response signifies a zero WTP. Figure 1 illustrates the structure of the WTP elicitation questions for this method.

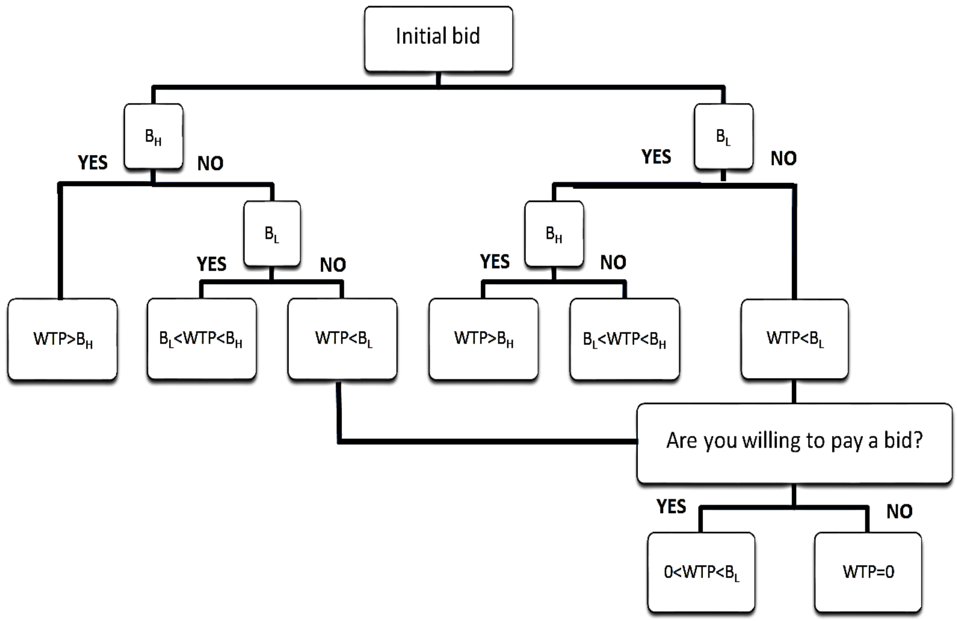

Figure1. The structure of OOHB-DC spike model to extract responder's WTP
Source: Research finding.

2.2 OOHB-DC Spike Model

Hanemann (1984) pioneered the utility difference model, offering a framework to develop Hicksian welfare measures for evaluating dichotomous survey responses and estimating willingness to pay (WTP). This model assumes that each respondent's discrete choice reflects a process of maximizing utility. In the context of power outages, individuals are willing to pay a bid to avoid disruptions if the utility derived from this payment exceeds the utility of experiencing an outage. The indirect utility function mathematically represents this concept as follows:

$V(Y, I-B; D) + \varepsilon_Y \geq V(N, I; D) + \varepsilon_N$

Or

$\Delta V = V(Y, I-B; D) - V(N, I; D) \geq \varepsilon_N - \varepsilon_Y$

In this model, "Y" denotes the state where a power outage occurs, while "N" indicates no outage. The indirect utility function is represented by "V", with "I" signifying household income, "D" capturing socio-demographic characteristics, and "B" representing the proposed bid. The terms "ε_Y" and "ε_N" denote error components. A positive ΔV indicates that respondents will answer "yes" to the bid, leading to the following relationship:

$Pr("Yes") = Pr(WTP \geq B) = 1 - G_{WTP}(B, \theta)$

Here, WTP represents the customer's willingness to pay, while $G_{WTP}(B, \theta)$ denotes the cumulative distribution function of respondents at bid B. Additionally, θ is a parameter vector capturing socio-economic characteristics that influence the likelihood of responding "yes" to a proposed bid.

In the OOHB-DC Spike model, the initial questionnaire is crafted from a pilot survey with a small group of participants, establishing bid intervals as (B_{H1}, B_{L1}), (B_{H2}, B_{L2}), ..., (B_{Hn}, B_{Ln}), where n denotes the number of intervals. These intervals are then evenly applied across the sample population, with an equal number of respondents first presented with either B_L or B_H bids. The interviewer proposes the bid, and the participant responds "yes" if willing to pay or "no" if unwilling.

As noted, the OOHB-DC spike model's elicitation process generates eight possible response combinations. When the lower bid (B_L) is offered first, respondents may answer "yes-yes," "yes-no," or "no." Conversely, when the higher bid (B_H) is presented initially, the responses can be "yes," "no-yes," or "no-no." Per the spike model, if a respondent answers "no-no" to B_H or "no" to B_L, they are asked an additional question about their willingness to pay any amount. A "yes" response indicates a positive WTP less than B_L, while a "no" response signifies a WTP of zero. So we have $I_i^{YY}, I_i^{YN}, I_i^{Y}, I_i^{N}, I_i^{NY}, I_i^{NN}, I_i^{TY}$ and I_i^{TN} as follow:

$I_i^{YY} = 1$ (ith interviewee's answer is "yes-yes")

$I_i^{YN} = 1$(ith interviewee's answer is "yes-no")

$I_i^Y = 1$(ith interviewee's answer is "yes")

$I_i^N = 1$(ith interviewee's answer is "no")

$I_i^{NY} = 1$(ith interviewee's answer is "no-yes")

$I_i^{NN} = 1$(ith interviewee's answer is "no-no")

$I_i^{TY} = 1$(ith interviewee's answer to additional question is "yes")

$I_i^{TN} = 1$(ith interviewee's answer to additional question is "no")

Here, "I" denotes the respondent index, and 1(.) represents an indicator function, which takes the value 1 if its condition is true and 0 otherwise. As previously noted, each individual's observed response is assumed to reflect a utility maximization process. To estimate the parameter vector θ, the logarithmic likelihood function is maximized. The log-likelihood function for the OOHB-DC spike model is formulated as follows:

$$ln(L) = \sum_{i=1}^{R}[(I_i^{YY} + I_i^{Y}) \times ln(1 - G_{WTP}(B_H, \theta)) + (I_i^{YN} + I_i^{NY}) \times ln(G_{WTP}(B_H, \theta) - G_{WTP}(B_L, \theta)) + I_i^{TY}(I_i^{NN} + I_i^{N}) \times ln(G_{WTP}(B_L, \theta) - G_{WTP}(0, \theta)) + I_i^{TN}(I_i^{NN} + I_i^{N}) \times ln(G_{WTP}(0, \theta))]$$

Kriström (1997) have showed assuming $\theta = (\theta_0, \theta_1)$ yields:

$$G_{WTP}(B, \theta) = \begin{cases} (1 + e^{-(\theta_0 + \theta_1 B})^{-1} & ; \quad B > 0 \\ (1 + e^{-(\theta_0})^{-1} & ; \quad B = 0 \\ 0 & ; \quad B < 0 \end{cases}$$

According to this equation the spike is defined by $(1 + e^{-(\theta_0})^{-1}$ and the mean WTP in the spike model is defined as follows:

$$C^{+} = (1/\theta_1) \times Ln(1 + \exp(\theta_0))$$

In order to analyze the effect of respondent's attitudes or socio-economic characteristics on the probability of answering "yes" to a given bid, it is necessary to include covariates in the model. If the covariates are considered, "θ_0" is replaced by "$\theta_0 + x_i^{'}\theta$", where "x_i'" is the vector of respondent's characteristics and "θ" is the parameter vector to be estimated.

2.3 Maximizing Log-Likelihood Spike Model

This study utilizes particle swarm optimization (PSO) to maximize the log-likelihood function of the OOHB-DC spike model. Introduced by Eberhart and Kennedy in 1995, PSO is a population-based stochastic search method operating in a multidimensional space. In this algorithm, each particle is assigned a fitness value determined by an objective function, with higher values indicating proximity to the target in the search space. Particles possess velocities that guide their movement, navigating the problem space by tracking the current optimal particles. The position and velocity of each particle in the subsequent iteration are updated based on the best particle location and the leader's position, as described by the following equations:

$$v(t+1) = v(t) + C_1 * rand(t) * \big(Pbest(t) - pos(t)\big) + C_2 * rand(t) * \big(Lpos(t) - pos(t)\big) \qquad pos(t+1) = pos(t) + v(t+1)$$

In the described algorithm, the current and subsequent positions of a particle are denoted by "t" and "t+1," respectively. The particle's velocity is represented by "v", and its position by "pos." The parameters "C_1" and "C_2" are fixed coefficients, while "rand" denotes a randomly generated vector applied in each iteration. The terms "Pbest" and "Lpos" refer to the particle's optimal historical position and the leader's position, respectively. If the updated objective function value surpasses the previous one, the particle relocates to the new position; otherwise, it remains stationary. The algorithm then proceeds to the next iteration, recalculating objective functions, and continues this cycle. For the maximization task, the input vector "θ" serves as the parameter set, with the log-likelihood of the OOHB-DC spike model acting as the objective function to be optimized.

2.4 Questionnaire Design

In the contingent valuation study, individuals were asked to imagine power outages occurring in different seasons and express their highest WTP to prevent them. The survey was organized into three distinct segments. The first segment introduced participants to the study's focus and objectives. The second segment collected demographic data, such as age, income, gender, education, and related personal details. The third segment included questions aimed at gathering WTP responses. The study utilized household electricity bills as the payment mechanism, chosen for its familiarity and direct relevance to the research topic. After drafting the survey and consulting with experts, a preliminary test was conducted one-on-one with researchers. This pre-test helped determine appropriate bid ranges and quantities through open-ended inquiries. Furthermore, the pre-test ensured that questions were straightforward, easily understood, and effectively elicited the required data (Brown et al., 2003).

3. Results and Discussion

The results of the study stem from analyzing 800 telephone interviews conducted in Kerman, Iran. Data collection occurred in May 2021, with telephone interviews chosen due to the ongoing COVID-19 pandemic. As previously noted, the pre-test with a focus group established the minimum and maximum bid values for the OOHB-DC survey. The bid sets applied in this research were determined based on these pre-test outcomes.

(50000;150000), (100000;200000), (150000;250000), (200000;300000), (250000;350000), (300000;400000), (350000;450000), (400000;500000), (450000;550000) and (500000;600000).

It is worth mentioning the exchange rate When the survey was implemented was USD 1 = Rials 250000.

Table 1 presents the responses to the WTP questions from the survey. Notably, 45% of participants indicated a WTP of zero. The data reveal that the proportion of “yes” responses to the proposed bid amounts generally declines as the bid value rises. For instance, as “Yes” or “Yes-Yes” responses reflect a preference for paying a higher bid, 14 participants (17%) were willing to pay more than 15,000 Rials, whereas only 3 participants (4%) were willing to pay above 45,000 Rials.

3.1 Estimation Results

Table 2 displays the outcomes of the OOHB-DC spike model estimation. The bid price coefficient is statistically significant at the 1% level and exhibits a negative value, suggesting that higher bid amounts reduce the likelihood of a “yes” response. According to Table 2, the estimated monthly household WTP to prevent power outages is 92,886 Rials (approximately USD 0.37), which is statistically significant. The p-value in this table tests the null hypothesis that all parameters are collectively zero.

Table 1. Responder's WTP to Suggested Bids

Bid amount		Higher bid is suggested first				Lower bid is suggested first				Sample size
		Yes	No Yes	No No-Yes	No No-No	Yes No	Yes Yes	No No	No Yes	
50000	150000	6 (8%)	18 (22%)	8 (10%)	8 (10%)	11 (14%)	8 (10%)	13 (16%)	8 (10%)	80 (100%)
100000	200000	3 (4%)	11 (14%)	12 (15%)	14 (17%)	13 (16%)	8 (10%)	11 (14%)	8 (10%)	80 (100%)
150000	250000	2 (3%)	10 (13%)	15 (18%)	13 (16%)	5 (6%)	6 (8%)	17 (21%)	12 (15%)	80 (100%)
200000	300000	3 (4%)	11 (14%)	16 (20%)	10 (13%)	6 (8%)	4 (5%)	21 (25%)	9 (11%)	80 (100%)
250000	350000	1 (1%)	6 (8%)	13 (16%)	20 (25%)	7 (9%)	4 (5%)	19 (23%)	10 (13%)	80 (100%)
300000	400000	2 (3%)	6 (8%)	11 (13%)	21 (25%)	3 (4%)	4 (5%)	18 (23%)	15 (19%)	80 (100%)
350000	450000	1 (1%)	1 (1%)	17 (21%)	21 (26%)	1 (1%)	2 (3%)	24 (31%)	13 (16%)	80 (100%)
400000	500000	0 (0%)	1 (1%)	19 (24%)	20 (25%)	1 (1%)	0 (0%)	26 (33%)	13 (16%)	80 (100%)
450000	550000	0 (0%)	0 (0%)	18 (23%)	22 (27%)	0 (0%)	0 (0%)	28 (35%)	12 (15%)	80 (100%)
500000	600000	0 (0%)	0 (0%)	26 (32%)	14 (18%)	1 (1%)	0 (0%)	21 (26%)	18 (23%)	80 (100%)
Total		18 (2%)	64 (8%)	155 (17%)	163 (23%)	48 (6%)	36 (5%)	198 (24%)	118 (15%)	800 (100%)

Source: Research finding.
Note: * The unit is Rials. ** The numbers in parentheses beside the number of responses are the percentage of sample size.

Table 2. Estimation Results of the Spike Model

Variables	**Coefficient Estimation (t-value)**
Constant	0.008 (-8.45)
Bid amount	-76.37 (-86.13)
Spike	0.99
Mean WTP	92886 Rials
95% confidence interval	81644 to 104127 Rials
99% confidence interval	80128 to 105643 Rials
Log-likelihood	-15237.26
Wald statistics (p-value)	341.12 (0.000)
Number of observations	800

Source: Research finding.

Table 3. Definitions and Sample Statistics of the Variables

Variables	Definitions	Mean	Standard Deviation
AGE	Dummy for the average of family age being larger than forty. (1 = Yes; 0 = No)	0.37	0.512
INCOME	Interviewee's households' income per month (unit: million Rials)	60.3	1.84
HOUSE SIZE	Dummy for the interviewee's house size being bigger than 200 m^2 (1 = yes ; 0 = no)	0.72	0.48
FAMILY SIZE	Number of the interviewee's family members	3.56	1.23
EDUCATION	Dummy for average educational level of the family in years being larger than twelve (1 = Yes; 0 = No)	0.58	0.53
OUTAGE EXPERIENCE	Dummy for the interviewee's having experienced power outages (1 = yes ; 0 = no)	0.34	0.49
DAMAGE AWARENESS	Degree of the interviewee's awareness of the damage caused by power outages (from 1 to3)	1.62	0.76

Source: Research finding.

Table 4. Estimation Results of the Spike Model with Covariates

Variables	Coefficient Estimation (t-value)
Constant	-0.004 (-4.25)
Bid amount	-43.56 (-21.5)
Spike	0.85
Age	-0.0013
Income	0.145 *
House size	-0.253 *
Family size	0.057
Education	0.024 *
Outage experience	0.126
Damage awareness	0.281 *
Log-likelihood	-13568.32
Wald statistics (p-value)	326.56 (0.000)
Number of observations	800

Source: Research finding.

Note: * denotes statistical significance at the 5% level.

In Kerman, the average monthly electricity bill for households was 1,120,650 Rials (approximately USD 4.48). Consequently, the mean WTP represents 8.2% of this monthly bill. To account for uncertainty in estimating the average WTP, confidence intervals (CIs) were employed instead of point estimates. As noted, the theoretical validity of contingent valuation models can be assessed by incorporating covariates into the estimation. Table 2 outlines the definitions and descriptive statistics of the variables included in this study, which comprise the dummy variables AGE, INCOME, HOUSE SIZE, FAMILY SIZE, EDUCATION, OUTAGE EXPERIENCE, and DAMAGE AWARENESS.

Table 4 presents the outcomes of the model estimation incorporating covariates. A positive (or negative) coefficient for a given variable indicates that higher values of that variable increase (or decrease) the likelihood of a “yes” response to the proposed bid amount. For instance, greater awareness of the damages resulting from power outages positively influences the acceptance of the bid price. Additionally, the coefficient signs reveal that individuals with larger families, higher educational attainment, greater household income, or prior experience with outages are more inclined to agree to a specific bid. Conversely, those residing in larger homes are less likely to accept the bid, likely due to their already substantial electricity expenses.

The estimation results in Table 4 reveal that the coefficients for INCOME, HOUSE SIZE, EDUCATION, and DAMAGE AWARENESS are statistically significant at the 5% level, indicating their influence on the probability of agreeing to the proposed bid. In contrast, the coefficients for AGE, FAMILY SIZE, and OUTAGE EXPERIENCE are not statistically significant, suggesting these factors do not substantially affect the likelihood of a “yes” response to the bid. In 2021, Kerman was home to an estimated 872,359 households. Multiplying this number by the average monthly WTP per household (92,886 Rials, as noted earlier) and extending it over 12 months yields an annual WTP of approximately 972 billion Rials (equivalent to USD 3.89 million). This figure represents the yearly economic value of preventing power outages in Kerman’s residential sector. It should be noted that differences in study objectives, methods, and regional contexts complicate direct comparisons with other research. Nonetheless, the findings of this study appear generally consistent with earlier work. For example, Ozbafli and Jenkins (2015) found that the average household WTP to avoid power outages was 13.8% of their monthly electricity bill, a result that aligns closely with the present study’s outcomes.

4. Conclusion

Power outages, though unavoidable, impact various sectors reliant on electricity. This study explored households' WTP to avoid such disruptions. The contingent valuation (CV) approach, commonly used for valuing non-market goods, was employed. Among CV techniques, the OOHB-DC method, known for its statistical efficiency, was selected and paired with a spike model to address zero WTP responses. The survey, conducted in May 2021, involved 800 participants in Kerman, Iran. Findings indicate that 45% of respondents expressed no WTP. The OOHB-DC spike model estimated a mean monthly WTP of 92,886 Rials (approximately USD 0.37) per household, equivalent to 8.2% of the average monthly electricity bill. Based on this, the total annual WTP for Kerman's households in 2021 was calculated at 972 billion Rials (roughly USD 3.89 million). Additionally, socioeconomic covariates were integrated into the model to examine their influence on WTP responses.

Statements and Declarations

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- Conflict of interest: The authors declare that there is no conflict of interest.

References

Arrow, K., Solow, R., Portney, P. R., Leamer, E. E., Radner, R., & Schuman, H. (1993). Report of the NOAA Panel on Contingent Valuation. *Federal Register*, *58*(10), 4601-4614. Retrieved from https://repository.library.noaa.gov/view/noaa/60900

Bateman, I. J., Langford, I. H., Jones, A. P., & Kerr, G. N. (2001). Bound and Path Effects in Double and Triple Bounded Dichotomous Choice Contingent Valuation. *Resource and Energy Economics*, *23*(3), 191-213. Retrieved from https://www.sciencedirect.com/science/article/pii/S0928765500000440

Carlsson, F., & Martinsson, P. (2009). Does it Matter When a Power Outage Occurs? A Choice Experiment Study on the Willingness to Pay to Avoid Power Outages. *Working Papers in Economics, 155*. Retrieved from https://gupea.ub.gu.se/bitstream/handle/2077/19627/gupea_2077_19627_1.pdf?sequence=1

Carson, R. T., Flores, N. E., & Mitchell, R. C. (1999). The Theory and Measurement of Passive-Use Value. Valuing Environmental Preferences: Theory and Practice of the Contingent Valuation Method in the US, EU, and Developing Countries, Retrieved from https://www.researchgate.net/

Cooper, J. C., Hanemann, W. M., & Signorello, G. (2001). One-and-one-half Bound Dichotomous Choice Contingent Valuation. Retrieved from https://escholarship.org/content/qt09c663b2/qt09c663b2.pdf

De Villiers, C., Cho, C. H., Turner, M. J., & Scarpa, R. (2023). Are Shareholders Willing to Pay for Financial, Social and Environmental Disclosure? A Choice-Based Experiment. *European Accounting Review*, *32*(1), 1-28. Retrieved from https://repository.up.ac.za/bitstreams/597c2234-7e1a-4196-9b4c-afe180ae99c5/download

Eberhart, R., & Kennedy, J. (1995). Particle Swarm Optimization. *Proceedings of the IEEE International Conference on Neural Networks* (4, 1942-1948). Retrieved from https://pdfs.semanticscholar.org/5694/91ee9dfe5e0752d4890421d611c296fcaf91.pdf

Galati, A., Migliore, G., Thrassou, A., Schifani, G., Rizzo, G., Adamashvili, N., & Crescimanno, M. (2023). Consumers' Willingness to Pay for Agri-Food Products Delivered With Electric Vehicles in the Short Supply Chains. *FIIB Business Review*, *12*(2), 193-207. Retrieved from https://journals.sagepub.com/doi/pdf/10.1177/23197145221112743

Gomes, S., Lopes, J. M., & Nogueira, S. (2023). Willingness to Pay More for Green Products: A Critical Challenge for Gen Z. *Journal of Cleaner Production*, *390*, 136092. Retrieved from https://www.sciencedirect.com/science/article/pii/S0959652623002500

Hanemann, W. M. (1984). Welfare Evaluations in Contingent Valuation Experiments with Discrete Responses. *American Journal of Agricultural Economics*, *66*(3), 332-341. Retrieved from https://www.jstor.org/stable/pdf/1240800.pdf

Hensher, D. A., Shore, N., & Train, K. (2014). Willingness to Pay for Residential Electricity Supply Quality and Reliability. *Applied Energy*, *115*, 280-292. Retrieved from https://www.sciencedirect.com/science/article/pii/S0306261913009008

Hu, W. (2006). Comparing Consumers' Preferences and Willingness to Pay for Non-GM Oil Using a Contingent Valuation Approach. *Empirical Economics*, *31*(1), 143-150. Retrieved from https://link.springer.com/article/10.1007/s00181-005-0027-4

Liu, X., He, J., Xiong, K., Liu, S., & He, B. J. (2023). Identification of Factors Affecting Public Willingness to Pay for Heat Mitigation and Adaptation: Evidence from Guangzhou, China. *Urban Climate*, *48*, 101405. Retrieved from https://www.sciencedirect.com/science/article/pii/S2212095522003236

Kim, K., & Cho, Y. (2017). Estimation of Power Outage Costs in the Industrial Sector of South Korea. *Energy Policy*, *101*, 236-245. Retrieved from https://www.academia.edu/download/97183160/150056.pdf

Kriström, B. (1997). Spike Models in Contingent Valuation. *American Journal of Agricultural Economics*, *79*(3), 1013-1023. Retrieved from https://onlinelibrary.wiley.com/doi/pdf/10.2307/1244440

McFadden, D. (1994). Contingent Valuation and Social Choice. *American Journal of Agricultural Economics*, *76*(4), 689-708. Retrieved from https://www.jstor.org/stable/pdf/1243732.pdf

Morrissey, K., Plater, A., & Dean, M. (2018). The Cost of Electric Power Outages in the Residential Sector: A Willingness to Pay Approach. *Applied Energy*, *212*, 141-150. Retrieved from https://drive.google.com/file/d/1GuJsWjf2O6bewhNXmVJB3oXbm0QUev-s/view

Ozbafli, A., & Jenkins, G. P. (2015). The Willingness to Pay by Households for Improved Reliability of Electricity Service in North Cyprus. *Energy Policy*, *87*, 359-369. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421515301002

Randall, A., Ives, B., & Eastman, C. (1974). Bidding Games for Valuation of Aesthetic Environmental Improvements. *Journal of Environmental Economics and Management*, *1*(2), 132-149. Retrieved from https://www.academia.edu/download/50339051/sdarticle.pdf

Ready, R. C., Buzby, J. C., & Hu, D. (1996). Differences between Continuous and Discrete Contingent Value Estimates. *Land Economics*, 397-411. Retrieved from https://www.jstor.org/stable/pdf/3147205

Reichl, J., Schmidthaler, M., & Schneider, F. (2013). The Value of Supply Security: The Costs of Power Outages to Austrian Households, Firms and the Public Sector. *Energy Economics*, *36*, 256-261. Retrieved from https://www.sciencedirect.com/science/article/pii/S0140988312002149

Speckemeier, C., Krabbe, L., Schwenke, S., Wasem, J., Buchberger, B., & Neusser, S. (2021). Discrete Choice Experiment to Determine Preferences of Decision-Makers in Healthcare for Different Formats of Rapid Reviews. *Systematic Reviews*, *10*, 1-8. Retrieved from https://link.springer.com/content/pdf/10.1186/s13643-021-01647-z.pdf

Tian, X., Yu, X., & Holst, R. (2011). Applying the Payment Card Approach to Estimate the WTP for Green Food in China. Retrieved from https://www.econstor.eu/bitstream/10419/50786/1/670816833.pdf

Tran, B. X., Do, A. L., Boyer, L., Auquier, P., Le, H. T., Le Vu, M. N., Dang, T. H. T., Cao, K. M., Le, L. D. T., Cu, L. T. N., Ly, B. V., Nguyen, D. A. T., Nguyen, M. D., Latkin, C. A., Ho, R. C. M., Ho, C. S. H., & Zhang, M. W. (2023). Preference and Willingness to Pay for the Regular COVID-19 Booster Shot in the Vietnamese Population: Theory-Driven Discrete Choice Experiment. *JMIR Public Health and Surveillance*, *9*(1), e43055. Retrieved from https://publichealth.jmir.org/2023/1/e43055/

Venkatachalam, L. (2004). The Contingent Valuation Method: A Review. *Environmental Impact Assessment Review*, *24*(1), 89-124. Retrieved from https://www.sciencedirect.com/science/article/pii/S0195925503001380

Woo, C. K., Ho, T., Shiu, A., Cheng, Y. S., Horowitz, I., & Wang, J. (2014). Residential Outage Cost Estimation: Hong Kong. *Energy Policy*, *72*, 204-210. Retrieved from https://www.sciencedirect.com/science/article/pii/S0301421514002791

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