Consumer Valuation of Poultry Stunning Methods: An Experimental Analysis of Willingness to Pay

by

Foster McCurry

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Approved by

Samir Huseynov, Chair, Assistant Professor of Agricultural Economics
Joel Cuffey, Associate Professor of Agricultural Economics
Sunjae Won, Assistant Professor of Agricultural Economics
Dennis Brothers, Associate Extension Professor of Agricultural Economics

Abstract

Animal welfare concerns have become increasingly important within food markets, yet relatively little research has examined consumer preferences for poultry stunning methods. This study investigates consumer willingness to pay (WTP) for chicken products produced using electrical stunning (ES) and controlled-atmosphere gas stunning (GS), while examining the effects of information provision, presentation order, consumer attitudes, and biometric responses on valuation behavior. The data was collected from 152 participants through an in-person experimental survey conducted at Auburn University. Respondents first reported a baseline willingness to pay for a typical two-pound package of chicken breast and were subsequently asked to evaluate products produced using alternative stunning methods. Participants were randomly assigned to either a brief or detailed information treatment and to one of two presentation orders. Throughout the experiment, eye-tracking, blink-rate, and facial-expression data were collected to measure visual attention, cognitive engagement, and emotional responses during decision-making. Consumer attitudes toward animal welfare and health concerns were measured using Likert-scale survey items and analyzed using exploratory factor analysis and Gaussian mixture clustering. Results identified three distinct consumer segments: Skeptics, Moderate Supporters, and Strong Advocates. Regression analysis revealed that attitudinal differences were among the strongest predictors of willingness-to-pay outcomes. Strong Advocates consistently reported higher premiums for electrically stunned products relative to Skeptics, while willingness-to-pay for gas-stunned products was more sensitive to interactions between consumer attitudes and experimental conditions. Information treatments alone produced

limited effects on valuation behavior. Presentation order emerged as one of the most consistent findings, with respondents tending to place greater value on the stunning method presented first. In contrast, biometric measures of attention, cognitive load, and emotional response provided limited explanatory power for willingness-to-pay outcomes. Overall, the results suggest that consumer preferences for poultry stunning methods are driven primarily by underlying attitudes toward animal welfare and health-related production attributes rather than by additional information or biometric indicators of engagement. These findings contribute to the growing literature on animal welfare valuation and provide insights for producers, processors, and policymakers considering investments in alternative poultry stunning technologies.

Artificial Intelligence (AI) Use Disclosure Statement

In the preparation of this thesis, the following Artificial Intelligence (AI) tools were used: ChatGPT (OpenAI), Elicit, and Grammarly. These tools were used primarily to assist with literature organization, citation verification, editing, proofreading, grammar correction, formatting suggestions, and improving clarity of written text. The author acknowledges full responsibility for the intellectual content of this work and has ensured that all AI-assisted sections have been reviewed and revised for accuracy and appropriate academic style. All AI-generated content was reviewed and validated for relevance, appropriateness, and accuracy before incorporation into the final document to maintain the scholarly integrity of this research.

Digital Accessibility Use Disclosure Statement

In the preparation of this thesis, Microsoft Word Accessibility Checker was used to help ensure that this document complies with applicable digital accessibility requirements. The author acknowledges full responsibility for the intellectual content of this work and has made a good faith effort to comply with digital accessibility requirements in publishing, wherein the nature of the content does not significantly change in order to do so. Furthermore, all content has been reviewed and revised to meet these requirements prior to final publication.

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List of Abbreviations

WTP	Willingness to pay
ES	Electric Stunning
GS	Gas Stunning
USDA	United States Department of Agriculture

Chapter 1. Introduction

Animal welfare concerns are increasingly receiving attention within the United States meat sector among consumers, policymakers, and industry stakeholders. In the United States, the poultry industry produces approximately 8.8 billion chickens annually, making it the largest meat sector in the food system (U.S. Department of Agriculture, 2025) Further, in 2024 total poultry sector sales were $70.2 billion, with broilers accounting for the majority of poultry sector value at $45.4 billion (U.S. Department of Agriculture, 2025). Consequently, even marginal changes in production practices have the potential to affect the welfare of billions of animals and generate substantial economic impacts throughout the supply chain.

Stunning methods are an often-overlooked area of animal welfare concerns. Stunning is the practice of rendering an animal unconscious before slaughter to reduce unnecessary harm. In the poultry industry, the conventional method for stunning is electric water bath stunning. With this method the live chickens are secured by their feet onto a conveyor belt that moves them through a water bath which has a controlled electrical current running through it. While this method is popular due to its efficiency and scalability, it may raise concerns from a welfare perspective (Berg and Raj 2015). A less common stunning approach is controlled atmosphere-gas stunning. This method allows the chickens to remain in transport containers that are placed on a conveyor belt, which takes the chickens into a room with a controlled mixture of gases, namely carbon dioxide, until they lose consciousness. This may be a more animal welfare-friendly option as it reduces the need for live shackling and generally yields more consistent results (Shields and Raj 2010).

The importance of these concerns is reflected in federal humane-handling guidelines. The USDA identifies both “stunning of animals and then allowing them to regain consciousness” and “otherwise causing unnecessary pain and suffering to animals” as egregious welfare violations (U.S. Department of Agriculture, 2021). Despite potential welfare benefits, adoption of controlled-atmosphere stunning systems requires substantial capital investment by poultry processors. Whether such investments are economically viable depends in part on whether consumers value welfare improvements and are willing to pay premiums for products produced under alternative stunning systems. While a growing literature demonstrates consumer concern for animal welfare, relatively little research has examined consumer valuation of poultry stunning methods specifically. Moreover, because stunning methods are largely invisible to consumers, willingness-to-pay responses may depend heavily on the information available at the time preferences are elicited.

This study investigates consumer willingness to pay (WTP) for chicken products produced using electrical stunning (ES) and gas stunning (GS). In addition to measuring consumer valuations for each stunning method, the study examines whether willingness to pay is influenced by information exposure, presentation order, and underlying consumer attitudes toward animal welfare and food-related health concerns. To address these questions, respondents participated in an in-person experimental survey in which they first reported their baseline willingness to pay for chicken products and subsequently evaluated products produced under alternative stunning methods. The remainder of this thesis is organized as follows. Chapter 2 provides a comprehensive review of relevant literature. Chapter 3 describes the experimental design and data

collection procedures. Chapter 4 presents the empirical framework and results. Chapter 5 discusses the findings of the experiment.

Chapter 2. Literature Review

2.1 Consumer Attitudes Toward Animal Welfare

Animal welfare has become an increasingly important consideration in food purchasing decisions. Historically, food demand has been driven by quality, taste, freshness, and health (Grunert 2006; Verbeke and Viaene 1999). However, as consumers have become disconnected from the systems in which their food is produced, ethical concerns have become an increasingly important factor in purchasing decisions. Numerous studies find that consumers express concern regarding housing conditions, transportation practices, handling procedures, and slaughter methods (Harper & Henson, 2001; McKendree et al. 2014; Verbeke 2009). These concerns have influenced both private and public responses to animal welfare issues. Food retailers have adopted animal welfare sourcing commitments, certification programs have expanded, and producers have altered production practices to address consumer expectations (Norwood & Lusk, 2011; McKendree et al., 2013). With that, animal welfare has evolved from a niche concern into an important component of product differentiation.

Despite widespread concern for animal welfare, consumers often possess limited knowledge regarding modern production practices (Harper & Henson, 2001; Verbeke, 2009). As a result, perceptions of animal welfare may differ substantially from actual production conditions. Nevertheless, previous research consistently finds that many consumers place value on production systems that are perceived to improve animal well-being (Lusk et al., 2006; Olynk et al., 2010).

2.2 Willingness to Pay for Animal Welfare Attributes

The current literature consists of many examinations of consumer willingness to pay for animal welfare attributes. Specifically, previous studies suggest positive valuations for cage-free eggs/chicken products, free-range poultry systems, and welfare-certified products (Olynk et al., 2010; Lusk et al., 2006; Norwood & Lusk, 2011). Similar findings have been found across multiple sectors including beef, pork, and poultry where consumers generally express increased willingness to pay for products produced with higher ethical standards. However, willingness-to-pay estimates vary across studies and consumer populations. Some consumers appear willing to pay significant premiums for welfare improvements (Lusk et al., 2006; Norwood & Lusk, 2011). Others exhibit little willingness to pay even when they express concern regarding animal welfare issues (Harper & Henson, 2001; Verbeke, 2009). This discrepancy between stated concern and purchasing behavior is often referred to as the animal welfare attitude-behavior gap (de Barcellos et al., 2011; Verbeke, 2009). Consequently, researchers recognize that consumer preferences for animal welfare attributes are highly heterogeneous.

2.3 Information, Labeling, and Credence Attributes

Animal welfare functions as a credence attribute which may explain heterogeneity in consumer responses (Darby & Karni, 1973). Most product characteristics can be directly verified by consumers with things such as appearance, size, or freshness. However, consumers generally cannot directly verify the conditions under which their food is produced. They instead must rely on information, labels, and certifications to make decisions on welfare-related attributes. The literature suggests that information plays a critical role in markets characterized by credence attributes

(Darby & Karni, 1973; Caswell & Mojduszka, 1996). Many studies demonstrate that information provision can influence consumers' perceptions of food products (Verbeke, 2005; Grunert, 2006; Lusk et al., 2006). Research examining animal welfare labels finds that information regarding production practices often increases consumer awareness and may influence purchasing decisions (McKendree et al., 2013; Tonsor et al., 2009). Similarly, studies investigating food labeling and certification programs suggest that communication strategies and framing effects can affect willingness-to-pay responses for credence attributes (Lusk et al., 2006). At the same time, the effects of information are not always uniform across consumers. Some individuals respond strongly to additional information, while others exhibit little change in preferences (Harper & Henson, 2001; Verbeke, 2009). These findings suggest that information effects may depend on preexisting attitudes, knowledge, and beliefs regarding animal welfare.

2.4 Biometric Approaches to Consumer Decision-Making

Traditional consumer research relies heavily on stated-preference surveys and choice experiments to evaluate consumer preferences. These methods provide valuable information regarding purchasing behavior. However, they may not fully capture the cognitive processes controlling decision-making (Duchowski, 2017; Orquin & Mueller Loose, 2013). Biometric measures are increasingly used as a complement to conventional survey methods (Orquin & Mueller Loose, 2013; Wedel & Pieters, 2007). In particular, eye-tracking technology has become increasingly common in consumer research because it provides objective measures of visual attention and information processing. Metrics such as fixation duration, fixation counts, and gaze patterns are frequently used to identify which information consumers respond strongly to during

decision-making procedures (Duchowski, 2017; Orquin & Mueller Loose, 2013).

Research has applied eye-tracking methods to a variety of food-related decisions, including nutritional labeling, product packaging, sustainability claims, and food safety information (van Herpen & van Trijp, 2011; Orquin & Mueller Loose, 2013). These studies generally find that visual attention influences information processing and subsequent choice behavior. Researchers have also utilized blink activity as an indicator of cognitive workload and mental effort during decision-making tasks (Siegle et al., 2008). Similarly, facial-expression analysis has been used to investigate emotional responses to advertisements, products, and food-related information (Grafsgaard et al., 2013). These approaches provide additional insight into the mechanisms underlying consumer behavior by capturing reactions that may not be fully reflected in stated-preference responses. Although biometric methods have become increasingly common in food and consumer research, relatively little work has applied these techniques to the evaluation of animal welfare-related production practices.

2.5 Poultry Stunning Methods and Research Gap

Stunning methods have received relatively little attention in consumer willingness to pay research compared to other animal welfare attributes. This is noteworthy as stunning is one of the final processes before slaughter that directly affects welfare outcomes. The most common methods for stunning in the United States poultry production are electrical water-bath stunning and controlled-atmosphere gas stunning. Electric stunning remains the dominant approach due to its efficiency, which lends well to large-scale production systems, as is common in the industry. However, animal welfare researchers have identified several potential welfare concerns associated with

electrical water-bath stunning, including stress associated with live shackling, variation in electrical contact, ineffective stunning, and the possibility of birds regaining consciousness before slaughter (Shields & Raj, 2010; Berg & Raj, 2015).

Chapter 3. Experimental Design

We collected data from an in-person experimental survey conducted at Auburn University's Center for Advanced Science, Innovation, and Commerce (CASIC) between May 27, 2025, and July 4, 2025. Participants required approximately seven minutes on average to complete the experiment and were compensated with $15 upon completion. A total of 152 respondents were recruited via email to complete the survey. Eligibility requirements included being at least 18 years of age, serving as the primary grocery shopper for their household, and consuming chicken products at least once per week. It was important to include only participants who regularly purchase chicken products because these individuals are more likely to possess established purchasing habits and prior experience evaluating poultry products in retail settings (Tonsor et al., 2009; Olynk et al., 2010). Restricting participation to primary household grocery shoppers further ensures that respondents routinely make food purchasing decisions like those simulated in the experiment. Consequently, the sample consists of consumers who are familiar with the types of tradeoffs and product evaluations examined in the valuation tasks (McKendree et al., 2013; Tonsor et al., 2009).

The target population consisted of Auburn University employees and members of the surrounding community. Because recruitment relied on voluntary participation through university-affiliated channels, the resulting sample should be interpreted as a convenience sample rather than a nationally representative sample of U.S. consumers. Consequently, the results should be viewed as evidence regarding consumer preferences within the sampled population rather than as nationally representative estimates. The study was approved by the Auburn University Institutional Review Board

(IRB Protocol STUDY00000569).

Upon arrival for their experimental sessions, respondents reviewed an informed consent document and provided consent before beginning the study. Participants then completed the survey using a computer workstation equipped with eye-tracking and facial-expression analysis software. Throughout the information and valuation stages of the experiment, biometric software continuously recorded respondents' eye movements, blink behavior, and facial expressions. After providing informed consent, respondents first reported their baseline willingness to pay for a typical package of chicken breast. Participants were then randomly assigned to one of two information treatments and subsequently evaluated two poultry stunning methods.

To account for potential presentation-order effects, the sequence in which the stunning methods were evaluated was randomized across respondents. Following the valuation tasks, participants completed an attitude survey and demographic questionnaire. The experiment was designed to collect both stated-preference responses and biometric measures of consumer decision-making. While willingness-to-pay responses provide direct evidence regarding consumer preferences, biometric measures offer additional information regarding the cognitive and emotional processes that occur while consumers evaluate information about poultry production practices.

Before evaluating either stunning method, respondents reported their baseline willingness to pay for a typical two-pound package of chicken breast. Participants were instructed to think about the chicken product they normally purchase and indicate the amount they would typically expect to pay in a retail setting. We used the baseline valuation to capture respondents' normal purchasing behavior to serve as a reference

point for the later valuation tasks. Consumers may vary greatly in their purchasing habits and grocery budgets, and using a respondent-specific baseline allows the analysis to isolate the true value respondents associate with the stunning methods. Without this, general differences in purchasing power may outweigh the stunning valuation in the analysis. Screenshots of the valuation tasks are provided in Appendix A.

Following the baseline willingness-to-pay elicitation, respondents were randomly assigned to one of two information conditions: a brief information treatment or a detailed information treatment. The purpose of the treatment was to examine whether the amount of information provided regarding poultry stunning methods influences consumer willingness to pay for chicken products produced under alternative slaughter processes. The brief treatment provided a concise overview of the stunning method, while the detailed treatment provided a more comprehensive description of how the method is implemented within commercial poultry production. Once assigned to an information condition, respondents remained in that condition throughout the experiment. Thus, respondents assigned to the brief treatment received brief information for both stunning methods, while respondents assigned to the detailed treatment received detailed information for both stunning methods. The complete text of all information treatments is provided in Appendix B.

After viewing information regarding the first stunning method, respondents were asked to indicate either the premium they would be willing to pay or the discount they would require relative to their previously reported baseline willingness to pay. Following completion of the first valuation task, respondents were shown information regarding the second stunning method at the same level of detail as their assigned treatment

condition and again reported their willingness-to-pay adjustment relative to baseline. To account for potential presentation-order effects, respondents were randomly assigned to evaluate either electrical stunning followed by gas stunning or gas stunning followed by electrical stunning. Stunning WTP responses were measured as premiums or discounts relative to each respondent's individual baseline valuation. Positive values indicate a willingness to pay more than the respondent's baseline purchase price, whereas negative values indicate a required discount. Combining the information treatment and presentation-order treatment resulted in four experimental groups: (1) Brief Information with ES first (2) Brief Information with GS first (3) Detailed Information with ES first (4) Detailed Information with GS first.

Chapter 4. Results

4.1. Attitude Segmentation

To measure consumers' latent attitudes towards animal welfare and health concerns, we used a survey module with eight 5-point Likert-scale statements (Miranda-de la Lama et al., 2019). This module of animal welfare statements expands on previous frameworks by incorporating both animal welfare and health-oriented statements, as consumer responses to alternative stunning methods may reflect multiple overlapping motivations. This is crucial for our research as, some consumers may primarily value humane treatment, while others may place greater emphasis on food safety, meat quality, or broader health-related concerns. Including both dimensions allows the analysis to capture a broader range of relevant consumer preferences.

Previous food preference studies have similarly found that consumers evaluate food products using multiple overlapping value systems rather than a single preference dimension, making multidimensional approaches particularly useful for market segmentation (Innes & Cranfield, 2009; Napolitano et al., 2010). However, it is always challenging to determine how to meaningfully translate survey responses into broader consumer preference groups. A naïve approach would be tallying pro-animal-welfare or pro-health statements that a respondent endorses. This approach could identify subjects with relatively more pro-animal-welfare or pro-health attitudes. However, the main shortcoming of the naïve approach is that it is binary meaning it ignores respondents who have more nuanced preferences. For instance, participants might show support to both "I think the industry needs higher standards for animal living conditions" and "I think the industry needs stricter regulations on humane slaughter"

statements. Notice that both statements pertain to the same underlying theme of animal welfare. Treating these items as completely independent inputs could overweight shared dimensions of belief and obscure their underlying attitudes (Costello & Osborne, 2005). Consumers may share similar broad concerns while differing in the intensity and combination of those concerns.

Combining factor analysis with clustering allows us to group respondent with similar response patterns while preserving more nuanced preference structures (Gifford & Bernard, 2006). However, the clustering approach has some shortcomings as well. For instance, higher-dimensional clustering can become less interpretable. (Aggarwal et al., 2001). As the number of dimensions increases, the difference between "close" and "far" clusters becomes less distinct and informative. With these issues in mind, we reduce the dimensionality of the data using factor analysis. This method extracts a smaller number of latent factors and uses those as the input to clustering (Innes & Cranfield, 2009). The eventual goal is avoiding over-clustering and identifying consumer groups that meaningfully explain observed WTP values.

Before using factor analysis, we first evaluate whether the method is appropriate for our data. Bartlett's test of sphericity evaluates whether the survey items are largely unrelated to one another. If the items are unrelated, factor analysis would provide little value. Rejection of the null hypothesis suggests that meaningful relationships exist across the survey items and that factor analysis may be appropriate (Bartlett, 1954; Marescotti et al., 2020). In our case, the test yields $\chi^2(28) = 445.7$, $p < 0.001$, rejecting the null hypothesis, and suggesting that factor analysis is suitable for our dataset. However, Bartlett's test alone may be insufficient because it is sensitive to sample size.

We also evaluate the Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy of our data, which evaluates how much variance is shared across the survey items (Kaiser, 1974; Marescotti et al., 2020). The average KMO value is 0.83, indicating a relatively strong level of shared variation in our sample. Individual item KMO values range from 0.75 to 0.87, suggesting that no individual survey items appear problematic. Meaning, the results suggest that our survey responses contain enough shared information to support factor analysis.

We now utilize exploratory factor analysis to identify underlying patterns in respondents' answers to the survey questions. Specifically, our goal is to determine whether respondents exhibit similar response patterns across groups of survey questions. Exploratory factor analysis is commonly used to identify smaller sets of underlying constructs while reducing the complexity of observed survey responses (France et al., 2026). A two-factor exploratory factor analysis using minimum residual extraction and *oblimin* rotation was performed (Revelle, 2016). Oblimin rotation allows the factors to remain correlated, which is appropriate for our case as animal welfare and health concerns may overlap across respondents. Allowing correlated factors is particularly important in food choice research, where consumers who place greater importance on animal welfare may also exhibit stronger health-related concerns (Napolitano et al., 2010; Innes & Cranfield, 2009). Restricting factors to be independent could therefore obscure meaningful relationships between these underlying attitudes. The factor structure is shown in table 1.

Table 1. Attitudinal Factor Structure

Item	Factor 1 (Pearson)	Factor 2 (Pearson)	Factor 1 (Polychoric)	Factor 2 (Polychoric)
1	0.41	-0.01	0.36	0.12

2	0.42	0.27	0.41	0.36
3	-0.12	0.80	-0.12	0.83
4	0.84	-0.01	0.91	-0.02
5	0.80	0.03	0.87	-0.01
6	0.22	0.61	0.08	0.79
7	0.23	0.54	0.17	0.65
8	0.66	-0.04	0.68	0.07

Note: This table displays the correlation of each survey item to factors

These findings suggest that respondents primarily organize their attitudes around two broader dimensions relating to animal welfare concerns and health-oriented concerns, rather than being one-dimensional. Some respondents appear primarily motivated by concerns regarding animal treatment and industry practices, while others place greater emphasis on perceived health, food quality, and safety outcomes. These dimensions provide a useful framework for understanding heterogeneity in consumer preferences (Innes & Cranfield, 2009; Gifford & Bernard, 2006). Items 1, 2, 4, 5, and 8 load primarily onto the first factor, which we label “Animal Welfare” orientation. Items 3, 6, and 7 load primarily onto the second factor, which we label “Health” orientation. Table 1 presents the factor loadings for the two-factor solution.

The loading pattern shown in Table 1 supports a two-factor structure with limited cross-loading, although item 2 exhibits mild cross-loading across both factors. Communalities measure how much of each survey item's variation is captured by the underlying factors (Costello & Osborne, 2005). Communalities broadly support this interpretation, though item 1 is notably weak. Item 1 has a communality of 0.17, meaning the two-factor solution explains a small portion of its variance. This is likely because item 1 captures a causal belief linking animal welfare to meat quality. The other animal welfare items more directly capture preferences and policy attitudes.

Nevertheless, we retain item 1 because it is conceptually relevant, while acknowledging that it is the weakest item in the solution.

We conduct the analysis twice, once using Pearson correlations and once using polychoric correlations. The comparative structure is in place to acknowledge that pearson correlations may diminish true relationships among ordinal Likert-scale items (Holgado-Tello et al., 2010; Marescotti et al., 2020). Despite the concern, the factor structure remained largely unchanged between the two, with similar loading patterns and factor correlations supporting the stability of the two-factor solution. Nevertheless, the stability of the factor structure across estimation methods increases confidence that the identified dimensions reflect genuine underlying attitudes rather than artifacts of the measurement scale.

With the factor structure in place, the overall fit of the model is assessed using standard fit indices. These tests reveal mixed conclusions of model fit. The chi-square test rejects the null hypothesis of perfect fit with $\chi^2(13) = 36.59$, $p < 0.001$. The RMSEA value of 0.109 further suggests a weak fit based on conventional thresholds. However, even when models display reasonable fit, the chi-square test is notoriously sensitive and frequently rejects the null hypothesis (Hu & Bentler, 1999). Similarly, RMSEA may overstate poor fit in models with relatively few degrees of freedom, as is the case here (df = 13) (Kenny et al., 2015).

Given the unsatisfactory results of the previous tests, we consider additional fit statistics. The RMSR value is relatively low at 0.05, and the model reproduces approximately 98% of the off-diagonal correlations, indicating a reasonable fit (Browne & Cudeck, 1992). The Tucker–Lewis Index (TLI) result of 0.88 suggests a marginal but

acceptable level of fit just below common thresholds (Hu & Bentler, 1999). Taken together, the fit statistics suggest that the model is imperfect but still provides a reasonable representation of the underlying response structure in our data. Importantly, the fit statistics do not suggest that the proposed dimensions are incorrect. Rather, they indicate that the two-factor solution captures most, though not all, of the variation present in respondent attitudes. Given the exploratory objective of identifying broad consumer preference dimensions, the model appears sufficiently accurate for subsequent segmentation analysis (Innes & Cranfield, 2009).

Cronbach's alpha may further support the consistency of the factor structure in our case. The animal welfare subscale yielded $\alpha = 0.79$, while the health orientation subscale yielded $\alpha = 0.76$. Generally, $\alpha \geq 0.70$ is considered an acceptable reliability threshold, suggesting that our factors are reliable and internally consistent (Cronbach, 1951; Makanyeza, 2014). Collectively, these results indicate that our survey respondents' attitudes can be summarized by two underlying dimensions: animal welfare concern and health orientation. These dimensions capture meaningful variation in consumer preferences while reducing the complexity of the original survey responses. From a behavioral perspective, consumers differ not only in whether they support alternative production practices, but also in the motivations underlying those preferences. The resulting factor scores provide a parsimonious representation of respondent attitudes and serve as the foundation for the consumer segmentation analysis presented in the next section.

Factor scores were standardized to reduce the impact of either factor dominating the other (Hair et al., 2019). Each respondent received factor scores representing their

position within each of the two dimensions. The standardized factor scores were clustered using Gaussian mixture models, with model selection based on the Bayesian Information Criterion (BIC) (Neath & Cavanaugh, 2012; Fraley & Raftery, 2002). This method is preferred to other approaches, such as k-means, as it allows for different shapes, sizes, and orientations of the clusters while providing soft probabilistic assignments (Fraley & Raftery, 2002; Scrucca et al., 2016). That flexibility is important here as consumer attitudes toward animal welfare and health concerns may vary considerably across respondents. The competing BIC model specifications shown in Table 2.

Table 2. Attitudinal Cluster Selection

Rank	Clusters	Model	BIC
1	3	VVV	-458.01
2	4	VVV	-427.12
3	5	VVV	-486.49
4	6	VVV	-502.70
5	7	VVV	-518.69

Note: This table compares the top five BIC models for attitude clustering

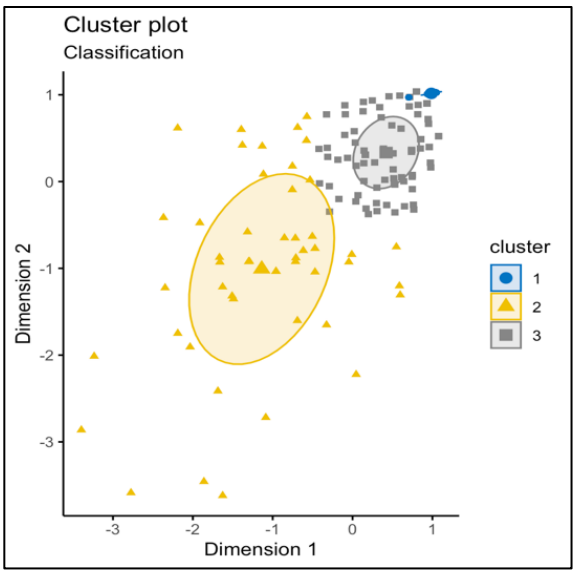
BIC model selection identified the VVV model with three clusters, where covariance varies in volume, shape, and orientation, providing flexibility to capture heterogeneity in respondent attitudes. The summary statistics for the selected three clusters are shown in Table 3 with the clusters visualized in Figure 1.

Table 3. Attitudinal Clustering Summary Statistics

Cluster	N	Mean (AW)	Mean (Health)	Mean (Uncertain)
Skeptics	49	-1.05	-0.89	0.056
Moderate Supporters	81	0.39	0.29	0.105
Strong Advocates	22	0.91	0.90	0.001

Note: This table lists the resulting statistics for attitude clusters

Figure 1. Attitudinal Cluster Visualization



Note: This figure shows the grouping of individuals within each cluster

The clusters are separated along a diagonal axis, with both animal welfare and health orientations increasing together. This pattern suggests that rather than having a distinct preference for animal welfare or health, respondents' preferences for the two are positively correlated. Respondents vary primarily in the strength of their overall alignment with these attributes. While a small number of respondents' placements are ambiguous between adjacent groups respondents are broadly well differentiated.

The Skeptics cluster received negative scores on both factors, indicating below-average concern for both animal welfare and health-related production attributes relative to the overall sample. Respondents in this group were generally less likely to agree with statements emphasizing the importance of animal welfare or the influence of production practices on product quality and health outcomes. Consequently, the label "Skeptics" was chosen to reflect their relatively low level of concern across both dimensions. The Moderate Supporters cluster exhibited positive scores on both factors, but the magnitude of these scores was considerably smaller than those observed for the

Strong Advocates cluster. These respondents demonstrated generally favorable attitudes toward animal welfare and health-related production practices while expressing less intense preferences than the most supportive consumers. The label "Moderate Supporters" reflects this intermediate position between the Skeptics and Strong Advocates groups. The Strong Advocates cluster received the highest positive scores on both factors, indicating strong agreement with survey items related to animal welfare, ethical treatment of livestock, and the importance of health-related production attributes. Relative to the other clusters, these respondents consistently expressed the greatest concern for production practices and the strongest support for attributes associated with improved animal welfare. Therefore, the label "Strong Advocates" was selected to reflect their consistently high levels of support across both attitudinal dimensions. Classification uncertainty is low across clusters, indicating that the assignments are generally well-defined. The results imply meaningful variation for analyzing willingness-to-pay outcomes among our respondents.

4.2 Attitudinal Models

Linear regression models were run for both Electrical Stunning (ES) and Gas Stunning (GS) willingness-to-pay premiums. Parallel specifications across the two stunning methods allow comparison of how consumer attitudes, information exposure, and presentation order are associated with willingness-to-pay outcomes. Models 1–5, shown in table 4, represent ES specifications and Models 6–10, shown in table 5, represent GS specifications. The objective is to determine whether willingness-to-pay premiums differ systematically across consumer attitude segments and whether those differences are influenced by information exposure and presentation order. If consumer

preferences are shaped by underlying welfare and health attitudes, respondents in different segments may value alternative stunning methods differently.

The models are defined as follows:

- Models 1 and 6: WTP as a function of consumer segment
- Models 2 and 7: Add the information treatment variable
- Models 3 and 8: Add presentation order and the interaction between consumer segment and information treatment
- Models 4 and 9: Add the full interaction structure between consumer segment, information treatment, and presentation order
- Models 5 and 10: Add baseline willingness-to-pay to control for baseline price sensitivity

The sequential model structure allows us to examine how willingness-to-pay outcomes change as additional explanatory variables are introduced. Beginning with consumer segments alone and progressively incorporating information treatments, presentation order effects, and interaction terms makes it possible to identify whether observed differences in valuation arise from underlying attitudes, experimental treatments, or the interaction of both. Controlling for baseline willingness-to-pay is particularly important because respondents may differ substantially in their general valuation of chicken products. Including this variable allows the analysis to isolate preferences for stunning methods from broader differences in price sensitivity.
The most comprehensive specification is defined as:

$$WTP_i = \beta_0 + \beta_1 \cdot Cluster_i + \beta_2 \cdot Info_i + \beta_3 \cdot Order_i$$

$$+ \beta_4 \cdot Baseline_i + \beta_5 \cdot (Cluster_i \times Info_i) + \beta_6 \cdot (Cluster_i \times Order_i)$$

$$+\beta_7 \cdot (Order_i \times Info_i) + \beta_8 \cdot (Cluster_i \times Info_i \times Order_i) + \varepsilon_i$$

where WTP_i represents the premium/discount reported by $Respondent_i$, $Cluster_i$ indicates consumer segment membership, $Info_i$ indicates assignment to the information treatment, $Order_i$ reflects presentation order, and $Baseline_i$ controls for initial willingness to pay.

All models were estimated using ordinary least squares (OLS) with heteroskedasticity-robust standard errors (HC1). Model fit was evaluated using the coefficient of determination (R^2), while comparisons across nested specifications assessed the contribution of additional explanatory variables and interaction effects. The willingness-to-pay variables were left-censored at -$5 by experimental design, so Tobit models were estimated as robustness checks for the fully specified models to assess whether the primary findings were robust to lower-bound censoring (Tobin, 1958; Wang et al., 1997). Together, these models provide a framework for evaluating whether consumer attitudes, information exposure, and experimental design features are associated with willingness-to-pay premiums for alternative stunning methods. The results also allow us to assess whether the consumer segments identified in the previous section correspond to economically meaningful differences in valuation behavior. Table 4 shows the regression figures for the Electric Stunning Models (Models 1-5). The results show the premium/discount value for poultry utilizing electric stunning and how additional variables affect both the estimated effects and overall model fit.

Table 4. Regression Results for Electric Stunning WTP (Attitude)

Variable	ES (1)	ES (2)	ES (3)	ES (4)	ES (5)
Moderate Supporters	0.25 (0.25)	0.27 (0.24)	0.83** (0.33)	0.70 (0.44)	0.71 (0.44)

Strong Advocates	1.10*** (0.35)	1.10*** (0.35)	1.24*** (0.47)	1.64** (0.75)	1.63** (0.77)
MoreInfo		-0.17 (0.22)	0.47 (0.35)	0.48 (0.47)	0.47 (0.47)
ESFirst			0.64*** (0.22)	0.32 (0.59)	0.29 (0.61)
WTP_Baseline					-0.02 (0.05)
Moderate Supporters x MoreInfo			-1.03** (0.46)	-1.19* (0.65)	-1.20* (0.65)
Strong Advocates x MoreInfo			-0.49 (0.71)	-1.47 (0.92)	-1.49 (0.93)
Moderate Supporters x ESFirst				0.30 (0.68)	0.31 (0.69)
Strong Advocates x ESFirst				-0.49 (0.99)	-0.46 (1.02)
MoreInfo x ESFirst				0.03 (0.71)	0.07 (0.75)
Moderate Supporters x MoreInfo x ESFirst				0.39 (0.92)	0.34 (0.95)
Strong Advocates x MoreInfo x ESFirst				1.64 (1.42)	1.62 (1.46)
Constant	-0.23 (0.18)	-0.16 (0.23)	-0.75** (0.29)	-0.60* (0.34)	-0.45 (0.51)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01;*

Dependent Variable: WTP Premium (Electrical Stunning)

Across the Electrical Stunning specifications, Strong Advocates consistently reported higher willingness-to-pay premiums relative to Skeptics. Strong Advocates reveal a statistically significant premium of approximately $1.10 per two-pound package in the baseline specification. This suggests that respondents with stronger animal welfare and health orientations reported relatively higher willingness-to-pay for Electrically Stunned chicken products. Moderate Supporters did not initially differ significantly from Skeptics. The information treatment variable did not independently predict willingness-to-pay outcomes, suggesting that additional descriptions of the stunning process alone may not alter valuation of Electrical Stunning products. Once presentation order and interaction terms were introduced, respondents who viewed Electrical Stunning first reported premiums approximately $0.64 higher, indicating a possible presentation-order effect. Moderate Supporters also became statistically

significant in these specifications, reporting premiums of approximately $0.83 relative to Skeptics. The interaction between Moderate Supporters and the information treatment variable became negative and statistically significant at approximately -$1.03, suggesting that additional information may have reduced the Electrical Stunning premium among Moderate Supporters. This interaction remained negative, though only marginally significant, once the full interaction structure was introduced. The remaining interaction terms did not produce statistically significant effects, and the presentation-order variable lost significance under the full interaction structure. Adding baseline willingness-to-pay as a control variable did not materially alter the estimated relationships, suggesting that the findings were not solely driven by general differences in respondents' baseline spending behavior. Collectively, the Electrical Stunning results suggest that consumer attitudes are more important than information exposure in explaining valuation differences. Respondents with stronger animal welfare and health orientations consistently reported higher willingness-to-pay premiums, while the information treatment produced limited independent effects. This pattern suggests that preferences for Electrical Stunning products may reflect pre-existing consumer attitudes rather than responses to additional information provided during the experiment. Table 5 shows the regression figures for the Gas Stunning Models (Models 6-10).

Table 5. Regression Results for Gas Stunning WTP (Attitude)

Variable	GS (6)	GS (7)	GS (8)	GS (9)	GS (10)
Moderate Supporters	0.43 (0.26)	0.43* (0.25)	0.76*** (0.29)	0.69** (0.34)	0.68** (0.34)
Strong Advocates	-0.45 (0.57)	-0.45 (0.57)	-1.23 (0.74)	0.76 (0.72)	0.77 (0.71)
MoreInfo		-0.005 (0.26)	0.08 (0.41)	-0.25 (0.54)	-0.25 (0.54)
ESFirst			-0.86*** (0.25)	-0.62 (0.55)	-0.59 (0.61)

WTP_Baseline					0.02 (0.05)
Moderate Supporters x MoreInfo			-0.76 (0.51)	-0.08 (0.67)	-0.07 (0.67)
Strong Advocates x MoreInfo			1.95** (0.98)	0.11 (1.02)	0.13 (1.02)
Moderate Supporters x ESFirst				0.20 (0.60)	0.19 (0.63)
Strong Advocates x ESFirst				-3.06** (1.18)	-3.08** (1.19)
MoreInfo x ESFirst				0.64 (0.82)	0.60 (0.86)
Moderate Supporters x MoreInfo x ESFirst				-1.53 (1.02)	-1.48 (1.07)
Strong Advocates x MoreInfo x ESFirst				2.77 (1.71)	2.79 (1.72)
Constant	0.01 (0.20)	0.01 (0.23)	0.38 (0.27)	0.27 (0.29)	0.11 (0.57)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01;*

Dependent Variable: WTP Premium (Gas Stunning)

The Gas Stunning specifications reveal stronger treatment sensitivity relative to the Electric Stunning specifications. Neither Moderate Supporters nor Strong Advocates differed significantly from Skeptics in the baseline specification. This suggests that attitude segmentation alone may not explain initial willingness-to-pay differences for gas-stunned chicken products. The information treatment variable also did not independently predict willingness-to-pay outcomes. Moderate Supporters became marginally significant once the information treatment variable was introduced. After presentation order and the interaction between cluster membership and information treatment were added, Moderate Supporters exhibited an estimated premium of approximately $0.76 with statistical significance. The presentation-order variable also became negative and statistically significant at approximately −$0.86, indicating that respondents who viewed Electrical Stunning first reported lower willingness-to-pay for Gas Stunning products. The interaction between Strong Advocates and the information treatment variable became positive and statistically significant at approximately $1.95.

This suggests that Strong Advocates exposed to additional information reported a relatively higher willingness-to-pay for gas-stunned chicken products. However, once the full interaction structure was introduced, the earlier information effect lost statistical significance. The interaction between Strong Advocates and the presentation-order variable then became negative and statistically significant at approximately −$3.06, suggesting that Strong Advocates who viewed Electrical Stunning first reported lower willingness-to-pay for Gas Stunning products. Controlling for baseline willingness-to-pay did not meaningfully alter the estimated relationships. Unlike the Electrical Stunning models, the Gas Stunning results suggest that willingness-to-pay responses depend more heavily on the interaction between consumer attitudes and experimental conditions. Strong Advocates exhibited a stronger positive response to information about Gas Stunning, while presentation order appeared to influence valuation outcomes. These findings suggest that consumer perceptions of Gas Stunning may be less established and more sensitive to contextual information than perceptions of Electrical Stunning.

Comparing the two stunning methods reveals an important distinction. Willingness-to-pay premiums for Electrical Stunning appear to be driven primarily by underlying consumer attitudes, whereas willingness-to-pay premiums for Gas Stunning are more sensitive to interactions between consumer attitudes, information exposure, and presentation order. This pattern suggests that consumers may possess more stable perceptions of Electrical Stunning, while evaluations of Gas Stunning remain more dependent on how information is presented and interpreted.

4.3 Attention Segmentation

To capture respondents' behavioral responses beyond self-reported preferences, biometric data were measured during the information and WTP decision stages of the experiment using eye-tracking and facial expression analysis software (Duchowski, 2017; Grafsgaard et al., 2013). Willingness-to-pay decisions may be influenced by cognitive and emotional processes that are not directly observable through the stated preferences (Orquin & Mueller Loose, 2013; Duchowski, 2017). The biometric measures included fixation time as a measure of visual attention, blink rate as a proxy for cognitive activity, and facial expression analysis for emotional valence (Duchowski, 2017; Grafsgaard et al., 2013). These data may offer a complementary lens through which consumer valuation behavior can be examined. Unlike survey responses, these measures capture behavioral reactions as they occur during the decision-making process. The challenge with biometric data is differentiating between behavioral responses induced by the experimental stimuli and participants' natural behavioral tendencies. Respondents may naturally convey a negative emotion, blink frequently, or have more frequent eye movements independent of the experiment's stimuli (Duchowski, 2017). Biometric responses were therefore normalized relative to each respondent’s baseline WTP stage, consistent with preprocessing approaches used in biometric consumer-choice research (Huseynov et al., 2019). Randomized experimental features may also mechanically influence biometric responses across respondents. For example, respondents assigned to longer information treatments may exhibit greater fixation time because of increased information exposure (Orquin & Mueller Loose, 2013). Residualization was therefore performed to reduce variation introduced by randomized experimental conditions before clustering, consistent with preprocessing

approaches used in biometric consumer-choice research (Huseynov et al., 2019).

Visual attention was measured using fixation time as a proxy for information engagement (Duchowski, 2017; Orquin & Mueller Loose, 2013). Three inputs make up the feature analysis: fixation time during the baseline, ES information, and GS information stages. Raw fixation measures may reflect differences in respondents' overall viewing behavior rather than differences in engagement with the experimental content. For example, some respondents naturally spend more time looking at screens than others. Derived measures were constructed to capture changes in attention relative to baseline behavior and differences in attention across the two stunning methods. The first feature,

$$InfoEngagement_i = \frac{T_i^{ES} + T_i^{GS}}{2} - T_i^{Base}$$

measures information engagement as the difference between fixation time from baseline and the information screens. The second feature,

$$GS\ vs\ ES = T_i^{GS} - T_i^{ES}$$

measures the asymmetry between the two stunning methods. With T_i^{Base}, T_i^{ES}, and T_i^{GS} representing fixation time during the baseline, ES information, and GS information stages, respectively. Any subjects with missing fixation data for any of the three input screens are dropped from the attention pipeline (n = 7 of 152), leaving n = 145 for clustering.

Gaussian mixture models were estimated and compared using the Bayesian Information Criterion (BIC) to identify respondents on the information engagement dimension. The model with the highest BIC value is the VVI model using two clusters. The selected VVI specification represents a variable-volume, variable-shape, axis-

aligned ellipsoidal covariance structure. The BIC model comparisons are presented Table 6.

Table 6. Attention Cluster Selection (BIC)

Rank	Clusters	Model	BIC
1	2	VVI	-822.74
2	2	VII	-823.11
3	3	VII	-825.06
4	2	VEI	-826.13
5	2	VVE	-828.16

Note: This table compares the top five BIC models for attention clustering

The next-best competing specification (VII) remained within one BIC unit of the preferred solution, while a three-cluster solution also appeared among the top competing models, indicating that the two-cluster specification remained preferred, though not overwhelmingly dominant. Nevertheless, we continue with the selected model. The two respondent groups were labeled Engaged Readers (n=32) and Skim Readers (n=113). Summary statistics are presented in Table 7.

Table 7. Attention Clustering Summary Statistics

Cluster	N	Info Engagement	GS – ES	Mean (Uncertain)
Skim Reader	113	- 871 ms	292 ms	0.181
Engaged Reader	32	3,076 ms	- 1,031 ms	0.113

Note: This table lists the resulting statistics for attention clusters

Engaged Readers spent approximately 3.1 additional seconds viewing the information screens, while Skim Readers spent approximately 0.9 fewer seconds viewing the information screens. This distinction suggests respondents vary in the level

attention given to the information provided during the experiment. While Engaged Readers devoted additional attention to the information screens, Skim Readers spent comparatively little time processing the material. Importantly, the clusters were differentiated less by a preference for either Electrical Stunning or Gas Stunning. Instead, the segmentation primarily captured differences in the overall amount of attention devoted to the information, regardless of the stunning method being viewed. This distinction provides a useful framework for examining whether greater attentional engagement is associated with differences in willingness-to-pay outcomes.

The attention-based segmentation regressions followed the same empirical specification structure as the attitudinal regressions described previously. Models 1–5 estimated willingness-to-pay outcomes for Electrical Stunning (ES), while Models 6–10 estimated willingness-to-pay outcomes for Gas Stunning (GS). The specifications progressively added information treatments, presentation-order effects, interaction terms, and baseline willingness-to-pay controls to evaluate whether visual engagement with the information treatments was associated with willingness-to-pay outcomes. Table 8 presents the regression results for the Electrical Stunning attention-based specifications (Models 1–5).

Table 8. Regression Results for Electrical Stunning WTP (Attention)

Variable	ES (1)	ES (2)	ES (3)	ES (4)	ES (5)
Engaged Reader	-0.24 (0.27)	-0.22 (0.27)	-0.21 (0.28)	-0.45 (0.35)	-0.48 (0.36)
MoreInfo		-0.09 (0.25)	-0.06 (0.28)	-0.38 (0.40)	-0.39 (0.40)
ESFirst			0.72*** (0.24)	0.39 (0.38)	0.37 (0.39)
WTP_Baseline					-0.02 (0.05)
Engaged Reader x MoreInfo			0.01 (0.46)	0.46 (0.63)	0.46 (0.64)
Engaged Reader x ESFirst				0.65 (0.60)	0.71 (0.65)

MoreInfo x ESFirst				0.72 (0.55)	0.74 (0.56)
Engaged Reader x MoreInfo x ESFirst				-1.16 (0.92)	-1.20 (0.95)
Constant	0.09 (0.14)	0.13 (0.18)	-0.20 (0.22)	-0.04 (0.27)	0.14 (0.47)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01; Dependent Variable: WTP Premium (Electric Stunning)*

Across all Electrical Stunning specifications, Engaged Readers did not differ meaningfully from Skim Readers in willingness-to-pay outcomes. In the baseline specification, the Engaged Reader coefficient was small and statistically insignificant at approximately −$0.24, suggesting that higher visual engagement with the information treatments was not initially associated with different valuations of Electrically Stunned chicken products. Like the attitudinal segmentation results, the information treatment variable did not independently predict willingness-to-pay outcomes. Once presentation order was introduced in Model 3, respondents who viewed Electrical Stunning first reported premiums approximately $0.72 higher, indicating a possible presentation-order effect. However, the Engaged Reader coefficient remained statistically insignificant across all Electrical Stunning specifications. In later models, the coefficient increased modestly in magnitude, reaching approximately −$0.48, but still failed to achieve statistical significance. Interaction terms involving the attention segmentation also remained statistically insignificant, and inclusion of baseline willingness-to-pay did not materially alter the estimated relationships. Overall, the results suggest that differences in visual engagement with the information treatments were not systematically associated with willingness-to-pay valuations for Electrically Stunned chicken products. Table 9 presents the regression results for the Gas Stunning attention-based specifications (Models 6–10).

Table 9. Regression Results for Gas Stunning WTP (Attention)

Variable	GS (6)	GS (7)	GS (8)	GS (9)	GS (10)
Engaged Reader	-0.53 (0.33)	-0.60* (0.33)	-0.30 (0.37)	-0.55** (0.25)	-0.51* (0.27)
MoreInfo		0.24 (0.28)	0.29 (0.31)	-0.23 (0.38)	-0.21 (0.39)
ESFirst			-0.99*** (0.28)	-1.40*** (0.43)	-1.36*** (0.44)
WTP_Baseline					0.03 (0.05)
Engaged Reader x MoreInfo			-0.47 (0.55)	0.47 (0.60)	0.46 (0.61)
Engaged Reader x ESFirst				0.65 (1.23)	0.57 (1.22)
MoreInfo x ESFirst				1.23* (0.63)	1.20* (0.63)
Engaged Reader x MoreInfo x ESFirst				-2.25 (1.47)	-2.19 (1.46)
Constant	0.26 (0.16)	0.14 (0.21)	0.56*** (0.20)	0.76*** (0.20)	0.50 (0.50)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01; Dependent Variable: WTP Premium (Gas Stunning)*

Unlike the Electrical Stunning specifications, several coefficients associated with Engaged Readers became negative and statistically significant in the later Gas Stunning models. In the baseline specification, the Engaged Reader coefficient was negative but statistically insignificant at approximately -$0.53. Once the information treatment was introduced in Model 7, the coefficient became marginally significant at approximately -$0.60, suggesting that respondents with higher visual engagement reported somewhat lower willingness-to-pay premiums for Gas Stunning products relative to Skim Readers. One interpretation is that greater attention to the information treatments did not necessarily translate into more favorable evaluations of Gas Stunning. Instead, respondents who spent more time processing the information may have become more critical of the production method or less receptive to its proposed benefits. The presentation-order effect again emerged as one of the largest estimated relationships in the models. Respondents who viewed Electrical Stunning first reported

lower willingness-to-pay premiums for Gas Stunning products, with coefficients ranging from approximately -$0.99 to -$1.40 across Models 8–10. In the fully interacted specifications, the Engaged Reader coefficient remained negative and statistically significant at approximately -$0.55 in Model 9 and marginally significant at approximately -$0.51 in Model 10. The interaction between MoreInfo and ESFirst also became positive and statistically significant in the later specifications, suggesting that respondents exposed to both the extended information treatment and the ES-first ordering reported relatively higher willingness-to-pay premiums than would otherwise be expected under the negative presentation-order effect alone. Despite several significant coefficients, the broader pattern of results remained relatively weak and inconsistent. Interaction terms involving the attention segmentation did not independently produce statistically significant effects, and inclusion of baseline willingness-to-pay did not materially alter the estimated relationships.

Collectively, these findings suggest that visual attention alone was not a strong determinant of willingness-to-pay behavior. While respondents differed substantially in the amount of attention devoted to the information screens, those differences rarely translated into meaningful valuation differences. This contrasts with the attitudinal segmentation results, where underlying consumer attitudes produced more consistent willingness-to-pay effects. These findings suggest that consumer attitudes may play a more important role in shaping valuation behavior than the amount of visual attention devoted to the information itself.

4.4 Cognitive Load Segmentation

Cognitive load was measured using blink count as a proxy. Higher blink rates are commonly associated with greater cognitive engagement, while lower blink rates are associated with lower cognitive engagement (Siegle et al., 2008). The same feature-construction framework was used, with blink count replacing fixation time. Respondents with insufficient blink observations (n=4 of 152) were excluded from the pipeline, leaving n=148 observations for clustering. Bayesian Information Criterion (BIC) model selection was again used to identify clustering solutions along the cognitive-engagement dimension. The preferred specification was a two-cluster VEE model, which produced the highest BIC value. Competing BIC specifications are presented in Table 10.

Table 10. Cognitive Load Cluster Selection (BIC)

Rank	Clusters	Model	BIC
1	2	VEE	-738.10
2	2	VII	-738.19
3	2	VEV	-742.35
4	2	VEI	-742.72
5	2	VVE	-742.80

Note: This table compares the top five BIC models for cognitive load clustering

Like the attention-based segmentation, several competing specifications remained within a relatively narrow BIC range of the preferred solution. The two resulting clusters were labeled High Blink Shift (n=39) and Low Blink Shift (n=109). Summary statistics are presented in Table 11.

Table 11. Cognitive Load Clustering Summary Statistics

Cluster	N	Info Engagement	GS – ES	Mean (Uncertain)

Low Blink	109	1.26	-0.63	0.093
High Blink	39	-3.53	1.75	0.061

Note: This table lists the resulting statistics for cognitive load clusters

High Blink Shift respondents show a substantially larger residualized blink-response during the information treatments relative to Low Blink Shift respondents. On the information-engagement dimension, High Blink Shift respondents display an average value of approximately −3.53, while Low Blink Shift respondents have an average value of approximately 1.26. The labels reflect the magnitude of the blink-response shift rather than the direction of the mean value. Again, the primary separation between the two clusters is along the information-engagement dimension rather than the GS-versus-ES asymmetry dimension. Like the attention segmentation, cognitive load segmentation primarily finds differences in overall engagement rather than between the two stunning method information screens. Again, this suggests that respondents differed more in the extent to which they broadly processed the information treatments than in their relative reactions to Electrical Stunning versus Gas Stunning specifically. The blink-based segmentation regressions follow the same structure as the previous attitude and attention-based models. Table 12 presents the regression results for the Electrical Stunning attention-based specifications (Models 1–5).

Table 12. Regression Results for Electric Stunning WTP (Cognitive Load)

Variable	ES (1)	ES (2)	ES (3)	ES (4)	ES (5)
High Blink Shift	0.12 (0.29)	0.13 (0.28)	0.32 (0.36)	0.59 (0.44)	0.61 (0.45)
MoreInfo		-0.16 (0.24)	-0.04 (0.26)	-0.09 (0.39)	-0.10 (0.39)
ESFirst			0.71*** (0.23)	0.64* (0.38)	0.63 (0.39)
WTP_Baseline					-0.02 (0.05)
High Blink Shift x MoreInfo			-0.34 (0.54)	-0.95 (0.72)	-0.99 (0.72)

High Blink Shift x ESFirst				-0.90 (0.73)	-0.95 (0.72)
MoreInfo x ESFirst				0.12 (0.51)	0.12 (0.51)
High Blink Shift x MoreInfo x ESFirst				1.54 (1.07)	1.60 (1.06)
Constant	0.01 (0.14)	0.09 (0.18)	-0.27 (0.22)	-0.24 (0.27)	-0.04 (0.44)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01; Dependent Variable: WTP Premium (Electric Stunning)*

Across all Electrical Stunning models, respondents classified as High Blink Shift do not meaningfully differ from Low Blink Shift respondents in their willingness-to-pay outcomes. In the baseline specification, the High Blink Shift coefficient remains small and statistically insignificant at approximately $0.12, suggesting that respondents exhibiting larger blink-response shifts during the information treatments did not initially value Electrically Stunned chicken products differently from respondents exhibiting lower blink-response shifts. Similar to the previous attitudinal and attention-based results, the information treatment itself does not independently affect willingness-to-pay outcomes. Once presentation order is introduced in Model 3, respondents who viewed Electrical Stunning first report significantly higher willingness-to-pay premiums of approximately $0.71, again indicating a substantial anchoring effect toward the first stunning method encountered. This presentation-order effect remains statistically significant in Model 4 before becoming statistically insignificant in the fully controlled specification. Although the High Blink Shift coefficient increases in magnitude across the later specifications, reaching approximately $0.61 in Model 5, the coefficient remains statistically insignificant throughout all Electrical Stunning models. Additionally, none of the interaction terms involving the blink-based segmentation produce statistically significant effects, and baseline willingness-to-pay does not meaningfully alter the primary findings. Overall, the results suggest that blink-based cognitive-response

differences do not systematically influence willingness-to-pay valuations for Electrically Stunned chicken products. Table 13 presents the regression results for the Gas Stunning attention-based specifications (Models 6–10).

Table 13. Regression Results for Gas Stunning WTP (Cognitive Load)

Variable	GS (6)	GS (7)	GS (8)	GS (9)	GS (10)
High Blink Shift	-0.27 (0.31)	-0.28 (0.31)	-0.01 (0.32)	-0.16 (0.29)	-0.20 (0.30)
MoreInfo		0.13 (0.28)	0.22 (0.31)	-0.06 (0.37)	-0.06 (0.38)
ESFirst			-0.97*** (0.27)	-1.35*** (0.45)	-1.34*** (0.46)
WTP_Baseline					0.04 (0.05)
High Blink Shift x MoreInfo			-0.47 (0.55)	-0.47 (0.63)	-0.40 (0.62)
High Blink Shift x ESFirst				0.26 (0.79)	0.35 (0.81)
MoreInfo x ESFirst				0.62 (0.63)	0.62 (0.63)
High Blink Shift x MoreInfo x ESFirst				-0.04 (1.20)	-0.14 (1.17)
Constant	0.22 (0.16)	0.15 (0.22)	0.53** (0.22)	0.72*** (0.21)	0.41 (0.48)

*Notes: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01; Dependent Variable: WTP Premium (Gas Stunning)*

Similar to the Electrical Stunning models, respondents classified as High Blink Shift do not meaningfully differ from Low Blink Shift respondents in their willingness-to-pay outcomes. In the baseline specification, the High Blink Shift coefficient is negative but statistically insignificant at approximately -$0.27, and the coefficient remains statistically insignificant across all remaining Gas Stunning specifications. As in the previous regression models, the presentation-order effect emerges as one of the strongest and most consistent findings. Respondents who viewed Electrical Stunning first reported substantially lower willingness-to-pay premiums for Gas Stunning products, with coefficients ranging from approximately -$0.97 to -$1.35 across Models 8–10. Unlike the attention-based segmentation models, none of the interaction terms involving the blink-based segmentation produce statistically significant effects in any specification. Additionally, the information treatment itself remains statistically insignificant throughout all Gas Stunning models, and baseline willingness-to-pay does

not meaningfully alter the primary findings. Overall, the blink-based regression results provide little evidence that differences in blink-response behavior systematically influenced willingness-to-pay valuations for Gas Stunning products. Instead, the results again suggest that presentation order remained substantially more important than biometric-response segmentation in explaining willingness-to-pay behavior.

4.5 Emotional Segmentation

Emotional responses were analyzed differently from the attention and blink data because most respondents displayed very little emotional variation throughout the experimental stages. The data consisted mostly of isolated emotional events, so responses were converted into binary indicators, consistent with approaches commonly used for sparse event data (King & Zeng, 2001). This reveals whether a positive or negative emotional response occurred during each stage. We define four binary indicators per subject:

$$pos\_resp_i^{ES} = 1\left(T_i^{ES,pos} > 0\right)$$

which indicates whether respondent i exhibited at least one positive-emotion frame during the Electrical Stunning information stage.

$$pos\_resp_i^{GS} = 1\left(T_i^{'GS,pos} > 0\right)$$

which indicates whether respondent i exhibited at least one positive-emotion frame during the Gas Stunning information stage.

$$neg\_resp_i^{ES} = 1\left(T_i^{ES,neg} > 0\right)$$

which indicates whether respondent i exhibited at least one negative-emotion frame during the Electrical Stunning information stage.

$$neg\_resp_i^{GS} = 1\left(T_i^{GS,neg} > 0\right)$$

which indicates whether respondent i exhibited at least one negative-emotion frame during the Gas Stunning information stage. The indicator function 1(·) equals 1 when at least one emotional response is detected during the corresponding stage and 0 otherwise. Table 14 reports the prevalence of positive and negative emotional-response events across the Electrical Stunning and Gas Stunning information stages.

Table 14. Emotional Prevalence Statistics

Indicator	Responders	N	Prevelence (%)
Positive Response – ES	3	147	2.0
Positive Response – GS	11	147	7.5
Negative Response – ES	19	147	12.9
Negative Response – GS	16	147	10.9

Note: This table reports the valence of emotional responses to each stunning method

The emotional-response variables exhibit substantial sparsity, with most respondents displaying no detectable emotional-response events during the experiment. Positive emotional responses were particularly rare during the Electrical Stunning stage, while negative emotional responses occurred somewhat more frequently across both information treatments. The prevalence patterns further justify the use of binary responder indicators rather than continuous clustering methods for the emotional-response analysis. Because most respondents recorded zero emotional-response events across the information stages, continuous Gaussian-mixture clustering would have been poorly suited for the structure of the data. Instead, the analysis proceeds using responder indicators to evaluate whether isolated emotional events were associated with willingness-to-pay outcomes, consistent with approaches commonly used for sparse event data (King & Zeng, 2001).

Because the emotional-response variables consisted primarily of sparse binary event indicators rather than continuous biometric measures, the emotional-response analysis proceeded using direct responder-indicator regressions rather than latent clustering methods. Separate regression models were estimated for Electrical Stunning (ES) and Gas Stunning (GS) willingness-to-pay premiums. The baseline specifications include the four emotional-response indicators directly, while the later specifications progressively introduce the information treatment, presentation-order effects, and baseline willingness-to-pay controls. Table 15 presents the regression results for the emotional-response indicator specifications.

Table 15. Regression Results for Emotional Valence

Variable	ES (1)	ES (2)	ES (3)	GS (4)	GS (5)	GS (6)
positive_response_GS	0.87**	0.99**	0.99**	-0.31	-0.49	-0.51
	(0.39)	(0.41)	(0.41)	(0.72)	(0.62)	(0.62)
positive_response_ES	-0.54	-0.52*	-0.58*	0.02	0.01	0.16
	(0.36)	(0.28)	(0.33)	(0.58)	(0.43)	(0.47)
negative_response_GS	0.40	0.34	0.33	-0.61	-0.51	-0.50
	(0.29)	(0.28)	(0.28)	(0.42)	(0.37)	(0.36)
negative_response_ES	-0.14	-0.08	-0.07	0.39	0.31	0.27
	(0.33)	(0.31)	(0.31)	(0.39)	(0.38)	(0.36)
MoreInfo		-0.10	-0.11		0.07	0.08
		(0.24)	(0.24)		(0.26)	(0.27)
ESFirst		0.73***	0.72***		-1.01***	-0.99***
		(0.23)	(0.24)		(0.28)	(0.29)
WTP_Baseline			-0.02			0.04
			(0.05)			(0.05)
Constant	-0.04	-0.31	-0.16	0.19	0.61***	0.24
	(0.15)	(0.21)	(0.43)	(0.16)	(0.20)	(0.50)

*Note: Robust standard errors (HC1) are reported in parentheses. * p < 0.10, ** p < 0.05, *** p < 0.01.*

Across the models, emotional-response variables generally provide weak and inconsistent explanations of willingness-to-pay behavior. The most consistent emotional-response effect appears in the Electrical Stunning regressions, where respondents exhibiting positive emotional responses during the Gas Stunning information stage report willingness-to-pay premiums approximately $0.87 to $0.99 higher for Electrically Stunned chicken products. This effect remains statistically significant after introducing information-treatment, presentation-order, and baseline willingness-to-pay controls, and the result remains substantively unchanged under Tobit estimation accounting for left-censoring at the experimental lower bound. In contrast, positive emotional responses during the Electrical Stunning stage are associated with modestly negative willingness-to-pay effects in the ES regressions, although these effects remain comparatively small and only marginally significant in the later specifications. Negative emotional-response indicators do not produce statistically

significant effects across specifications. Like the previous attitudinal and biometric analyses, presentation-order effects remain among the strongest and most consistent findings. Respondents who viewed Electrical Stunning first reported willingness-to-pay premiums approximately $0.72 higher for Electrically Stunned products and approximately $1.00 lower for Gas Stunning products across the later specifications. Despite Gas Stunning information generating somewhat more positive emotional-response events overall, these responses did not translate into stable willingness-to-pay premiums for Gas Stunning products. Overall, the emotional-response regressions suggest that isolated emotional events were comparatively weak predictors of willingness-to-pay behavior relative to underlying consumer attitudes and presentation-order effects.

Chapter 5. Discussion and Conclusions

This study examined consumer willingness to pay for chicken products produced using electrical stunning and controlled-atmosphere gas stunning. The results indicate that consumers generally exhibited modest differences in valuation across stunning methods, with willingness-to-pay outcomes influenced more strongly by underlying consumer attitudes and experimental context than by information exposure alone. The attitudinal analysis identified three consumer segments: Skeptics, Moderate Supporters, and Strong Advocates. Respondents with stronger animal welfare and health orientations generally reported higher willingness-to-pay premiums for products produced under alternative stunning methods. These relationships were particularly consistent within the Electrical Stunning models, where consumer attitudes emerged as the most stable predictor of valuation behavior. In contrast, willingness-to-pay responses for Gas Stunning appeared more sensitive to contextual factors. Several results suggested that information treatments and presentation order interacted with underlying consumer attitudes, indicating that consumer perceptions of Gas Stunning may be less established and more dependent on how information is presented. The biometric analyses produced more limited evidence. While respondents differed substantially in visual attention, blink activity, and emotional responses, these measures rarely translated into consistent willingness-to-pay differences. Across most specifications, biometric segmentation variables explained relatively little variation in consumer valuations when compared with attitudinal measures. One of the most consistent findings throughout the study was the presence of presentation-order effects. Respondents who evaluated Electrical Stunning first generally reported higher

willingness-to-pay premiums for Electrical Stunning products and lower premiums for Gas Stunning products. This pattern suggests that consumers may anchor subsequent evaluations around the first production method encountered.

The findings provide several implications for poultry processors, retailers, and animal welfare organizations. First, the results suggest that consumer concern for animal welfare does not automatically translate into large economic premiums. Although some consumer segments expressed higher willingness to pay for products associated with alternative stunning methods, average premiums were generally modest. This finding is consistent with the broader literature documenting an attitude-behavior gap in animal welfare purchasing decisions. Second, the limited impact of the information treatment suggests that simply providing more information may not substantially alter consumer valuations. Consumers appear to rely heavily on preexisting beliefs and attitudes when evaluating animal welfare-related production practices. As a result, educational campaigns alone may have limited effectiveness in generating demand for products produced under alternative stunning systems. Third, the stronger interaction effects observed for Gas Stunning suggest that consumer perceptions of this production method remain relatively undeveloped. Because most consumers have little prior knowledge regarding poultry stunning practices, perceptions may be particularly sensitive to framing, communication strategies, and product presentation. This finding may be important for processors considering investments in controlled-atmosphere stunning systems, as consumer acceptance may depend on how information is communicated at the point of purchase. Finally, the results indicate that substantial investments in alternative stunning technologies may be difficult to justify based solely

on consumer willingness-to-pay premiums. While animal welfare improvements may provide important ethical and operational benefits, the market incentives available through consumer demand alone may be insufficient to offset the capital costs associated with adoption. This finding is particularly relevant given the significant infrastructure investments required for controlled-atmosphere stunning systems.

This study contributes to the existing literature in several ways. First, while previous animal welfare research has primarily focused on housing systems, certifications, and production practices, relatively little attention has been devoted to poultry stunning methods. This study extends the literature by directly examining consumer valuation of electrical and gas stunning systems. Second, the study contributes to research on credence attributes by demonstrating that consumer responses to welfare-related production practices depend on both underlying attitudes and information context. The results reinforce the importance of consumer heterogeneit when evaluating willingness-to-pay for anima welfare improvements. Third, the study

elicited through a hypothetical survey environment. Although efforts were made to encourage realistic responses, stated preferences may differ from actual purchasing behavior in retail settings. Third, consumer familiarity with poultry stunning methods is likely limited. Respondents may therefore have formed opinions during the experiment rather than relying on previously established preferences. This limitation is particularly relevant when interpreting information-treatment effects. Fourth, the biometric measures may not fully capture the cognitive and emotional processes underlying consumer decision-making. While eye-tracking, blink activity, and facial-expression analysis provide useful behavioral indicators, they represent imperfect proxies for attention, cognitive effort, and emotional response.

Several opportunities exist for future research. Future studies could examine consumer preferences for stunning methods using nationally representative samples to improve external validity. Researchers may also investigate how willingness-to-pay responses vary across different geographic regions, demographic groups, and retail environments. Experimental auction methods or field-market studies could be used to compare hypothetical willingness-to-pay measures with actual purchasing behavior. Such approaches would provide additional evidence regarding the extent to which consumers are willing to financially support alternative stunning systems. Additional research could also evaluate the effectiveness of different communication strategies. Because Gas Stunning appeared particularly sensitive to contextual presentation, future studies may examine how labels, certifications, visual information, and retailer messaging influence consumer perceptions. Finally, future work could further explore the role of biometric measures in food-choice research. Larger samples and alternative

biometric indicators may help identify behavioral mechanisms that are not fully captured through traditional survey methods.

Animal welfare continues to play an increasingly important role in food markets, yet relatively little is known about how consumers value poultry stunning practices specifically. This study finds that consumer willingness to pay for alternative stunning methods is influenced primarily by underlying attitudes toward animal welfare and health concerns, while information exposure alone produces relatively limited effects. Gas Stunning valuations appear more sensitive to presentation context than Electrical Stunning valuations, suggesting that consumer perceptions of alternative stunning technologies remain underdeveloped. Perhaps the most important finding is that consumer attitudes matter more than consumer attention. While biometric measures captured differences in how respondents processed information, these behavioral differences rarely translated into meaningful differences in willingness-to-pay outcomes. Instead, preexisting beliefs and values consistently emerged as the strongest predictors of consumer valuation. Taken together, the results suggest that although some consumers value animal welfare improvements associated with alternative stunning methods, the resulting willingness-to-pay premiums may be insufficient to independently drive widespread industry adoption. Consequently, future changes in poultry stunning practices will likely depend not only on consumer demand, but also on processor incentives, retailer requirements, certification programs, and broader societal concerns regarding animal welfare.

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Appendices

Appendix A: Valuation Tasks

Figure 2. Baseline Valuation Task

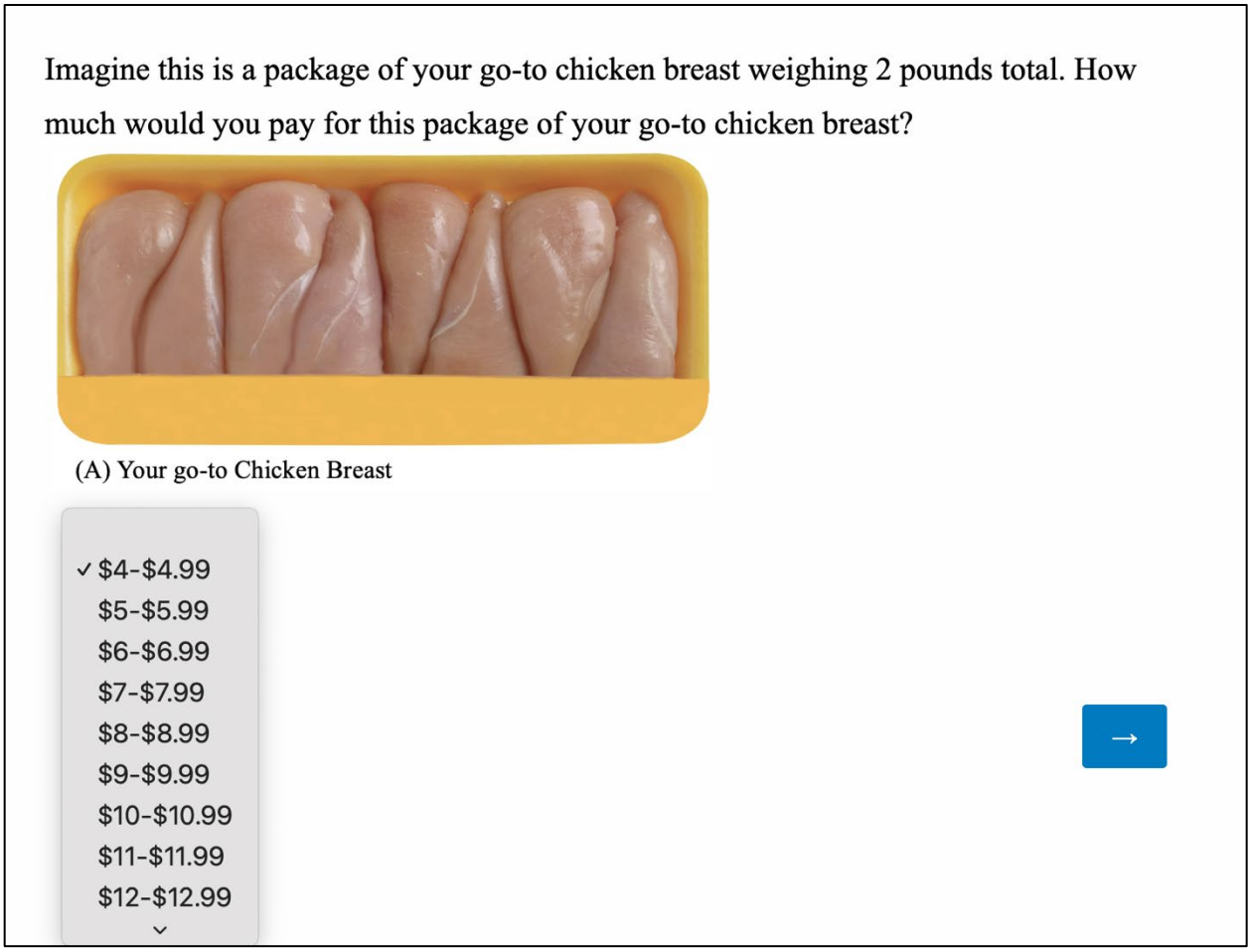

Figure 3. Electric Stunning Valuation Task

Previously, you mentioned the amount that you spend to purchase 2 pounds of your go-to chicken breast is in the range of $4-$4.99. How much are you willing to pay for 2 pounds of your go-to chicken breast with the additional certification mentioned in option (B) compared to the amount you previously stated you would pay for your go-to chicken breast in option (A)?

(A) Your go-to Chicken Breast

(B) Your go-to Chicken Breast + Electrical Stunning Certification

If you would pay more for option (B), place the cursor into greater than zero values. If you would pay less for option (B), place the cursor into less than zero values. If you would pay the same amount for both, place the cursor at zero.

-5 -4 -3 -2 -1 0 1 2 3 4 5

Change in willingness to pay

Figure 4. Gas Stunning Valuation Task

Previously, you mentioned the amount that you spend to purchase 2 pounds of your go-to chicken breast is in the range of $4-$4.99. How much are you willing to pay for 2 pounds of your go-to chicken breast with the additional certification mentioned in option (B) compared to the amount you previously stated you would pay for your go-to chicken breast in option (A)?

(A) Your go-to Chicken Breast

(B) Your go-to Chicken Breast + Gas Stunning Certification

If you would pay more for option (B), place the cursor into greater than zero values. If you would pay less for option (B), place the cursor into less than zero values. If you would pay the same amount for both, place the cursor at zero.

-5 -4 -3 -2 -1 0 1 2 3 4 5

Change in willingness to pay

Appendix B: Information Treatments

Figure 5. Electric Stunning Brief Information Treatment

What is Electrical Stunning?

Electrical Stunning is a method used to render chickens unconscious before slaughter. This is done by placing them in water with a low-voltage electrical current.

Figure 6. Gas Stunning Brief Information Treatment

What is Gas Stunning?

Gas stunning is a method used to render chickens unconscious before slaughter. This is done by placing them in a tunnel filled with carbon dioxide (CO_2).

Figure 7. Electric Stunning Detailed Information Treatment

Electrical Stunning Steps:

1. Chickens are secured by their feet on a conveyor belt.
2. The conveyor belt moves the chickens through the stunning area where their heads are submerged in water with a low-voltage electrical current. The electricity causes them to temporarily lose consciousness.
3. Once they exit the stunning area, the chickens are unconscious and ready to continue the slaughter process.

Figure 8. Gas Stunning Detailed Information Treatment

Gas Stunning Steps:

1. Caged chickens are placed on a conveyor belt.
2. The chickens enter the stunning tunnel where carbon dioxide (CO_2) is slowly introduced and increased over time. Exposure to the gas eventually causes them to temporarily lose consciousness.
3. Once they exit the stunning area, the chickens are unconscious and ready to be slaughtered.