The Impact of Sustainability on Consumer Preference Judgments of Product Attributes

Kosa Goucher-Lambert
Department of Mechanical Engineering,
Carnegie Mellon University,
Pittsburgh, PA 15213
e-mail: kgoucher@andrew.cmu.edu

Jonathan Cagan
Department of Mechanical Engineering,
Carnegie Mellon University,
Pittsburgh, PA 15213
e-mail: cagan@cmu.edu

Despite significant interest from consumers, sustainable products often struggle to find success in the marketplace. This failure is frequently attributed to the perception that consumers remain unwilling to sacrifice product attributes such as form, function, or price in order to adopt a product whose environmental impact is less than that of a competing product. This work aims to better understand how knowing a product's environmental impact affects preference for that product's disparate attributes. Three products of various monetary investments and numbers of relevant features were explored through a conjoint analysis experiment that uncovers consumer preference for discrete form, function, and price attributes. In this work, single use spoons, reusable water bottles, and home washing machines were used for analysis. These three products were decomposed into form, function, and price attributes that were varied in discrete levels. After a form-only ratings-based conjoint analysis study was conducted to find high, medium, and low preference form designs for each participant, two separate form–function–price discrete choice studies were conducted for each of the three products. These two discrete choice trials were identical in all aspects except in the second trial participants were provided with calculated environmental impact values for all design configurations; the presented environmental impact information was a dependent variable based on a life cycle analysis calculation using the current product configuration being shown to the participant. Further, adding this information raises the decision to one of a social or moral choice. Results show that when participants are provided with this additional piece of information, their preference for form, function, and price attributes of a product is greatly impacted. In particular, we find that for the products chosen here, the importance of functional attributes increases in the context of environmental impact metrics, while the importance of form decreases and the importance of price decreases modestly. In other words, placing the preference judgment within a social or moral choice context changes decisions about product preferences. [DOI: 10.1115/1.4030271]

1 Introduction

Decreasing society's impact on the environment remains one of the most pressing concerns of our time. Yet, despite recent behavioral, technological, and legislative advances in the fight against the degradation of the world's natural environment, its quality continues to decrease. Recently, the National Academy of Engineering has declared finding ways to achieve an environmentally sustainable society as one of today's grand challenges [1]. Due to the global nature of this challenge, it remains a focal point of academic, industrial, and governmental agendas. While many fields have a role to play in addressing this problem, in the context of engineering design, substantial effort is being placed on decreasing the environmental impact of newly designed products and processes. However, product developers often face the additional challenge that, despite stated interest from consumers, many sustainable products have received limited commercial success [2,3]. This is a puzzling reality, as market research reveals that consumers desire environmentally sustainable products [4].

One example of a sustainable product being unsuccessful in the consumer marketplace, despite meeting the environmental needs of consumers, was the initial offering of the Honda Insight hybrid vehicle in 1999 [5]. While this product met the environmental needs of target consumers, many perceived the form of the vehicle to be strange. A redesign of the Insight, including modifying the form, allowed this vehicle to appeal to a larger audience, and ultimately helped it to gain traction with consumers. This alteration, along with a portion of the population having a greater demand for sustainable products, helped the Insight to become a success.

The example of the Honda Insight fits into one of the more widely held explanations regarding the lack of success of green products: that consumers are not always willing to sacrifice additional product features, such as cost, performance, or aesthetics to purchase a more sustainable product [2]. Additionally, researchers have proposed that consumers may not trust marketing of sustainable products, or are unaware of a product's sustainable features during purchasing evaluations [6].

This paper is aimed at investigating these issues within a consumer preference context. Specifically, we seek to better understand the decision-making process of consumers when they are evaluating a product for which the environmental impact is known. By doing so, how preference for product attributes is shifted in the context of known environmental impact values can be identified. This information can provide designers and product developers with useful insights regarding how to tailor product form and features, to maximize consumer preference and the success of their products.

The role that the environment plays on both individual and group preference behavior is a poorly understood area of decision research. For design engineers, it is critical to understand preferences of potential consumers, as well as how these preference judgments are made. Many techniques have been developed to aid in understanding consumer preference. Recently, popular methods within the engineering design community have included conjoint analysis and discrete choice analysis. The recent popularity of these methods in the engineering design field rests in their ability to decompose products into discrete and continuous attributes [7].

Conjoint analysis, originating in economics and psychology literature, provides a way to mathematically capture preference in a

Contributed by the Design Automation Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received June 5, 2014; final manuscript received March 26, 2015; published online June 8, 2015. Assoc. Editor: Harrison M. Kim.

utility function [8–12]. In conjoint analysis, data are typically collected using a survey-type format, where users rate, rank, or choose between different offerings that are composed of different combinations of carefully chosen product attributes [7]. Traditionally, the representation of these product attributes was limited to descriptive text. However, more recently Orsborn et al. [7] and Kelly et al. [13] introduced extensions of traditional conjoint analysis, which are able to derive utility functions based on aesthetic preference. Orsborn et al. introduced visual conjoint analysis by utilizing Bezier curves to parameterize sport utility vehicles (SUVs), to determine optimal SUV forms outside of the original design space [7]. Kelly et al. developed a separate approach to determine the most preferred shape of a bottle using conjoint analysis with aesthetic attributes, and then used this information within an engineering optimization framework [13]. Since these initial applications, there have been several examples of utility functions being derived from aesthetic attributes in engineering design contexts, including studies exploring tradeoffs between form and function, such as that from Sylcott et al. [14].

While preference for form and function has been thoroughly explored within the engineering design literature, studies that examine the effect of sustainability on preference are much less common. Reid et al. examined the perceived environmental friendliness of vehicles based solely on their forms [15]. In that work, participants were asked to rate 2D vehicle silhouettes based on how environmentally friendly their designs appeared. Ewing and Sarigöllü used discrete-choice analysis to examine preferences for fuel efficiency in vehicles. Attribute stimuli were presented using exclusively descriptive text [16]. MacDonald et al. examined how participants evaluated configurations of paper towel designs based on their recycled paper content [3]. In addition to these works, there are examples of work that seek to optimize both engineering design considerations and environmental sustainability together through the integration of a consumer discrete choice study into an optimization framework [17].

While these works as well as others provided contributions to the field, there are several limitations, which are addressed here. First, they do not simultaneously consider visual and descriptive stimuli together with respect to sustainable considerations. We expect that allowing participants to state preferences for products with both of these types of stimuli will lead to more complete preference decisions. Second, prior work has not incorporated calculated environmental impact values directly using an environmental impact assessment methodology. Instead, previous work looks to add sustainability by including a separate variable into the design of experiments, which varies in predefined levels and is not reflective of the current design configuration. Including calculated environmental impact metrics will allow study participants to have a more accurate and complete understanding of the environmental impact of the presented design alternatives. This will also provide a means by which slight variations in the environmental impact of a product can be captured, and communicated to participants. Additionally, the main goal in many discrete choice works regarding environmental impact is often to determine willingness to pay for sustainability. In these works, as mentioned previously, environmental impact attributes are included as an independent variable in the experimental design [2,18–20]. Again, here environmental impact calculations are dependent on the form and feature attributes of a given design configuration. Including the environmental impact as a dependent variable creates a decision for participants that is dependent on information that they already have access to, however it is being recast in the context of a social choice decision in a form that they would likely not directly relate to the other independent variables.

This work extends previous research that studies the role sustainability plays in preference judgments by providing a more complete description of form and feature variations and their environmental impact. A multiproduct conjoint analysis experiment is utilized, which scales a product's purchasing commitment (price), approximate number of functional attributes available, and the variability in the product's physical form. Using these measures, three products were chosen to reflect different levels within this space (low, medium, and high): single-use spoons, reusable water bottles, and home washing machines. In addition to varying form, function, and price, the environmental impact of each product configuration is provided, based on an Eco-Indicator 99 life cycle assessment (LCA) analysis [21]. Two hypotheses are explored: first, the products will be evaluated differently when their environmental impact is known; second, that there exists a relationship between this difference and the monetary investment and number of relevant features of a product. The methods used to complete this work are presented in Sec. 2. This is followed by the presentation and discussion of results from a 94-person study in Secs. 3 and 4. Finally, conclusions and areas of future work are discussed.

2 Methods

This section describes the methods for determining the effect of environmental impact information on product preference judgments using conjoint analysis and discrete choice analysis. First, products were chosen for analysis, which provided relatable preference judgment scenarios for participants. Once these products were selected, their form design and feature configurations were analyzed in order to determine effective attributes to vary during the experiment. Three rounds of pilot studies were used to help inform the attributes that were included in the final experiment. It was critical that these attributes when varied were able to substantially influence participant preference. Experimental design methods were used to create surveys for participants consisting of different configurations of the chosen products. Preference models were then generated using response data, whose quality was validated using three metrics: mean absolute error (MAE), hit-rate (HR), and likelihood ratio index (LRI).

2.1 Product Selections and Decompositions. Three products were chosen for analysis: single-use spoons, reusable water bottles, and home washing machines. These products were selected based upon two criteria. The first was that the individual products appropriately spanned a wide range of product classes and relative prices. The second criterion was that the available attributes for each product needed to have a significant effect on the environmental impact assessment. This needed to be accomplished using the minimum number of attributes possible, which was a requirement of the conjoint framework. To accomplish this, we purposefully chose a product that required relatively low monetary investment and had a low number of available features (spoons), one with medium investment and number of features (water bottles), and one with relatively high monetary investment and number of features (washing machines). This sample of products were chosen due to the ability to estimate these products' environmental impact values, the response to feature variations participants had to these products during a focus group as well as pilot testing of the experiment, and as exemplars of the range of products in this space.

The product forms were all decomposed such that a large design space could be reasonably represented with a limited number of attributes. The form attributes, and levels of these attributes, were selected subjectively by the authors, and refined by selecting those for the final experiment that resulted in the most noticeable form variations to participants during pilot testing. During pilot tests, participants were shown sample forms that were varied from a norm based upon different form attribute selections, and asked to rate the appeal of the forms, as well as how differentiated they felt the new form was from the initial form. Additionally, it was intended that the form variations would result in a wide variety of variation in environmental impact values. Using this information the final form attributes were selected for inclusion in the experiment, and then the design space was parameterized based upon these attributes. Three-dimensional forms of each configuration were created in Solidworks. The three-dimensional forms were

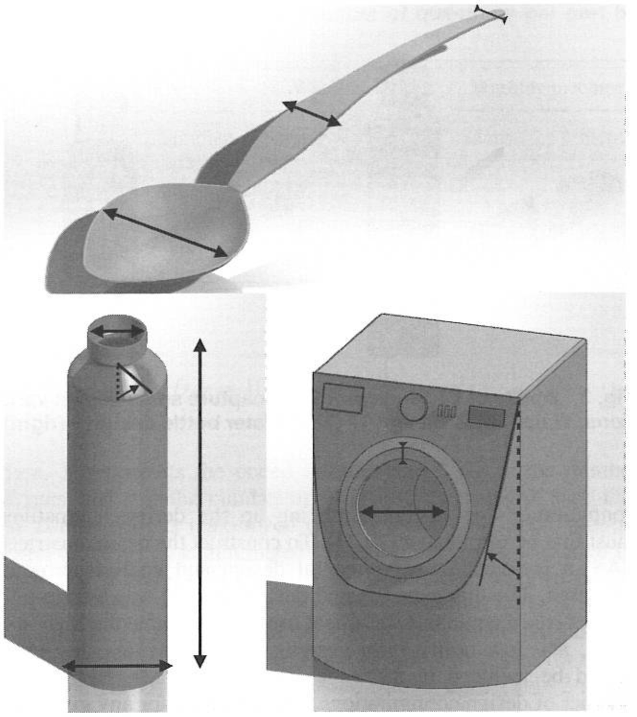

Fig. 1 Product form variation with marked attributes: (top) spoon, (bottom left) water bottle, and (bottom right) washing machine

the representations shown to participants during the final experiment. An example form for each product is shown in Fig. 1 with form attributes indicated.

Water bottle forms were parameterized using a single cubic Bezier curve, expressed as a function of four control points. Variation in the control points altered the height and width of the bottle, the width of the mouth opening, and the curvature of the neck. The four control points were each represented at three levels, yielding 81 (3^4) candidate form design configurations. Similarly, three-dimensional CAD models were created for the spoon and washing machine forms. The spoon forms utilized three characteristic widths (the bottom of the handle, the center of the handle, and the width of the bowl) each represented at three levels yielding 27 candidate form designs. The washing machines explored a design space around a basic front-loading model. Form variation was achieved using four attributes (front surface curvature, window size, door size, and control position) each represented at three levels yielding 81 candidate form designs.

In addition to form attributes, function and price attributes were selected for each product. Functional attributes were selected in order to create maximum emotional investment from participants, as well as a range of environmental impact values from the possible design configurations. Insights into how attributes affect environmental impact metrics are described in Sec. 2.2. A focus group was utilized to aid in the selection of functional attributes. During the focus group, participants were given a list of functional attributes for each product, and asked to self rank the attributes that they considered the most important. The most important functional attributes were included in the experiment based upon these results.

Price attributes were selected by examining common products available within that product class in the market. The selected price gradients reflect current market prices for these products. Table 1 shows the final functional and price attributes, along with their respective discrete levels that were used in the study. A final pilot study examined the impact of price on participant preference, and to see if any of the attributes (including price) was a dominating factor in preference decisions. Based upon these analyses the attribute selections appropriate for inclusion in the final experiment was finalized.

2.2 LCA.

Environmental impact values were calculated for all candidate designs using the Eco-Indicator 99 (EI99) LCA method [21]. EI99 is a metrics based damage-oriented method specifically developed for use during product development [21]. The method assigns values called points, which use weights to express the total environmental load of a product or process. Eco-Indicator points incorporate three types of environmental damage into their value: human health, ecology, and resources [21]. Base scenario EI99 assessments were carried out for limited designs of all three products in order to determine the decision variables that most affected the environmental impact of each product. For spoons, this was disposal (disposal method); for water bottles this was manufacturing (material); and for washing machines this was the use phase (cycle time and load volume).

Each product utilized a unique functional unit to calculate the environmental impact score. A functional unit describes the boundary of the analysis and helps define what is included in the LCA. For the spoons, the functional unit was a single use, including disposal. For water bottles, only the manufacturing and disposal of the water bottle was considered. The washing machines assumed a life cycle of 4000 washing cycles. For the washing machines, disposal was excluded from the analysis.

Due to the fact that the EI99 value is a dependent variable based upon the given form and function attributes, the score that is assigned to each design alternative will vary. Figure 2 describes the average contribution of the form and function attributes for each of the three products for all design and attribute combinations. For each of the three products, functional attributes contribute the majority of the weight in the EI99 scores; however, the spoon and water bottles in particular have a sizeable contribution from the product form.

A key feature of the EI99 analysis was that it allowed the environmental impact metric to capture small variations in form and feature configurations. For example, consider the two water bottle configurations displayed in Fig. 3. While configurations 9 and 17 have relatively similar forms in comparison to the other designs within the design space, they still differed in the volume of material required. For the "rigid-plastic" designs, configuration 9 required a volume of 0.2916 kg of polycarbonate, where as configuration 17 required 0.3372 kg of polycarbonate. When

Table 1 Function and price attributes and levels used for discrete choice study

Product	Attribute	Level 1	Level 2	Level 3
Spoon	Disposal method[a]	Trash	Compost	Recycle
	Price ($/20 spoons)	1.99	3.99	5.99
Water bottle	Material[a]	Aluminum	Soft plastic	Rigid plastic
	Cap style	Screw-off	Suction	Push–pull
	Price ($)	7.50	15.00	22.50
Washing machine	Max load qty. (lbs)[a]	8	14	20
	Cycle time (min)[a]	30	60	90
	Price ($)	399	599	799

[a]Influenced environmental impact scores.

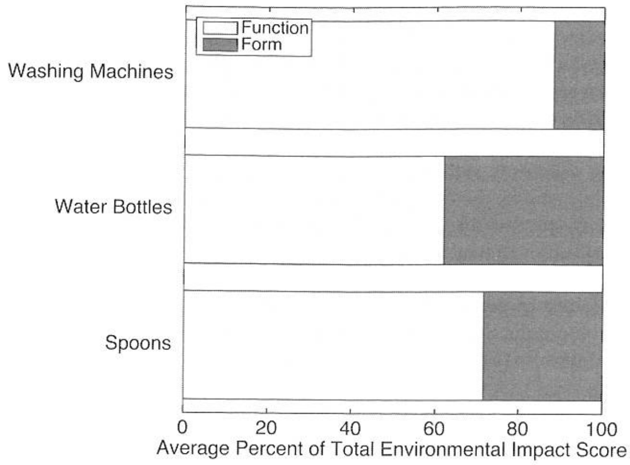

Fig. 2 Attribute contributions to environmental impact scores

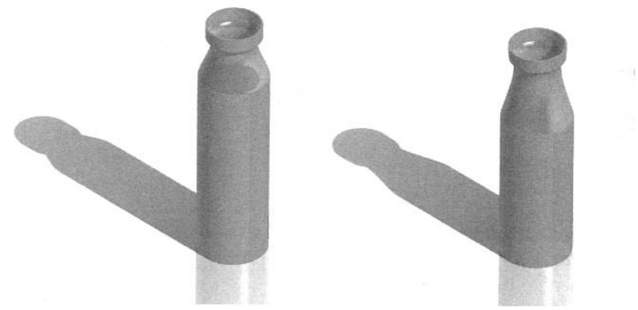

Fig. 3 Ability of Eco-Indicator 99 to capture small design variations. Water bottle design 17 (left). Water bottle design 9 (right).

considering the production of the raw materials, the injection molding production processes, and disposal in municipal waste, this results in a 15% difference in environmental impact values.

During the experiment, EI99 scores for each design alternative were converted into 1–10 values, where 10 represented a high environmental impact. The rationale behind this representation was to make environmental impact values more interpretable to participants. To do this, the environmental impact of all design alternatives was first calculated using the EI99 methodology described above. Next, the EI99 values were sorted from low to high, and the absolute distance between the lowest and highest score was taken. This range was then subdivided into 10 evenly spaced quadrants, representing the ten possible scores from 1 to 10. Finally, all remaining designs were assigned a value between 1 and 10 based upon where they fell within this range.

2.3 Experimental Design. A choice-based experimental approach was used to uncover participants' utility: a dimension representing the amount of want–satisfaction that, in the context of a conjoint experiment, is provided by a specific design alternative [22]. In a choice experiment [22,23], the total utility associated with alternative j out of a set of all alternatives J can be defined by Eq. (1a). In this equation, the total utility u_j for the jth design alternative is a function of the observable (v_j) and unobservable (ε_j) portions of the total utility. Additionally, Eq. (1b) shows how v_j can be expressed as a function of the design alternative x_j and unknown regression parameters $\boldsymbol{\beta}$

$$u_j = v_j + \varepsilon_j \tag{1a}$$

$$u_j = \beta' x_j + \varepsilon_j \tag{1b}$$

Equation (1b) is a linear function that in the case of this experiment consists of three independent attributes: form, function, and price. These three factors are assumed to not interact with one another. In order to calculate $\boldsymbol{\beta}$, a design matrix, $\boldsymbol{X}$, containing configurations of attributes making up the design alternatives, must first be formulated [22,23]. To construct the design matrices, SAS, a pre-existing experimental design and analysis program was used. The first experimental design (Part 1) was a form-only ratings-based conjoint experiment used to determine the high, medium, and low utility form designs for each participant, which would be included in the remainder of the study. Because the number of design configurations would be high for any given section of the experiment, a full-factorial design (all possible combinations of attributes and levels) could not be used, and instead, a fractional factorial design was implemented. The fractional factorial design allows users to see a subset of the possible combinations of design alternatives, while still ensuring that the number of times that different design attributes and levels of these attributes appears is consistent throughout the experiment.

After Part 1, the other two sections featured identical discrete choice analysis designs, the first of which included form–function–price tradeoffs (Part 2), and the second of which included the same design configurations with the additional information of the environmental impact values (Part 3). The highest, lowest, and average rated forms were determined for each participant in Part 1 of the experiment, and included in Parts 2 and 3. The environmental impact values were directly dependent on the form and functional attributes of the presented design configurations. Choice sets were formed using SAS by taking the full-factorial design as a surrogate set and reorganizing it into a fractional factorial design. The SAS algorithm used to complete this portion of the design of experiments assumes a multinomial logit model based upon the null hypothesis that all of the $\boldsymbol{\beta}$ values are zero [23]. The experiment flow is illustrated in Fig. 4.

There are several ways to determine the quality of a fractional factorial design. For a linear model, such as the ratings-based experiment used for the form-only portions of the study, models are typically evaluated based on balance, orthogonality, and efficiency [22,24]. A balanced design requires that all levels of all attributes appear equally. Orthogonality requires all pairs of attributes appear in equal numbers. There are several efficiency metrics that can measure the general quality of an experimental design. In this work, the D-efficiency is used

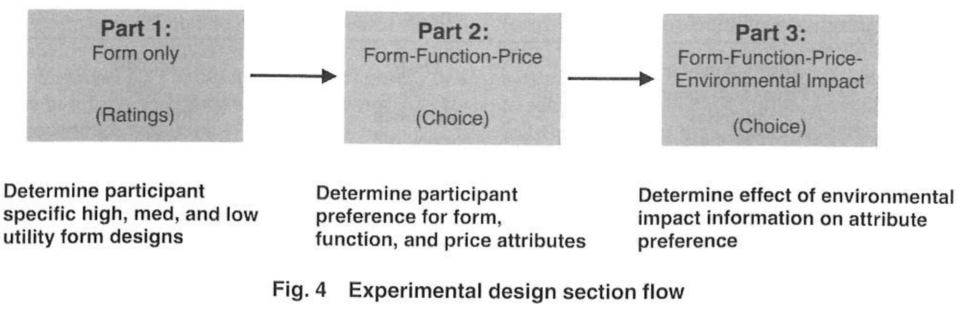

Fig. 4 Experimental design section flow

Table 2 Experiment outline: number of questions per part by product

Part	Spoon		Water bottle		Washing machine	
	Sample	Holdout	Sample	Holdout	Sample	Holdout
1	9	6	18	6	18	6
2	9	6	12	6	12	6
3	9	6	12	6	12	6
Total	45		60		60	

$$D_{\text{eff}} = 100 \times \frac{1}{N_{\text{D}}\left|(X'X)^{-1}\right|^{1/p}} \tag{2}$$

Here, X represents the coded design matrix, N_{D} is the number of runs, and p is the number of attributes. Choosing X such that the D-efficiency is maximized ensures that the variance, proportional to $(X'X)^{-1}$, is minimized [23]. For choice sets, a relative D-efficiency is computed, equal to the D-efficiency divided by the number of choice sets. All designs were main effect designs, meaning only main effects could be estimated without confounding higher-level interaction effects. Holdout runs were added for model validation purposes (further discussed in Sec. 2.5). Table 2 shows the number of sample and holdout questions used in each section.

The experimental design used in this study assumes that the form of the utility function remains unchanged between Parts 2 and 3 of the experiment, yet the $\boldsymbol{\beta}$ values necessarily do change between these two conditions. This assumption has been made to explicitly test whether or not the environmental impact information has influenced preference judgments under the same conditions as the preference judgments in absence of this information. Due to the fact that participants are considering the same design alternatives in both conditions, viewing a dependent variable (environmental impact) in one of these conditions should not alter participant preference for form, function, and price attributes.

2.4 Survey Interface. A graphical user interface was constructed in MATLAB in order to administer the experiment with participants. The interface prompted participants through the various sections of the experiment, and provided instructions and clarifying statements regarding the content of the study. The interface was designed such that any number of participants could complete the study at a given time. During Part 1, which was the form-only rating based portion of the experiment (Fig. 5), participants rated the shown form on a 1–10 scale using the radio-button display on the interface.

During the form–function–price and form–function–price–environmental impact portions of the experiment (Parts 2 and 3—Fig. 6) participants selected one design alternative again, using a radio-button display. For each part for each product, participants were asked to read an introductory paragraph describing the task, and explaining any terminology that would be needed for that portion of the experiment. This information could also be accessed during the study directly below the radio-button interface.

For choice trials, the attributes were presented in the same manner for all trials. The product form was displayed at the top of the screen, followed by functional attributes, and then the price attribute. For the environmental impact condition, the environmental impact information was shown at the bottom of the screen, directly underneath the price attribute (as shown in Fig. 6).

2.5 Data Collection. Participants were recruited through the Carnegie Mellon Center for Behavioral and Decision Research and offered \$10 compensation for participation. Additional participants were recruited through two Carnegie Mellon Mechanical Engineering senior and graduate-level courses and compensated with course credit. The complete population consisted of both Carnegie Mellon students and community members ages 20–36. There were 71 (73%) male and 26 (27%) female participants (97 initial participants). Data for three participants were omitted due to data collection errors (resulting in 94 participants used in the study).

2.6 Utility Estimations. The completed experiment required utility estimations to determine participant preferences for the presented attributes. In order to include product forms that evoked a greater emotion from participants, high, medium, and low utility designs were determined for each participant. This was done for each of the three products. To do this, a traditional ratings-based conjoint experiment was performed in order to gather user response information ranging from 1 (low) to 10 (high). The parameter weights, $\boldsymbol{\beta}$, were solved for using ordinary least squares regression (Eq. (3)). Here, X is the binary coded design matrix and $\boldsymbol{y}$ is a vector containing participant ratings for each design alternative [24]

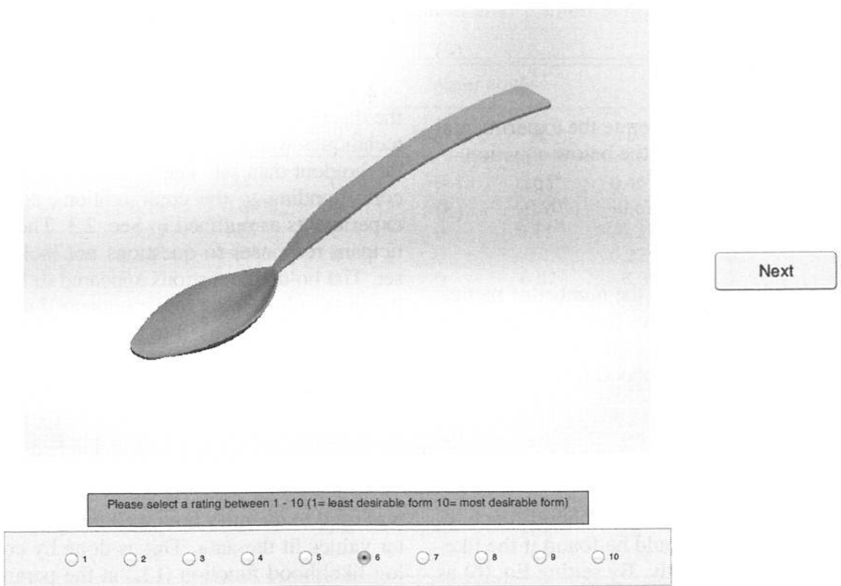

Fig. 5 Survey interface example from Part 1 for the spoon

Fig. 6 Survey interface from Part 3 for the water bottle

$$\hat{\beta} = \left(X'X\right)^{-1}X'y \tag{3}$$

Once this was complete, a utility score for each design alternative was obtained. All forms within the full-factorial design space for each product were then sorted in accordance with their utility scores. The highest ranked form was then taken as the high utility form design for that product, the lowest as the low utility form, and the middle ranked form as the middle utility design. This process was repeated for each of the three products included in the study.

In order to find the relative importance of attributes from the choice data, a partworth logit model using maximum likelihood estimations to solve for $\boldsymbol{\beta}$ was used, as outlined in Train as well as Sylcott et al. [22,25]. The logit model is formulated on the assumption that each unobservable portion of the utility is an independently and identically distributed double exponential. With this assumption, the logit probability, P_j, that a participant chooses alternative j is expressed in the below equation

$$P_j = \frac{e^{v_j}}{\sum_{k\in J} e^{v_k}} \tag{4}$$

The probability that the logit model will generate the experimental data is expressed as the likelihood shown in the below equation

$$L(\beta) = \prod_j P_j^{n_j} \tag{5}$$

In Eq. (5), P_j is the logit probability and n_j is the number of participants who have selected that design alternative. The goal is to maximize the logit probability. To express the logit probability with more mathematical convenience, the log-likelihood function is used

$$\mathrm{LL}(\beta) = \sum_j n_j \ln\left(P_j\right) \tag{6}$$

Simply, this is done by taking the log of the likelihood function. Doing so maintains the same optima as would be found if the likelihood function was to be calculated directly. By setting Eq. (6) as the objective function, and maximizing with respect to $\boldsymbol{\beta}$, the optimal $\boldsymbol{\beta}$ values can be found. These values maximize the collective preference of the group of participants for which response data is collected.

After calculation of the optimal $\boldsymbol{\beta}$ values, the importance values of each attribute can be solved for. Attribute importance (IMP) assesses the importance of an individual attribute against all attributes by examining the range in the maximum and minimum utilities [25]

$$\mathrm{IMP}_j = 100 \times \frac{\mathrm{RANGE}_j}{\sum_{j\in k}\mathrm{RANGE}_k} \tag{7}$$

where RANGE defines the absolute difference between the minimum and maximum $\boldsymbol{\beta}$ values for a given attribute, j, out of all attributes, k. Importance scales the range in values for each attribute's utility and as a result provides a concise way of normalizing the weight an individual attribute has in a participant's overall preference, compared to the other attributes included in the study. Contrary to utility, the normalization of importance values allows it to be suitable to use as a means to compare the weight of attributes between different studies.

2.7 Model Validation.

In order to gauge the performance of the discrete choice model, a variety of techniques were used. These techniques were applied to both the in sample data set, as well as the holdout data set. The in sample data set was the data collected corresponding to the configurations determined by the design of experiments as outlined in Sec. 2.3. The holdout data set were participant responses to questions not included in the in sample data set. The holdout questions appeared to be identical in every way to the in sample data set to participants during data collection.

The first metric used to gauge model performance was the LRI [25]. The LRI

$$\mathrm{LRI} = 1 - \frac{\mathrm{LL}\left(\hat{\beta}\right)}{\mathrm{LL}(0)} \tag{8}$$

was used to quantify how well the model at the calculated parameter values fit the data. This is done by comparing the value of the log-likelihood function (LL) at the parameter estimates to the LL of the null model. LRI ranges from 0 to 1, with 1 being when the model fits the data perfectly, and 0 when it is equivalent to the null model. The LRI can only be used to compare models resulting from identical experimental designs (where LL (0) is the same). Because the experimental design for each product is identical for both the trials with and without environmental impact information (Parts 2 and 3), the LRI metric can be used as a means for comparing the performance of the model between these two trials. Typically, a LRI value between 0.2 and 0.4 is considered to indicate that the model is a good fit for the data [9].

Two other measures used in this work to evaluate the performance of the models are the MAE, and the HR [22]. The MAE (Eq. (9)) compares the predicted share ($s_{j,\text{pred}}$) with the observed share ($s_{j,\text{obs}}$) by averaging the absolute difference between these two values for each design alternative, and dividing by all alternatives (J) [22]

$$\text{MAE} = \frac{\sum_{j=1}^{J} \left| s_{j,\text{pred}} - s_{j,\text{obs}} \right|}{J} \tag{9}$$

The HR (Eq. (10)) assumes the maximum utility alternative as predicted by the model should be selected by each participant

$$\text{HR} = \frac{1}{N \cdot k} \sum_{k} n_{\text{h}} \tag{10}$$

with this assumption, the amount of times this alternative is chosen is measured as a hit. In Eq. (10), N is the number of participants, k is the number of choice sets, and n_{h} is the number of participants who selected the alternative with the highest utility predicted by the model. Both of these metrics were examined for the in sample, as well as the holdout questions. This allowed for the predictive ability of the model to be determined, by comparing results for the MAE and HR for the in sample data, to that of the holdout sample.

3 Results

3.1 Logit Model. The collected data were analyzed in a group model using the methods described in Sec. 2. Table 3 (supported by Table 4) provides the calculated utilities for each attribute and level, as well as LL values and validation results for the form–function–price trial (A), the form–function–price–environmental impact trial (B), and null models (trials A and B) of the discrete choice experiment described previously. Again, the form-only conjoint analysis study was used to determine high, medium, and low preference product forms for each participant, and hence the results from this portion of the study were omitted from the results presented in Table 3.

For the spoon and washing machine trials, utilities for all levels of all attributes were significant, with each attribute contributing significantly to participants' overall utility for that product. For the water bottle, all levels of all attributes were significant, with the exception of the water bottle cap-style (x_3), for which participants showed little reaction. In general, examination of the utilities both before and after the presence of the environmental impact information indicates that attribute level utility was greatly impacted between these two trials (discussed further in Sec. 4).

The validation metrics used (LRI, MAE, HR) all show that the model performed well for all three products, with values for the MAE consistently below 5%, HR above 60%, and LRI ranging between 0.21 and 0.36. In particular, low values for the MAE for the model both before and after the presence of the environmental impact information points to the strength of the model in predicting the choices of participants during the study. While trial B outperformed trial A for the spoon, there was a decrease in values for the LL, HR, and LRI in both the water bottle and the washing machine experiments. This shows that for these products, the model performance slightly decreased between trials.

Holdout tasks were included in the experiment to measure the ability of the model to predict participant responses on tasks that were not used in the model generation. Analysis of these holdout tasks shows that the model performance is consistent with out of sample data. In particular, values for the HR remained consistent with in sample data.

Group importance values for each product, calculated using Eq. (7), are shown in Table 5. For the group data, importance values are calculated using the single attribute $\boldsymbol{\beta}$ values as given by the results of the logit model (Table 3). Importance allows us to characterize how much influence a given attribute had in a participants' overall preference decision. The difference between these two trials is captured by their delta. Examining the magnitude of this difference and its sign indicates the effect that the environmental impact metrics had on participants' overall preference. A negative sign indicates that the importance of the given attribute decreases when the participant is aware of the environmental impact metrics, and a positive sign indicates that the attribute became more important. A high magnitude attribute indicates that the participant evaluation of that attribute was significantly affected by the environmental impact metrics.

Table 3 Discrete choice model results ($n = 94$); A, prior to inclusion of environmental impact information and B, after inclusion of environmental impact information

		Spoon				Water bottle				Washing machine			
	β	Null A	Null B	A	B	Null A	Null B	A	B	Null A	Null B	A	B
	x_{11}	0	0	0.60[a]	0.44[a]	0	0	0.65[a]	0.45[a]	0	0	0.42[a]	0.20[b]
	x_{13}	0	0	−0.78[a]	−0.69[a]	0	0	−0.90[a]	−0.62[a]	0	0	−0.59[a]	−0.31[a]
	x_{21}	0	0	−0.65[a]	−1.27[a]	0	0	0.11[b]	−0.29[a]	0	0	−0.83[a]	−0.57[a]
	x_{23}	0	0	0.24[b]	0.44[a]	0	0	−0.18[b]	0.22[b]	0	0	0.61[a]	0.40[a]
	x_{31}	0	0	0.63[a]	0.60[a]	0	0	0.02	−0.03	0	0	0.52[a]	−0.88[a]
	x_{33}	0	0	−0.86[a]	−0.83[a]	0	0	−0.04	−0.04	0	0	−0.64[a]	0.30[a]
	x_{41}	—	—	—	—	0	0	0.84[a]	0.73[a]	0	0	0.95[a]	0.65[a]
	x_{43}	—	—	—	—	0	0	−0.98[a]	−0.92[a]	0	0	−1.12[a]	−0.87[a]
In Sample	LL	−929.43	−929.43	−706.86	−637.98	−1239.23	−1239.23	−904.57	−977.21	−1239.23	−1239.23	−792.90	−932.97
	LRI	—	—	0.24	0.31	—	—	0.27	0.21	—	—	0.36	0.25
	MAE	21%	21%	3%	4%	24%	24%	3%	3%	24%	21%	3%	3%
	HR	—	—	61%	67%	—	—	65%	62%	—	—	70%	63%
Holdout	LL	−619.61	−619.61	−424.08	−394.96	−813.22	−813.22	−435.02	−466.47	−813.22	−813.22	−408.71	−509.39
	MAE	21%	23%	4%	3%	27%	24%	4%	3%	25%	19%	5%	3%
	HR	—	—	73%	75%	—	—	70%	67%	—	—	71%	55%

[a] $p \leq 0.01$.
[b] $p \leq 0.1$.

Table 4 Model parameter definitions for all products (see Table 3)

	X_{11}	X_{13}	X_{21}	X_{23}	X_{31}	X_{33}	X_{41}	X_{43}
Spoon	Form (high utility)	Form (low utility)	Disposal method (trash)	Disposal method (compost)	Price (low)	Price (high)	NA	NA
Water bottle	Form (high utility)	Form (low utility)	Material (aluminum)	Material (flexible plastic)	Cap style (screw-off)	Cap style (push–pull)	Price (low)	Price (high)
Washing machine	Form (high utility)	Form (low utility)	Load qty. (8 lbs)	Load qty. (20 lbs)	Cycle time (30 min)	Cycle time (90 min)	Price (low)	Price (high)

3.2 Bradley–Terri–Luce (BTL) Method. To explore the impact of providing participants with information regarding a product's environmental impact on their preferences in more depth, the data were analyzed on an individual level. To do this, individual preferences were examined using the collected choice data, where individual preference functions were generated for all participants using the methodology outlined in Orsborn et al. utilizing the BTL method [7]. Here, the parameter estimates are simply the probability that a given design alternative is selected, divided by the number of times that the alternative was offered. From the BTL method, individual level parameter estimates can be calculated, and hence individual importance values can be obtained.

To analyze the individual preference data from the BTL method, the importance values for each participant were calculated using Eq. (7). To compare these values directly with the results obtained from the logit model, these individual values were averaged across all participants. The resulting averaged values are shown in Table 6, along with standard error values for the averages. The results obtained from averaging the individual importance values display the same trends as the data obtained from the logit model. For all products, the importance of form and price decreased after the environmental impact information was introduced, while the importance of function increased, consistent with the group results of Table 5.

In addition to averaging importance values across participants obtained from the BTL method, three metrics were selected, by which the influence of the environmental impact information on the individual could be determined. These three metrics were: change in rank order, change in highest utility design, and average maximum importance value difference. The change in rank order metric sought to identify how many participants the rank ordering of the importance values changed for, before and after the presence of the environmental impact information. Change in highest utility design captures how many participants changed their most preferred design after they were aware of the environmental impact of the product. Finally, the average maximum importance value difference looked at the change in importance values for all attributes between the two trials for each product. The attribute for each product that varied the most after the participants were aware of the environmental impact was taken as the maximum difference. This value was then averaged across all participants to get a sense for how much participants were influenced by the environmental impact information. The results of these metrics are shown in Table 7.

4 Discussion

4.1 Discussion of Results. Our first hypothesis was that products would be evaluated differently when their environmental impact is known. For all products examined here, the introduction of environmental impact information caused participants to value the form and price of a product less, while valuing its functional attributes more. However, for all products the price attribute was the attribute that changed the least between trials. The most noticeable differences in preferences before and after the addition of the environmental impact information were seen with the spoons. For the spoons, the importance of form and price dropped by 11% and 7%, respectively, while the importance of its function increased by 18%. The water bottles and washing machines both experienced drops in importance values for form attributes, while the importance of price stayed relatively constant. As was seen with the spoon, the importance of functional attributes for these products became much more important with the added environmental impact information.

The fact that functional attributes become significantly more important during the trial where participants are conscious of the product's environmental impact is likely due to the link between function attributes and the environmental impact metrics themselves. While form attributes also significantly affected the environmental impact metrics, it is possible that participants found it easier to connect how the functional attributes changed the environmental impact metrics. This is interesting because no information was provided to participants regarding how environmental impact metrics were calculated, or what attributes played a role in this calculation.

Our second hypothesis was that there exists a relationship between the difference in the way that a product is viewed in the context of sustainability, and that product's relative monetary investment and number of relevant features. When looking at the three products from this perspective, there are no attribute categories (form, function, or price) that either increased or decreased in importance moving from low monetary investment and number of relevant features (spoon) to high monetary investment and number of relevant features (washing machine). Instead, importance differs between the three products, with no consistent characteristic

Table 5 IMP values for logit model ($n = 94$) before and after the presence of environmental impact information

Product	Attribute	Before EI99 (%)	After EI99 (%)	Delta
Spoon	Form	35	24	−11%
	Function	27	45	18%
	Price	38	31	−7%
Water bottle	Form	41	32	−9%
	Function	10	19	9%
	Price	50	49	−1%
Washing machine	Form	18	11	−7%
	Function	46	55	9%
	Price	36	34	−2%

Table 6 IMP values for BTL model ($n = 94$) before and after the presence of environmental impact information

Product	Attribute	Before EI99 (SE)	After EI99 (SE)	Delta (%)
Spoon	Form	52 (2.0)%	37 (1.9)%	−15
	Function	22 (1.1)%	40 (1.5)%	18
	Price	26 (1.9)%	23 (1.7)%	−3
Water Bottle	Form	46 (1.7)%	44 (1.8)%	−2
	Function	9 (1.0)%	12 (1.2)%	3
	Price	45 (1.7)%	43 (1.7)%	−2
Washing machine	Form	19 (1.4)%	14 (1.3)%	−5
	Function	46 (1.3)%	52 (1.4)%	6
	Price	35 (1.8)%	34 (1.6)%	−1

Table 7 Effect of environmental impact information on individual preferences through three metrics ($n = 94$)

Product	Spoon	Water bottle	Washing machine
Change in rank ordering (participants)	69	75	85
Change in highest utility design (participants)	65	70	74
Avg. max importance value difference	19.8%	15.2%	18.6%

of these elements influencing preference within the context of environmental impact. For example, the importance of form after the introduction of the environmental impact information is 24%, 32%, and 11% for the spoons, water bottles, and washing machines, respectively. As mentioned previously, spoon attributes were altered the most by the environmental impact metrics. This is likely due to the fact that, because the spoon had fewer attributes that were being evaluated, it was not only easier for participants to determine the attributes that were affecting environmental impact metrics but it was also easier for participants to make sacrifices (such as price) for sustainability because the tradeoffs were clearer.

The analysis performed with the logit model provided insights into how environmental impact information may affect product preferences for a group. A group preference model, such as the logit model, is useful in contexts such as marketing where it is important to understand how the included information impacts a large group of people. However, it is difficult to understand how preference judgments may be impacted at an individual level using such a method. Understanding individual level effects is critical for design.

For individuals, the presence of the environmental impact information had a large influence on how important different product attributes were in driving their preferences. For the spoon trial, individuals had, on average, at least one attribute whose importance value varied by nearly 20% between trials, 15% for water bottles, and nearly 19% for washing machines. When examining the importance *ranking* of individuals, it can be seen that the importance rank order for 69 out of 94 individuals varied between trials for the spoons, 75 out of 94 for the water bottles, and 85 out of 94 for the washing machines. Additionally, the most preferred product configuration (combination of the highest utility level for each attribute) changed for 65 out of 94 individuals for the spoon trial, 75 individuals for the water bottle and 74 participants for the washing machine trials. Together these findings show that for individuals, not only does the importance of product attributes vary but the *most preferred* designs vary as well, once participants are aware of a product's environmental impact. These results illustrate both the magnitude of the affect of environmental impact information on preference judgments, as well as the diversity of these affects.

At both the group and individual levels, the environmental impact information was found to be very influential in participant preference decisions. Due to the fact that the environmental impact information is a dependent variable, it was unexpected that it would influence preference in the ways noted above. One possibility is that the environmental impact information causes participants to deviate from what would be their rational behavior because of the differing ways in which information is being presented to them [26]. This is unlikely to be the reason for the results seen here due to the fact that participants are stating their preference responses in the absence of risk and reward, and therefore have little motivation to alter their preferences due to these factors.

Table 8 Mean participant self-ranked attributes taken from exit survey ($n = 94$)

Product	Attribute	Before EI99 (SE)	After EI99 (SE)
Spoon	Form	1.90 (0.09)	1.99 (0.09)
	Function	2.02 (0.09)	2.11 (0.08)
	Price	2.07 (0.08)	1.92 (0.08)
Water bottle	Form	1.67 (0.08)	1.80 (0.08)
	Function	2.29 (0.09)	2.23 (0.09)
	Price	2.04 (0.08)	1.97 (0.08)
Washing machine	Form	2.31 (0.09)	2.49 (0.08)
	Function	1.99 (0.08)	1.83 (0.08)
	Price	1.70 (0.07)	1.68 (0.07)

An exit survey was conducted at the end of the study to provide additional insights into how participants perceived the importance of form, function, and price attributes during each of their preference judgments. This exit questionnaire asked participants to self-rank the importance of the form, function, and price attributes before and after the presence of the environmental impact information for each of the three products. By doing so, the participants were forced to critically consider the importance of the various attributes, and recall their opinions on these attributes from different times within the study. The rankings were recorded on a scale from 1 (most important) to 3 (least important). The aggregated results from this data are summarized in Table 8 below. A lower value in Table 8 indicates that participants more frequently ranked that attribute highly (more importantly).

The results from the exit survey indicate that participants often reflected that the presence of the environmental impact information had a smaller effect on the importance of the form, function, and price attributes during their preference judgments than would be anticipated based upon the data in presented in Tables 5–7. To further understand the results from the exit-survey and how these may differ from the experimental results, the number of participants who had a change in their rank order of the attributes before and after the environmental impact information was introduced was determined. The results from the rank order analysis for the exit survey data are shown in Table 9. Here, only 22 of the 94 participants changed their rank order for the spoons and washing machines, and only 17 for the water bottles. When values in Table 9 are compared to those in Table 7, it can be seen that significantly fewer individuals reported a difference in the way they ranked the attributes during the exit survey compared to the experimental results from their study response data. The fact that there exists a significant difference between self reported results, and calculated results from the choice models are an interesting area to consider in future work.

When examining the results from this study, it is useful to consider the participants from which data was collected. Of the 94 participants who completed the study, 70 were engineering students at Carnegie Mellon University. The gender distribution (73% male) is reflective of the engineering population at this institution. Future work should examine the effect of the participant's background (gender, education, etc.) on results.

4.2 Insights for Design. The results of this work present a step toward understanding the complex ways in which sustainability impacts preference judgments. Based upon the results from the three products used in this experiment, insights can be formed that have implications for designers and product developers working on sustainable products. For these individuals, it is imperative to consider the shifting values of consumers when they are evaluating a product in the context of sustainability. In particular, one finding of this work demonstrated how functional attributes become more influential in the preference decision-making process when participants are aware of that product's environmental impact. With this

Table 9 Change in participant self-ranked attribute order from exit survey ($n = 94$)

Product	Spoon	Water bottle	Washing machine
Change in rank ordering (participants)	22	17	22

in mind, design teams should take care to ensure sustainable products at least match, or even exceed consumer expectations of a product's functionality. These functional attributes become more important, and as a consequence are judged more critically by consumers when they are considering sustainability.

Unfortunately, products that are designed and marketed to be sustainable are often perceived to not meet the same level of functionality for equal price as a less sustainable competitor [4]. This perception may have influenced the decision-making process during this experiment. It is possible that when individuals were considering the environmental impact of the design configurations, they were more critical with their judgments, especially regarding functional attributes. One hypothesis is that this could be the reasoning behind the increase in functional importance during the environmental impact trials in this work.

In this study, the importance of form decreased during environmental impact evaluations. While the form of a sustainable product should still be considered, the results of the products in this work indicate that aesthetic attributes become less important. That being said in two of the three products chosen for examination, despite its decrease between the two trials, form remained the most important attribute even after the introduction of the environmental impact metrics. Therefore, while form may lose importance during sustainable product evaluations, in many product classes it remains a critical aspect in preference, and cannot be neglected.

As noted previously, in this work no support was found for the hypothesis that there exists a link between a product's monetary investment and number of relevant features, and the impact on preference judgments in the context of sustainability. Here, only parameters of products within a specific class that existed at different levels of monetary investment and number of relevant features were varied. Within this context, participant responses were very dependent on the features of the products being considered. It would be interesting to consider additional product classes within the same context that provide an additional set of tradeoffs for participants. For example, with a sports car, the form is an emotional part of the vehicle and may become much more important in the context of sustainability than it was when participants were considering washing machines. Furthermore, including additional products with future work will be critical in determining how closely the findings found from the three products studied here generalize to additional products.

Another feature of this study, as well as multi-attribute decisions involving sustainability in general, is that they introduce social and moral aspects into the decision making process. Decisions involving social and moral choice have been shown to require individuals to think differently from decisions that are in absence of a social or moral component. Previous work in the cognitive psychology literature has found social and moral choice decisions to be both significantly more difficult and emotional for participants [27]. While the data collected for this experiment did not provide the framework to explore such questions in detail (e.g., reaction time was not recorded for choice responses—a measure commonly used to determine the difficulty participants experienced answering questions), future work should consider ways to classify other elements of sustainable product preference judgments, as they may relate to a larger strategy that applies more broadly to social or moral decision making.

Finally, a few comments regarding the accuracy of the environmental impact metrics used in this work. It is acknowledged that the environmental impact values presented in this work are susceptible to sources of error, which are unable to be fully captured. As Bras points out, LCA analysis are subject to several sources of error, including accuracy of source data, interdependency of source data, weighting methodologies, and location uniqueness [28]. Future work will continue to consider the impact of these issues on results. However, for the purposes of this study, the values obtained from the Eco-Indicator LCA method provided sufficient depth and accuracy to explore participant preferences surrounding sustainability.

5 Conclusion

This work explored the role that sustainability plays on product preference judgments. Using a 94-person study, we found that there are significant differences in the importance of aesthetic, functional, and price attributes before and after the presence of environmental impact metrics. When modeling participants as a group using a logit model, participants tended to value product form less when considering its environmental impact, while a product's function becomes significantly more important under the same circumstances for the products utilized in this study. Analysis of the same data using the BTL method showed that these trends are also evident at an individual level. In this context, individual preference variations are found to be significant. These variations not only have a pronounced effect on how individuals weight different attributes, but it also impacts what they consider to be their most preferred design configurations. We acknowledge that group preference models such as the logit model are not always able to accurately capture changes in preference, due to the fact that individual level preferences are highly differentiated. This differentiation can often make the net sum of these effects negligible in such a model. However, in this work consistency was found at the individual level. Additional sources of error in this study could be attributed to a number of experimental factors: participants not having strong enough preferences for the products selected, the ordering of the choice tasks and trials, the experiment not mirroring true judgment tradeoffs, and fatigue. In addition to taking the aforementioned possible sources of error into account, future work could also consider the effect of adding additional attributes (not environmental impact) into the experimental design to assess the sensitivity of the results specifically to sustainability. This research provides the foundation to pursue followup work in order to better understand the complex role sustainability plays in product preference decisions.

Acknowledgment

This work was partially funded by the National Science Foundation under Grant No. CMMI1233864.

References

[1] Perry, W., Broers, A., El-Baz, F., and Harris, W., 2008, *Grand Challenges for Engineering*, National Academy of Engineering, Washington, DC.
[2] Bennett, J., and Blamey, R., 2001, "Yea-Saying and Validation of a Choice Model of Green Product Choice," *The Choice Modeling Approach to Environmental Valuation*, J. Bennett, and R. Blamey, eds., Edward Elgar, Cheltenham, UK, pp. 178–201.
[3] MacDonald, E., Allison, J. T., and Whitefoot, K., 2010, "An Investigation of Sustainability, Preference, and Profitability in Design Optimization," ASME Paper No. DETC2010-29055.
[4] Olson, E., 2012, "It's Not Easy Being Green: The Effects of Attribute Tradeoffs on Green Product Preference and Choice," J. Acad. Mark. Sci., **41**(2), pp. 171–184.
[5] Cagan, J., and Vogel, C., 2013, *Creating Breakthrough Products*, Financial Times Press, Upper Saddle River.
[6] She, J., and MacDonald, E. F., 2013, "Trigger Features on Prototypes Increase Preference for Sustainability," ASME Paper No. DETC2013-12973.
[7] Orsborn, S., Cagan, J., and Boatwright, P., 2009, "Quantifying Aesthetic Form Preference in a Utility Function," ASME J. Mech. Des., **131**(6), p. 061001.
[8] Luce, R., and Tukey, J., 1964, "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement," J. Math. Psychol., **1**(1), pp. 1–27.
[9] Louviere, J., Hensher, D., and Swait, J., 2000, *Stated Choice Methods*, Cambridge University Press, Cambridge.

[10] Green, P. E., and Wind, Y., 1975, "New Way to Measure Consumers' Judgments," Harv. Bus. Rev., **53**(4), pp. 107–117.
[11] Green, P., 1974, "On the Design of Choice Experiments Involving Multifactor Alternatives," J. Consum. Res., **1**(2), pp. 61–68.
[12] Luce, R. D., 1977, "The Choice Axiom After Twenty Years," J. Math. Psychol., **15**(3), pp. 215–233.
[13] Kelly, J. C., Maheut, P., Petiot, J.-F., and Papalambros, P. Y., 2011, "Incorporating User Shape Preference in Engineering Design Optimisation," J. Eng. Des., **22**(9), pp. 627–650.
[14] Sylcott, B., Cagan, J., and Tabibnia, G., 2011, "Understanding Consumer Tradeoffs Between Form and Function Through Metaconjoint and Cognitive Neuroscience Analyses," ASME J. Mech. Des., **135**(10), p. 101002.
[15] Reid, T. N., Gonzalez, R. D., and Papalambros, P. Y., 2010, "Quantification of Perceived Environmental Friendliness for Vehicle Silhouette Design," ASME J. Mech. Des., **132**(10), p. 101010.
[16] Ewing, G., and Sarigiii, E., 2000, "Assessing Consumer Preference for Clean-Fuel Vehicles: A Discrete Choice Experiment," J. Public Policy Mark., **19**(1), pp. 106–118.
[17] Skerlos, S. J., Morrow, W. R., and Michalek, J. J., 2006, "Sustainable Design Engineering and Science: Selected Challenges and Case Studies," *Sustainability Science and Engineering*, Vol. 1, M. A. Abraham, ed. Elsevier, New York, pp. 477–525.
[18] Alriksson, S., and Oberg, T., 2008, "Conjoint Analysis for Environmental Evaluation—A Review of Methods and Applications," Environ. Sci. Pollut. Res. Int., **15**(3), pp. 244–257.
[19] Guagnano, G. A., 2001, "Altruism and Market-Like Behavior: An Analysis of Willingness to Pay for Recycled Paper Products," Popul. Environ., **22**(4), pp. 425–438.
[20] MacDonald, E. F., Gonzalez, R., and Papalambros, P. Y., 2009, "Preference Inconsistency in Multidisciplinary Design Decision Making," ASME J. Mech. Des., **131**(3), p. 031009.
[21] PreConsultants, 2000, "Eco-Indicator 99 Manual for Designers," *Ministry of Housing, Spatial Planning and the Environment*, Amersfoort.
[22] Sylcott, B., Michalek, J. J., and Cagan, J., 2013, "Towards Understanding the Role of Interaction Effects in Visual Conjoint Analysis," ASME Paper No. DETC2013-12622.
[23] Kuhfeld, W. F., 2010, "Marketing Research Methods in SAS: Experimental Design, Choice, Conjoint, and Graphical Techniques," SAS Technical Papers No. MR-2010.
[24] Tovares, N., Cagan, J., and Boatwright, P., 2014, "Experiential Conjoint Analysis: An Experience-Based Method for Eliciting, Capturing, and Modeling Consumer Preference," ASME J. Mech. Des., **36**(10), p. 101404.
[25] Train, K., 2003, *Discrete Choice Methods With Simulation*, Cambridge University Press, Cambridge, Chap. 6.
[26] Kahneman, D., and Tversky, A., 1979, "Prospect Theory: An Analysis of Decision under Risk," Econometrica, **47**(2), pp. 263–291.
[27] Greene, J., Sommerville, B., Nystrom, L., Darley, J., and Cohen, J., 2001, "An fMRI Investigation of Emotional Engagement in Moral Judgment," Science, **293**(5537), pp. 2105–2108.
[28] Bras, B., 2013, "Recurring and Unresolved Problems in Sustainable Design," ASME Paper No. DETC2013-13459.