Inside the Mind: Using Neuroimaging to Understand Moral Product Preference Judgments Involving Sustainability

Kosa Goucher-Lambert[1]
Department of Mechanical Engineering,
Carnegie Mellon University,
Pittsburgh, PA 15213
e-mail: kgoucher@andrew.cmu.edu

Jarrod Moss
Department of Psychology,
Mississippi State University,
Starkville, MS 39762
e-mail: jarrod.moss@msstate.edu

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

Trying to decide whether to purchase a sustainable product often puts decision makers in a difficult situation, especially if the more sustainable option provides less desirable features or costs a premium. This paper theorizes that adding sustainability as a variable during product choice evaluations create decisions that are moral choice scenarios, where benefit to society is weighed against personal gain. From an engineering design perspective, modeling user preferences in this context can be extremely difficult. While several methods exist to assist researchers in eliciting consumer preferences, the vast majority relies upon conscious input from the potential consumers themselves. More critically, these methods do not afford researchers the ability to understand the cognitive mechanisms underlying what someone may be feeling or thinking while these preference judgments are being made. In this work, functional magnetic resonance imaging (fMRI) is used to investigate the neural processes behind multi-attribute product preference judgments. In particular, this work centers on uncovering unique features of sustainable preference judgments: preference judgments that involve products for which the environmental impact is a known quantity. This work builds upon earlier work that investigated how preference judgments are altered in the context of sustainability. A deeper look at participant decision making at the time of judgment is examined using neuroimaging with the goal of providing actionable insights for designers and product developers.
[DOI: 10.1115/1.4035859]

1 Introduction

To understand consumer behavior, engineering design teams utilize a wide array of both qualitative and quantitative methods. Qualitative methods such as interviews, focus groups, and task analysis can provide a context to understand personal experiences. However, it can be challenging to use qualitative information to abstract and predict future behavior. On the other hand, quantitative methods such as stated preference modeling techniques (for example, conjoint analysis and discrete choice analysis) continue to be utilized due to their ability to model and predict consumer preferences. Yet, these methods provide no insight into people's rationale while they make their preference judgments. Despite their power, both qualitative and quantitative research methods are both ultimately limited by the fact that in the vast majority of cases they rely on direct input from the users themselves. This can be problematic, as potential users may not accurately represent their own true preferences. Furthermore, these individuals may be unable to express what they are truly thinking, feeling, or desiring.

One way that researchers can explore complex decision-making scenarios at the time of judgment is through the use of neuroimaging techniques. From a cognitive neuroscience point of view, understanding how the brain implements the cognitive processes associated with decision making is an important intersection between cognitive psychology, neuroscience, and engineering design. Neuroimaging methods provide a powerful set of tools to capture the neural processes underlying brain functions—including choice decisions. One such method available to researchers is fMRI. Recent progress in the design and analysis of fMRI data has enabled advances in understanding how the brain produces valuations of multi-attribute decisions.

Recent advances, paired with the rising number of researchers studying the brain, have allowed new research areas to begin using fMRI to learn about distant domains. Neuromarketing and neuroeconomics are emerging fields, which among other goals, look to use neuroimaging techniques to gain advanced insights for product success [1]. Despite the incorporation of fMRI into new research areas, the applications of fMRI in engineering design research have been rare [2,3]. This is largely due to the challenge of adapting existing experimental paradigms familiar to design researchers for use with neuroimaging methods. For example, essential to the design of fMRI experiments is the fact that brain activation as measured by fMRI as a result of a stimulus is a strictly relative measure. Using an fMRI scanner, brain imaging data can be collected. Once collected, brain imaging data is analyzed by measuring the relative change in the blood oxygen level dependent (BOLD) contrast signal in different brain regions during the performance of two or more experimental conditions. The result is that researchers are only able to determine brain activation as a comparison between two or more separate experimental conditions. This comparison is a key feature of fMRI interpretation, because results must always be examined knowing what they are compared against (e.g., task activation versus rest).

fMRI may be particularly beneficial in helping to understand preference judgments that are challenging to obtain accurate data for using traditional behavioral methods. For example, this is the case when dealing with preference decisions that involve unique tradeoffs, such as those including moral or ethical judgments. One such example is preference judgments involving sustainable products. Sustainable products have largely underperformed in the

[1]Corresponding author.
Contributed by the Design Theory and Methodology Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received August 11, 2016; final manuscript received January 26, 2017; published online February 27, 2017. Assoc. Editor: Andy Dong.

consumer marketplace; the reasons for this are unclear, especially due to the fact that consumer studies have shown that individuals desire environmentally smart products [4]. Decades of research support the fact that social desirability bias often prevents people from expressing their opinion if it may cause them to appear negatively [5,6]. In addition to this, several models and theories exist which link personal qualities, motivations, and behavior within the context of environmentally conscious behavior [7]. For example, Heberlein proposed a theory of altruistic behavior to explain environmentalism [8]. Many researchers have used this framework to show how this relates to Schwartz's theory of moral norm-activation, including the value-belief-norm (VBN) theory of environmentalism norm-activation [9,10], including the value-belief-norm (VBN) theory of environmentalism from Stern et al. [11]. VBN looks to describe nonactivist environmentalism behavior using a causal chain of five variables, including personal values and ecological worldview [12]. Work published by Fleming et al. has shown that, when faced with a difficult decision, users tend to prefer the option that most represents the status quo [13]. It is possible that when forced to make a more complex preference judgment involving sustainable tradeoffs, users may revert to the status quo (less sustainable) option.

Previous research has shown that consumers often do not trust sustainable marketing claims. Furthermore, it has been put forth that people are often unaware of a product's environmentally friendly features during product evaluations [14,15]. Goucher-Lambert and Cagan showed that, when a product is evaluated with its environmental impact present, users tend to perceive functional attributes as more important; furthermore, esthetics become less important when the environmental impact information is present [16]. Despite these consistent results across the sampled population using a preference modeling approach, the work failed to provide insight into the mental thought processes of the decision makers. Qualitative methods employed by Goucher-Lambert and Cagan were in conflict with quantitative (preference modeling) results, as self-reported responses from study participants did not match what their preference models predicted [16]. Why did the environmental impact affect preference judgments? The work from Goucher-Lambert and Cagan highlights the fact that recent attempts at understanding the complex ways that people evaluate sustainable products are incomplete.

The current work seeks to utilize fMRI to understand brain functions and areas of brain activation associated with multi-attribute preference decisions involving the moral choice context of sustainability. By having participants complete a preference decision (visual conjoint) experiment while inside of an magnetic resonance imaging (MRI) scanner, traditional preference data can be supplemented and enhanced using brain activation data. We propose that combining these two sources of information will lead to a more complete picture of preference, as well as the decision-making process for sustainable product decisions. Together, this information can help inform designers and product developers on how users evaluate sustainable products.

In this experiment, two conditions are explored and compared; one where preference judgments were made with a product's environmental impact information present, and the second where this information was excluded. It is hypothesized that the behavioral results from the previous study from Goucher-Lambert and Cagan will be supported by the data collected in this study. Behavioral results can be more effectively interpreted using neural activation data by studying the brain regions that are active while participants complete sustainable preference judgments. The collected neuroimaging data will be analyzed using a general linear model (GLM) approach to understand different brain regions active in each experimental task. Furthermore, it is hypothesized that environmental preference judgments will be more difficult for participants. This will be explored by examining reaction time values (higher implying greater difficulty) and whether emotion- and moral-related brain activation areas are present during sustainable preference decisions. Figure 1 shows the entire scope of the research project, which combines behavioral and neuroimaging results to better inform the design research community regarding sustainable preference decisions.

2 Background

There have been limited applications of neuroimaging techniques, and in particular fMRI, to design research. fMRI is the only one of several neuroimaging techniques available to researchers. The optimal neuroimaging technique to choose for a given study is dependent on the nature of the study being conducted and, among other factors, requires a tradeoff between the spatial and temporal resolutions offered by each method [17]. While there are limited works using other neuroimaging techniques, such as electroencephalography (EEG) [18], there were two works that utilized fMRI within the engineering design community [2,3] (discussed in further detail below). In addition to these works, the current project draws on previous contributions from the engineering design community in preference modeling and sustainable preference judgments, as well as the contributions from cognitive psychology and neuroscience fields as it relates to emotional, complex, and multi-attribute decision making.

2.1 Preference Modeling and Multi-Attribute Decision Making in Engineering Design. In this work, empirical preference data were collected using visual conjoint analysis. Conjoint and discrete choice analyses have been applied to several engineering design research projects over the last 10 years (for example, see Refs. [3,19–22]). The appeal of these methods is largely based on the fact that they allow products or systems to be decomposed into a set of controlled continuous or discrete attributes, which span a predefined design space. These attributes are expressed at different values (i.e., levels) and can be grouped into combinations that are presented to participants to rank, rate, or choose between. The chosen combinations of attributes are determined based on design of experiment techniques, where either a full factorial or, more commonly, a fractional factorial design is used. With response information, preference weights can be determined using various modeling and estimation techniques. The calculated preference weights can then be used to predict preference for alternatives not presented to participants during the study.

Traditionally, the attributes used in conjoint and discrete choice studies are text based in nature and sometimes also have discrete images chosen a-priori. Recently, however, researchers have expanded upon this to include continuously varying attributes, such as two- and three-dimensional visual forms, as well as experience-based preference judgments, such as those being enabled by virtual reality [19,20,22,23]. Orsborn et al. introduced visual conjoint analysis, which allows utility functions to be derived based on preference for continuous two-dimensional esthetic attributes [20]. Visual conjoint analysis has been used by

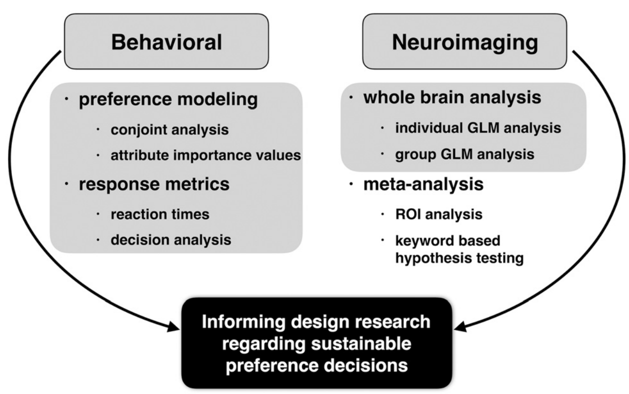

Fig. 1 Experimental outline. The key contributions presented in this paper are highlighted.

several researchers to explore form preference alone, as well in tradeoff with additional attributes [24].

Preference judgments involving attributes based on form or functional features have been explored in engineering design research studies. However, the numbers of studies that have explored questions regarding sustainability are very limited. In She and MacDonald's work on sustainable design features, the authors found that adding trigger features that reminded participants of the environment increased participant preference for sustainable products [25]. MacDonald et al. also examined how participants evaluated different combinations of paper towel designs, including environmental considerations using text-based attributes [21]. Reid et al. studied how the perceived environmental friendliness of different vehicles was impacted by the two-dimensional forms of those vehicles [26]. Goucher-Lambert and Cagan combined visual and text-based stimuli to explore how the presence of design-dependent environmental impact information impacted consumer preference [16]. In the study by Goucher-Lambert and Cagan, the calculated environmental impact values were dependent on the form–function design combination being displayed. Results from this study were discussed in the Introduction.

2.2 Decision Making and Preference in Functional Magnetic Resonance Imaging Research. To date, there are several examples of works within the neuroimaging communities that use fMRI to investigate decision making and, more specifically, preference decisions. Neuroimaging studies that examine decision making have focused almost exclusively on decisions where only one attribute of the choice decision differs. This scenario has primarily been modeled using gambling and rewards tasks. Researchers have begun to extend beyond these more simplistic designs by exploring multi-attribute decisions.

Zysset et al. used a multi-attribute framework where participants were selecting an apartment to rent [27]. With the support of neuroimaging data, Zysset et al. proposed that there are two levels of processing present during decision making with multiple attributes: process and control levels. The process level is responsible for integrating information, with areas of activation in the superior parietal lobe—an area of the brain involved in the integration of unbound information [28]. On the other hand, the control level is responsible for interpreting information, with activation found in the anterior insula—a part of the brain which appears to be related to risk taking (not only in decision making) [29,30].

Preference is another active area of brain research. The diverse tasks that have been studied include abstract paintings and real world objects [31], sports cars [32], wine taste and price [33], and facial attractiveness [34]. These works have supported reward-based stimuli for abstract concepts (nonprimary rewards), based in the ventromedial prefrontal cortex.

More recently, researchers from distant fields have began applying neuroimaging methods to understand more about behavior, such that products can be more effectively matched to people. For example, Neuro Information Systems (NeuroIS) seeks to use neuroscience to better understand the use of information and communication technologies. Some recent pilot work in NeuroIS used an EEG-based passive brain–computer interface to examine like/dislike decisions related to car designs at an unconscious state. Another area, Neuromarketing, has been growing rapidly since 2002; this field has several promising applications, such as product preference decisions and brand evaluations [35–38]. Primarily, the contributions up to this point have been in identifying various brain mechanisms that help to support information processing involved in user decision making [39]. More advanced methods of analysis, including machine learning techniques (i.e., multivoxel pattern analysis), have shown additional promise in characterizing brain activation patterns related to some preference decision contexts [40,41].

There have been two studies within the design theory and methodology literature that utilized fMRI. Alexiou et al. used fMRI to examine design thinking using an apartment layout task [2]. Here, the researchers wanted to explore whether design could be distinguishable from other related tasks such as problem solving. Results showed that the design task recruited a more extensive set of brain regions compared to the problem-solving task. Additionally, the authors suggest brain regions, such as the dorsolateral prefrontal cortex and anterior cingulate cortex, which may be particularly relevant to design. Sylcott et al. demonstrated the feasibility of using fMRI within a consumer choice context for engineering design [3]. In that study, participants were shown a variety of car form and functional attributes using a meta-conjoint approach. From their analysis, they found that form and function judgments recruit both similar and different brain activation networks, with emotion-related areas being active when these attributes are in conflict.

The current work deals with sustainable preference decisions. Neuroimaging investigations focused on environmental impact have been rare. It is possible that a connection can be made between decision making regarding the environment and social norms. Research into social norms has found that brain regions such as the anterior cingulate cortex and anterior insula are positively correlated with conforming to social norms [42,43]. Additionally, the medial prefrontal cortex has been found to be activated when learning about advice being used to guide behavior [44]. In a recent fMRI study, Sawe and Knutson investigated how much value people place on environmental studies using a donation task [45]. This study found that willingness to donate, as well as the value of natural resources, was predicted by brain activation. It has been suggested that environmental decisions may fit into a larger research paradigm of emotional and moral decision making [46–48]. It has been shown that individuals use different mental processes for personal moral decisions, nonpersonal moral decisions, and nonmoral decisions [46]. In the current study, we hypothesize that sustainable preference judgments will recruit emotion- and moral-related areas of activation compared to trials where the environmental impact is not included.

3 Methods

The experiment introduced in this paper investigated multi-attribute decision making in a consumer-based product evaluation context. Participants were asked to rate or choose between different product alternatives comprised of various attributes that were controlled by conjoint analysis techniques. The study required two sessions of data collection. The first session was a behavioral session and was used to determine participant-specific preference functions across the attribute design space, which then populated the experiment during the second session involving the fMRI. The procedure used in each of the two sessions is outlined below.

3.1 Participants. For this experiment, 11 healthy, right-handed, native English-speaking adults (four female/seven male, mean = 24 years, SD = 3.4 years, range 18–31 years) were selected to complete the fMRI part of the study. Based on a region of interest (ROI)-based power analysis of pilot data, this sample size was shown to have acceptable power in the ROIs used in the power analysis. The power analysis was conducted using the FMRIPOWER software [49]. Participants were recruited through the Carnegie Mellon Center for Behavioral and Decision Research, a Carnegie Mellon University undergraduate Mechanical Engineering class, and from a Masters program focusing on product innovation. Participants for the fMRI part of the study were screened based on their responses to a standard fMRI medical background form. Additionally, participants were screened based on their preference judgment consistency measured using the results of their behavioral data from a related task administered by the researchers [16]. Written informed consent was obtained from all participants prior to testing in accordance with protocol approved by Carnegie Mellon University's Institutional Review Board. For their participation, all participants were compensated monetarily.

If participants completed the fMRI part of the study, they were also presented with a digital image of their brain.

3.2 Prescan Behavioral Session Procedure. The fMRI experiment sought to determine the neural characteristics of multi-attribute preference decisions involving sustainability. Participants qualifying for the fMRI study were scheduled for a 2 hr. session; the first hour was done outside of the MRI scanner and used to prepare the stimuli and the participant for the brain scan, which was completed during the second hour. During the first hour, participants engaged in a behavioral study where they were asked to rate the desirability of the form of various water bottles. Participants were asked to rate the desirability of a product's form on a 1–10 scale. Using response values, visual conjoint analysis was used to determine a unique esthetic attribute preference function for each participant [20]. The preference weights for all attribute levels, $\boldsymbol{\beta}$, were solved for using ordinary least squares regressions

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

In this equation, $\boldsymbol{X}$ is the binary coded design matrix containing information regarding the question profiles, $\boldsymbol{y}$ is a vector containing participant ratings for each design alternative, and $\hat{\beta}$ are the estimated parameter values. The results from the visual conjoint analysis were used to determine a customized high-, medium-, and low-utility form design for each participant, which then populated the choice trials seen during the fMRI session. Next, participants engaged in a training exercise for the task done inside the MRI scanner. Participants were first explained the protocol for the experiment and given a list of attribute descriptions to study. Participants then completed a sample experiment run consisting of 18 preference decision trials.

3.3 Functional Magnetic Resonance Imaging Session Procedure. The task completed in the MRI scanner involved a preference task where participants were asked to choose between two different forms and feature combinations for various water bottles. The attributes used to create the water bottle alternatives were form (high utility, medium utility, low utility), function (material: aluminum, hard plastic, soft plastic), and price ($9.99, $14.99, $19.99). In addition, each water bottle was paired with an operationalized dependent property based on the composition of the alternative specific configuration being shown. There were two different properties that could be added onto the alternative, creating two different conditions for the experiment. The *Environmental Condition* (Fig. 2, Top) included calculated environmental impact values for each configuration. Environmental impact values were calculated using the Eco-Indicator 99 life cycle assessment methodology [50]. The *Control Condition* (Fig. 2, Bottom) included a material property, Poisson's ratio (the negative ratio of transverse to axial strain), along with the shown alternative. Poisson's ratio was included in the trials without the environmental impact information in order to keep the amount of text stimuli on the screen (decision variables) consistent between conditions. Data from pilot subjects indicated that this attribute did not significantly alter decision making and attribute importance weightings compared to the Control condition in the previous study by Goucher-Lambert and Cagan [16]. A detailed explanation for Poisson's ratio was included in the training exercise given to all participants prior to fMRI data collection.

Preference decision trials were presented in the MRI environment using the E-PRIME software package [51]. Subjects lay supine in the scanner, with the stimulus displayed using a projector and a mirror fixed to the head coil. A six run, slow event-related design was used, with each run consisting of 18 preference decision trials. Each preference decision trial was shown twice, once in each condition. The design alternatives making up the individual preference trials were first created using discrete choice analysis

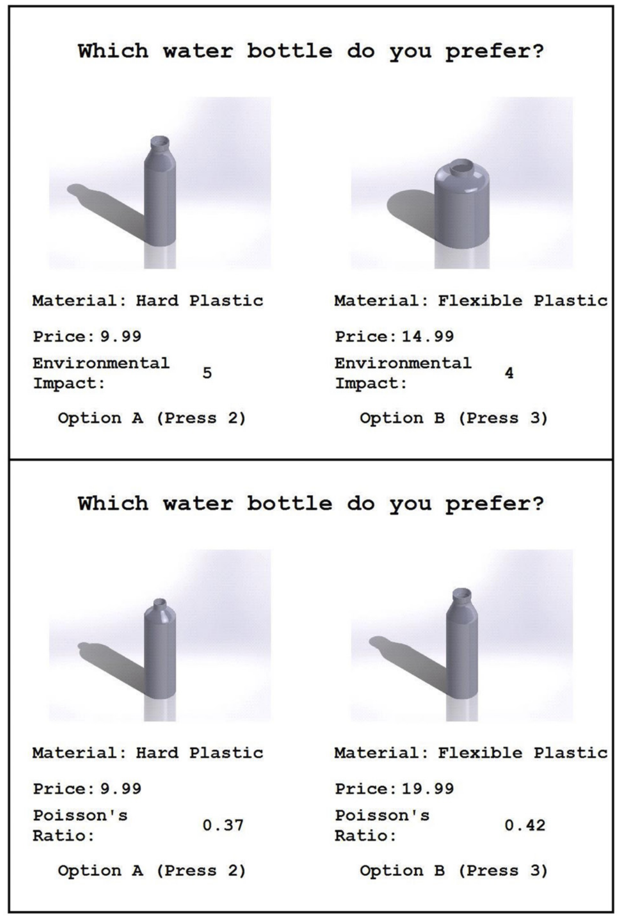

Fig. 2 EPRIME task example: Environmental condition (top) and Control condition (bottom)

design of experiment techniques and arranged into profiles using the SAS software package's *MktEx* and *Choiceff* macros [52]. The *nodup* option was used to ensure no duplicate options were included in the experiment to enforce novel preference judgments during scanning. Experiment trials were all randomized within and between runs.

Trial timing is described in Fig. 3. During each trial, the first design alternative was shown on the left side of the screen for 4 secs. Immediately following this, the second design alternative was added on the right side of the screen for 2 secs. Participants then had 6 secs. to make a choice between the two designs (with both alternatives up on the screen). Responses were made using a response pad strapped to participant's right hand. If a response was made before the end of the 6 secs., the remaining time was added to the intertrial interval using a blank screen. After the choice selection, participants performed an 8 secs. tone discrimination task. Here, participants were presented with either a high- or low-frequency tone and had to respond using the response pad. The tone discrimination task was assumed to be unrelated to the preference decision task and thus allowed the brain's BOLD response from the preceding decision trial to return to baseline.

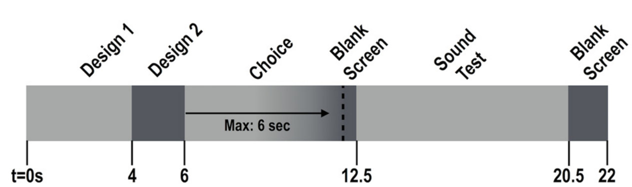

Fig. 3 fMRI trial timing outline

Additionally, active baseline conditions are generally preferred over resting baseline conditions [53]. Following this, the next trial began.

3.4 Functional Magnetic Resonance Imaging Data Acquisition. Functional MRI data were collected from a Siemens 3 T Verio MRI scanner (SYNGO MR B17 software) at the Scientific Imaging and Brain Research Center located in Carnegie Mellon University campus in Pittsburgh, PA, using a 32-channel phased array head coil. Functional images were acquired using a T2*-weighted echo-planar imaging (EPI) pulse sequence (31 oblique axial slices, in-plane resolution 3 mm × 3 mm, 3 mm slice thickness, no gap, repetition time TR = 2000 ms, echo time TE = 29 ms, flip angle = 79 deg, Generalized Autocalibrating Partial Parallel Acquisition = 2, matrix size = 64 × 64, field of view = 192 mm). Six runs of data were acquired, each consisting of 200 volume acquisitions. In addition, high-resolution anatomical scans were acquired for each participant using a T1-weighted MP-RAGE sequence (1 mm × 1 mm × 1 mm, 176 sagittal slices, TR = 2300 ms, TI = 900 ms, flip angle = 9 deg, Generalized Autocalibrating Partial Parallel Acquisition = 2).

3.5 Functional Magnetic Resonance Imaging Data Preprocessing. Raw neuroimaging data were preprocessed and analyzed using the AFNI (analysis of functional neuroImages) software package (June 2015 version) [54]. A custom automated Nipype (PYTHON language) preprocessing script was used to complete the preprocessing of the neuroimaging data into a form suitable for data analysis [55]. Preprocessing steps within the pipeline included slice scan time correction, 3D rigid-body motion correction, high-pass temporal filtering, and spatial smoothing. Slice time correction aligned all slices within a brain volume to the first slice in that volume. Next, data from the functional image acquisitions were realigned to the first image of each run, and then again from this image, to the first run of each subject. The rigid-body rotation, translation, and three-dimensional motion correction algorithm examined the data to remove any time points where excessive motion occurred from the analysis. A high-pass Gaussian filter was used to remove low-frequency artifacts in the data. To further reduce the effects of noise, a probabilistic independent component analysis method called MELODIC from the FSL software package was used [56]. Here, the time course associated with each component correlated with motion was examined to remove the top 10% of such components. Furthermore, the top 10% of high-frequency noise components were eliminated by rank ordering the components by their Fourier transform determined power. The top 10% of components showing the greatest TR-to-TR signal change (i.e., a discontinuous spike) were also removed. To reduce signal noise, the signal from each voxel was spatially smoothed (7 mm full width at half maximum). Furthermore, the anatomical image from each subject was co-registered to his or her corresponding functional images. The structural and functional images were transformed into Talairach space with 3 mm isometric voxels using AFNI's *auto_tlrc* algorithm.

3.6 Individual-Level Functional Magnetic Resonance Imaging Analysis. The collected fMRI data were first analyzed using a voxel-wise general linear model. Boxcar regressors were constructed for each condition (Environmental and Control) that were set to 1 starting 4 secs. prior to a response (indicating a choice decision was made) and 0 otherwise. Four seconds were selected based on the analysis of pilot testing, which demonstrated that the maximum BOLD activation from the multi-attribute choice decision task occurred in the beginning 4 secs. prior to the choice selection. These two boxcar regressors were convolved with a canonical hemodynamic response function to generate the two regressors included in the general linear model. The resulting coefficients for each regressor represent the average level of activation for that condition in a given voxel. These coefficient values were then used in the group-level analysis to contrast the two conditions.

3.7 Group-Level Functional Magnetic Resonance Imaging Analysis. To analyze group-level effects, AFNI's 3DTTEST was used to perform t-tests for the Environmental and Control contrast using participant-specific coefficient values from their individual-level contrasts. All results were corrected for multiple comparisons using family wise error (FWE) cluster size thresholding. AFNI's 3DCLUSTISM tool was used to determine the optimal cluster size, allowing for an FWE corrected p value of $p = 0.05$ (individual voxel p value $= 0.02$; cluster size $(k) = 25$).

3.8 Behavioral Data Analysis. The behavioral data collected in this experiment included participant response information for each of the conjoint preference trials explained previously. Using the collected information, individual preference values for each level of each attribute could be determined. Here, the Bradley–Terry–Luce (BTL) equation was used (Eq. (2)); to calculate parameter estimates using the probability, a given design alternative is selected (w_i), divided by the number of times that the alternative was offered (w_j)

$$P(j) = \frac{w_i}{w_j} \tag{2}$$

The BTL equation has been shown to successfully model individual preferences in a number of engineering design studies [3,16,20].

Calculated preference weights were used to determine attribute importance. Importance defines the influence of one attribute compared to other attributes in dictating a participant's overall preference. This value is determined by examining the range in utility values between levels of a specific attribute. A high-importance value indicates an attribute was very influential in driving preference.

In addition to preference modeling data, response metrics were also captured during the study. This included reaction time and decision analysis. Reaction time was measured during fMRI trials using the response glove participants used to make selections in the MRI machine (respondents wore a glove and selected a button with the glove to indicate their choice). The goal of the reaction time measurement was to make a physical estimation of the difficulty of each condition type for participants, with longer reaction times indicating a higher level of difficulty. In this work, reaction time was measured from the instant participants that were able to make a judgment (the start of block labeled "Choice" in Fig. 3) to the time they physically pressed the selection button.

Decision analysis was performed on participant responses to gain behavioral insights into participant decision making. One way this was done was through recording the environmental impact value of chosen design alternatives. Environmental impact values were only presented to participants in the Environmental condition; however, a value for the environmental impact was calculated for each alternative regardless of whether it was presented to participants or not. The calculated environmental impact value of the chosen alternative data was recorded for each participant selection in both conditions. Each experimental condition included the same choice decision trials (however presented in different orders); therefore, any differences in the environmental impact values of the chosen alternative was attributed to a difference in decision-making strategy between the conditions.

4 Results

The collected data were analyzed to determine how user preference judgments altered with the presence of the environmental impact information. The results from the conjoint experiment conducted during the fMRI experiment were analyzed and compared to previous results from Goucher-Lambert and Cagan. Neuroimaging results from the fMRI experiment were examined to provide deep insight into the mental processes supporting preference decisions involving sustainability.

4.1 Behavioral Data Results. Preference modeling techniques and response metrics (reaction time, decision analysis) were both used to assess participant's preference decisions. The results from these analyses were then compared to previous results from Goucher-Lambert and Cagan [16]. All of the behavioral data presented in this section were collected during the fMRI part of the study in conjunction with neuroimaging data.

Table 1 summarizes the attribute importance values for the form, function, and price attributes in both experimental conditions (taken from the fMRI session data). The general trend of the data shows that the importance for form attributes decreased during the Environmental condition compared to the Control condition. In addition, the importance of functional product attributes increased and price decreased under these same conditions. Despite the overall decrease in importance with the presence of the environmental impact information, esthetics was the most important decision variable to participants in both conditions. Function was the most impacted by sustainability, as this attribute became nearly 20% more important to participants in trials where the environmental impact information was shown.

Figure 4(*a*) shows the reaction time for both experimental conditions. Participants responded more quickly in the Environmental Condition (mean = 1630 ms) compared to the Control Condition (mean = 1850 ms) with a high degree of significance ($p < 0.005$).

Figure 4(*b*) shows the mean environmental impact score of chosen product alternatives. From the graph, it can be seen that participants chose products with a low environmental impact much more frequently in the Environmental condition, compared to the control condition ($p \ll 0.001$). This indicates that being conscious of a product's environmental impact led to participants choosing more environmentally friendly options.

4.2 Functional Magnetic Resonance Imaging Data Results. Neuroimaging data were analyzed using the methods outlined in Sec. 3. Individually, each condition (Environmental and Control) was contrasted separately against activation during the tone discrimination decisions. This was due to the fact that pilot results showed that the tone discrimination task activated a different set of brain regions compared to any of the regions of interest for this study. Doing so allowed for the extraction of condition-specific activation. From this, the individual condition contrasts were then used to create contrasts between the two conditions explored in this study. This contrast between the Environmental and Control conditions was used to understand how the presence of environmental impact information impacts preference judgments.

Significant areas of activation are summarized in Table 2. The activation data in Table 2 are taken as a contrast (subtraction) between the Environmental and Control conditions. Positive activation clusters, measured using the t-statistic (t), from the two-condition contrast indicates that there is greater brain activation in the Environmental condition compared to the Control condition. Table 2 also includes the Brodmann area (BA), positional coordinates in Talairach space (x, y, z), and the cluster size (k) associated with each activation cluster.

Overall, there were ten significant activation clusters found. Of these, four were positive action clusters, as indicated by the t-test, meaning that areas of activation in these regions are greater when participants were considering the environmental impact information. Negative activations are areas of the brain that were more active in the Control condition. This can also determine aspects of the decision-making process that may have required less mental effort for participants during the Environmental condition.

Positive clusters of activation are visualized in Figs. 5 and 6. These figures show results mapped onto a 3D template brain in standardized Talairach space. The views presented were selected based on their ability to show the maximum coverage of important results. Because these are surface mapping figures, some features of active clusters on the internal portions of the brain are not visible. The intensity of the color indicates the t-statistic value, with yellow (lighter) being a lower t-statistic and red (darker) being a higher t-statistic. Two particularly interesting clusters of activation are 3 and 9 as labeled in Table 2. Cluster 3 in the right dorsomedial prefrontal cortex is an area of the brain that prior research has found to be associated with self-referential, social, and theory of mind (what will others and people of society think of my actions) activation [57,58]. Cluster 9 in the left inferior/middle temporal gyrus is also in a region typically associated with theory of mind and social cognition [59].

Negative clusters of activation are visualized in Fig. 7. Here, the t-statistic is mapped through the intensity of blue, with darker hues indicating more neural activation. Of the ten significant clusters found in the Environmental–Control contrast, six of them were negative activation clusters; meaning in these locations, neural activation was greater in the Control condition compared to the Environmental condition. Virtually, all of this activation occurs in the occipital gyrus and other regions of the brain that are associated with vision and visual processing. Furthermore, there are significant areas of activation, such as cluster 5 in the right fusiform gyrus that are associated with object and word forms. These regions of the brain help to translate visual objects and words (i.e., bottle) into shapes. Together these results indicate a robust effect of increased neural effort spent on visual and form processing during the Control condition.

Table 1 Attribute importance values from conjoint model. Data collected during MRI session ($N = 11$).

	Form (SE)	Function (SE)	Price (SE)
Control condition	61.95 (5.34)%	16.09 (4.51)%	21.95 (3.68)%
Environmental condition	53.18 (6.13)%	34.24 (5.49)%	12.58 (2.81)%
Difference	−8.77 (8.13)%	18.15 (7.10)%	−9.38 (4.63)%

5 Discussion

5.1 Discussion of Results. It was hypothesized that the behavioral results from the preference models constructed from data collected during the fMRI experiment would support results from the Goucher-Lambert and Cagan study. In the work by Goucher-Lambert and Cagan, an increase in importance was observed for functional attributes, and a decrease was seen for form and price attributes during environmental impact trials. In the visual conjoint analysis results here, the same trends were observed. The sample size in this work included 11 participants chosen for the fMRI part of study. While this is significantly less than the 94 participants who completed the study by Goucher-Lambert and Cagan, the consistency in the trends between the two measurements provides validation.

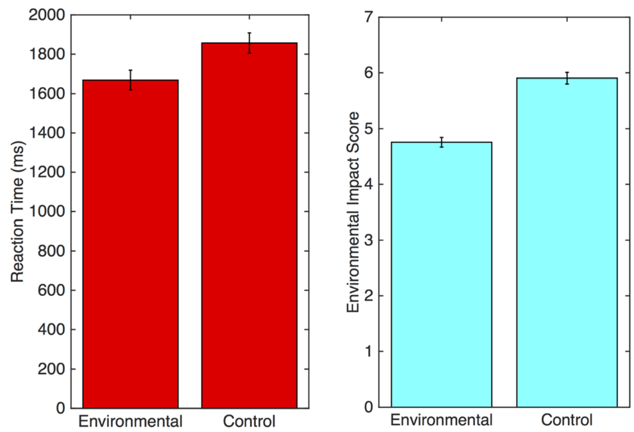

Fig. 4 Behavioral analysis: mean reaction time (*a*) and environmental impact of chosen options (*b*), each with ±1 SE ($N = 594$ (11 participants with 54 observations per condition))

Table 2 fMRI results from Environmental–Control Condition contrast ($N = 11$)

	Region	B.A	x	y	z	k	t
1	R cuneus and middle occipital gyrus	18,19	−16.5	97.5	20.5	357	−8.65
2	R fusiform gyrus	37	−31.5	46.5	−9.5	304	−6.59
3	R dorsomedial prefrontal cortex	8, 9	−7.5	−49.5	41.5	65	8.89
4	R middle/inferior frontal gyrus	47, 10	−52.5	−49.5	−0.5	55	3.86
5	R fusiform/middle occipital gyrus	18, 19, 37	−31.5	82.5	−12.5	52	5.45
6	R postcentral gyrus	3	−34.5	31.5	65.5	37	−5.02
7	L cuneus and precuneus	31, 18	13.5	79.5	17.5	33	−4.43
8	R postcentral gyrus	5	−22.5	37.5	65.5	30	−4.76
9	L inferior/middle temporal gyrus	20, 21	61.5	7.5	−15.5	27	4.71
10	L inferior occipital gyrus	18, 19	40.5	82.5	−9.5	26	−4.89

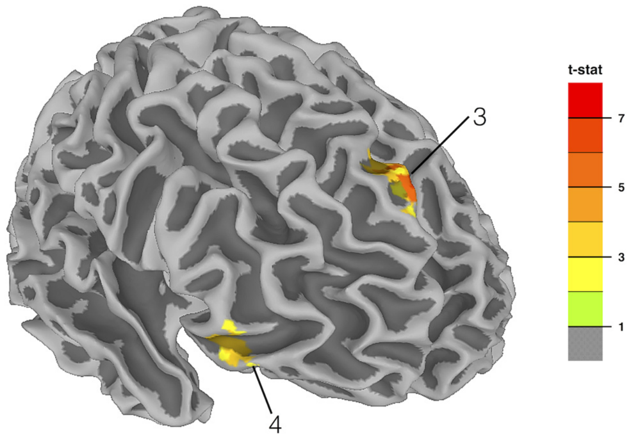

Fig. 5 Right hemisphere neural activation from Environmental–Control contrast. See Table 2 for cluster numbering.

In addition to the matching trends in preference modeling data, fMRI data also directly support multiple behavioral results. For example, brain regions such as the inferior occipital gyrus, precuneus, and cuneus were found to be more active in the Control condition compared to the Environmental condition. These are brain regions involved in vision and visual processing. Based on this, there appears to be support in neural activation data for the fact that individuals spend more mental effort capturing and analyzing form information when the environmental impact was not a preference decision attribute. This is particularly meaningful due to the fact that many potentially interfering factors that could impact brain activity associated with visual processing have been accounted for. These include the layout of the preference trial GUI and the amount of information present on the screen, both of which were consistent between the two experimental conditions. Additionally, the analysis of neuroimaging data was time locked to when a decision was made (participants physically pressed a response button).

Behavioral data were also examined using measures to capture characteristics of decision difficulty. Reaction time was measured for each response. It was hypothesized that the Environmental condition would be more difficult for participants (longer reaction time), due to the complex features involved in making a decision where environmental impact is a factor. However, the opposite occurred: participants spent significantly less time-evaluating products where environmental impact was a factor. This indicates that presenting the environmental impact as part of a preference decision makes the decision easier for participants. Prior research has utilized reaction time as a measure of difficulty [27,60]. However, much of the work in this area qualifies reaction time as a measure of difficulty when the decision types are the same. Here, it may be possible that the cognitive processes in the Environmental condition are qualitatively different than the control case (utilizing theory of mind processes, for example). Another explanation could be that that sustainability may be classified as an *impersonal* moral judgment. An impersonal moral judgment is one that contains moral connotations but allows the decision maker to separate him/herself from responsibility of any consequences that may occur as a result of the decision (e.g., (impersonal) voting on policy that may ruin a protected wildlife region versus (personal) ruining a wildlife region by personally dumping pollutants). Work by Greene et al. also found that participants made impersonal moral judgments significantly faster compared to personal moral judgments or nonmoral judgments [46]. This trend was particularly evident when participants decided on a morally "appropriate" course of action.

Neural activation data also helped to uncover unique features of sustainable preference judgments that would be impossible to

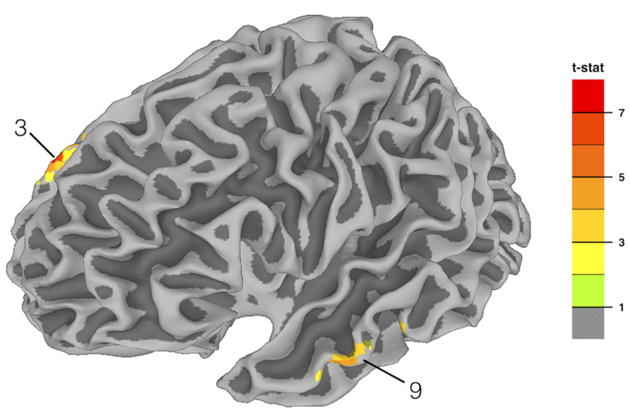

Fig. 6 Left hemisphere neural activation from Environmental–Control contrast. See Table 2 for cluster numbering.

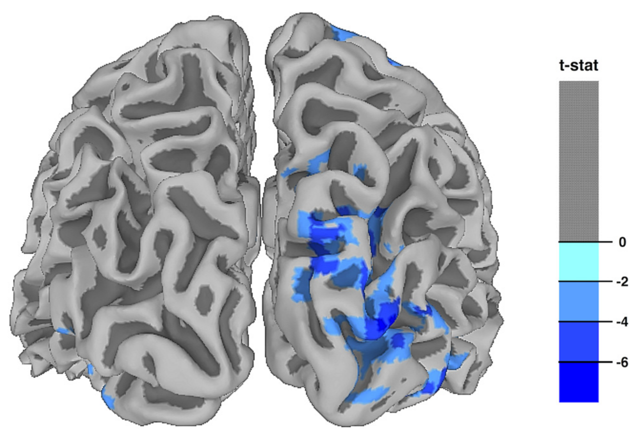

Fig. 7 Posterior view of neural activation from Environmental–Control contrast

obtain any other way. Behavioral decision analysis identified that the mean environmental impact of the chosen alternatives was significantly less when participants were presented with environmental impact information. This is the case even though the environmental impact calculation is a *dependent* variable based on the form and function information otherwise presented. Despite this result, it was unclear which features were different in the environmental impact trials. fMRI data analysis found activation in regions of the superior/medial frontal gyrus and the inferior/middle temporal gyrus when participants were engaged in the Environmental condition decision trials. These brain regions are heavily associated with several processes, including self-referential thoughts and theory of mind [59]. Self-referential and theory of mind are qualities of mental thought where one seeks to imagine others' thoughts and how other people may interpret their own actions. Theory of mind, in particular, allows one to interpret the beliefs, intents, and desires of other people. From this, it would appear that participants are highly aware of their actions and how others may view their choices while making sustainable preference judgments.

5.2 Using a Meta-Analytic Approach to Further Investigate Empirical Neuroimaging Data. Some of the limitations of this work result from the negative impacts of reverse inference conclusions on the interpretation of the collected neuroimaging data. Reverse inference conclusions result from reasoning backward from observed brain activity and making claims about particular behavior or cognitive processes, which were not directly tested [61]. Additionally, the sample was relatively small. To address these shortcomings, among others, a meta-analytic approach was undertaken, where the fMRI dataset collected for this study was reexamined and analyzed using regions of interest (ROIs) generated from the results of NeuroSynth, a meta-analytic database [62]. The meta-analytic approach was based on comparisons to a dataset comprised of external fMRI results. Previous research has noted, as well as demonstrated, the benefits of using meta-analyses to add value beyond that of single-fMRI studies [63,64].

The keywords chosen for the meta-analysis were based upon whole brain neuroimaging results from this work ("theory of mind," "moral," and "vision") as well as additional hypotheses regarding broad activation networks that may be present during environmental impact decisions ("emotion" and "empathy"). NeuroSynth, an open sourced meta-analytic tool, was used to extract neural activation from an expansive neuroimaging publication database (~4000 studies) [62]. Doing so allowed ROIs to be defined independently of the current data. Each keyword represented the broad activation network related to a different behavioral process of interest. A unique meta-analysis was performed for each keyword, drawing data only from studies within the database relevant to the keyword being explored.

The level of brain activity was examined for the empirical dataset within each ROI extracted using the meta-analytic technique. The level of brain activity for the Control and Environmental conditions was compared within each meta-analytically defined ROI. Results (shown in Table 3) were interpreted by examining the total number of ROIs that had a higher level of mean activation during the environmental impact condition, and the strength of this activation throughout all of the ROIs. Fisher's method of combined significance was used to obtain a group significance estimate associated with all ROIs for a given keyword. Overall, the meta-analyses indicated strong support for distributive networks associated with moral, theory of mind, and vision (deactivation) during the environmental impact condition.

This approach found significant support for moral and theory of mind activation based on a broad network of brain regions. It appears evident; both through the meta-analytic approach, as well as the models constructed using only the raw fMRI data, that theory of mind and moral decision making are key drivers in sustainable preference judgments. In particular, the moral activation highlights the type of decision judgments individuals are making, one where people are highly conscious of the larger societal issues involved with sustainability, and the other where the products they buy may impact the well-being of the earth on a larger scale. The data also displayed that there was a deactivation in visual processing-related brain regions during sustainable preference judgments. Empathy and emotion appear to be features of difficult decisions and not necessarily a unique feature of sustainable preference decisions. Neural activation was found in Emotion and Empathy ROIs for both the Control and Environmental conditions.

Critically, the meta-analytic approach helped to mitigate some of the negative effects of reverse inference conclusions by using externally defined ROIs to examine the empirical neuroimaging data collected as a part of this study. Doing so led to strengthened conclusions from the empirical data and helped to demonstrate that the brain activation in the environmental impact condition was a result of the behavioral processes put forth in this work. Furthermore, using hundreds of externally sourced datasets compliments the behavioral and neuroimaging trends seen in this work.

These results highlight that including environmental impact information about a design changes the cognitive processes that go into making a product choice. The choices made in the current study are examples of multi-attribute decision making. When there is no conflict among attributes, a set of brain regions involved in cognitive control is active when evaluating and integrating different attributes in order to make a decision [27]. However, when there is conflict, there are many methods or heuristics that can be used to combine conflicting attributes [65]. One method is to weight the utility of each attribute to calculate a combined utility. The results of this study and prior work show that the inclusion of environmental impact information leads to a decrease in weighting of form information and an increase in weighting of the functional attributes of the product [16]. The meta-analysis results provide some insight into why this might occur.

The meta-analysis shows that regions related to moral cognition and theory of mind were more active in the environmental impact condition. Studies of moral cognition have commonly examined vignettes in which a person is asked to make a decision based on morals [46,48,66,67]. For example, would one divert an oncoming train that was going to kill five people to another track if doing so would only kill one person? These studies have shown that a network of brain regions including the ventromedial prefrontal cortex, dorsomedial prefrontal cortex, posterior cingulate cortex, superior temporal sulcus, temporal pole, and inferior parietal cortex is active in moral decisions [48]. However, these brain regions involve a number of cognitive processes that are likely not unique to moral cognition.

A separate meta-analysis of moral cognition across 67 studies found a similar set of brain regions involved in moral cognition [68]. This meta-analysis also found that moral cognition significantly overlapped with regions found by doing a meta-analysis of theory of mind studies and empathy studies. This overlap was such that the moral cognition regions appear to be a combination of subsets of the brain regions involved in theory of mind and empathy. Some progress has been made at teasing apart the different functions of these brain regions and why they overlap in moral reasoning and theory of mind. For example, one study found that the process of attributing a belief to another person was closely tied to the right inferior parietal cortex, potentially explaining why this region is seen in both theory of mind and moral reasoning studies [69].

In the current results, it appears that the dorsomedial prefrontal cortex is a region that overlaps between the first two rows of Table 3, indicating that the processes implemented in this region is common to both theory of mind, moral reasoning, and reasoning about environmental impact. There are a number of processes that might

Table 3 Summary of results from meta-analytic ROI analysis examining the number of ROIs with greater mean neural activation level in Environmental versus Control condition

Keyword	# of ROIs	Environmental > Control	$p < 0.1$	$p < 0.05$	Fisher's group p
Moral	5	5	2	2	0.02
Theory of mind	10	10	2	2	0.04
Empathy	14	7	2(1)	2(1)	0.25
Emotion	7	4	1	0	0.26
Vision	7	0	3(3)	0	0.05

Note: Numbers inside parentheses indicate significant ROI clusters where Control > Environmental.

be involved in these types of tasks. One possibility is that making inferences about other people's beliefs is involved in all three tasks. For example, in assessing the environmental impact, people could consider what others may think of them for choosing such a product. This hypothesis is consistent with research that shows that this region might be involved with maintaining a self-model that must be updated in order to see how one's actions might be perceived by others [70]. While the exact nature of the involvement of moral cognition and theory of mind processes is not yet well understood, one conclusion is that the presence of environmental impact changes the nature of the decision processes that people engage in. These additional processes impact the relative weighting of attributes in the decision-making process resulting in less attention being paid to visual form, which is consistent with the result of a relative decrease of activation in visual processing regions in the control condition.

5.3 Implications for Design Research and Future Directions. From a high-level perspective, this work demonstrates the benefits of using neuroimaging to understand the decision-making process within a design-related context. Neuroscience can help design researchers understand the underlying mechanisms involved in choices and decisions that are observed. Doing so allows these mechanisms to be generalized and eventually used to develop ways where decisions can be influenced more effectively [71]. Finding ways to more effectively extract information from user studies, and apply them to the design of new products, is a major goal of design research. While more work is needed to realize the full potential of neuroimaging methods as it applies to design research, this work represents a step toward understanding the benefits of new insights from such cross-disciplinary work.

The main aim of the current research was to gain a deeper level of understanding of preference judgments involving sustainability. Behavioral methods for capturing user preferences in complex decision situations, such as those involving sustainability, can only scratch the surface of the participants' mental thought processes during decisions. A deeper understanding of these thought processes can inform the design team about aspects of the product that are important to the customer and may otherwise be ignored or differently understood. The work by Goucher-Lambert and Cagan illustrated how environmental impact values can have a large effect on behavioral responses regarding products [16]. In particular, that work showed that the importance of function increases while importance of form decreases in preference decisions where the environmental impact is present. This relationship was validated in the current study. More importantly, however, pairing these results with the added information from neuroimaging results adds a greater level of understanding and insight into previously obtained behavioral results. Future work can further link activated brain regions with other associations that may inform the design process at an even deeper level. For example, using other neuroimaging modalities (e.g., EEG) to examine similar research topics can add to our understanding of open questions relevant to design by providing a more holistic picture of the temporal resolution impacting these mental processes.

Product design practitioners can utilize insights from this work to more effectively target users of sustainable products. Both behavioral and neuroimaging results support the fact that, for commoditized products, users value function more, but cost and esthetic features less, when the environmental impact is a conscious decision attribute. More research is needed to apply these results to decision-making contexts outside the laboratory, as well as to new and distant product domains. One example of a distant domain to explore in future work could be high-value lifestyle products. For instance, as a manufacturer of alternative fuel vehicles, results from this work indicate that it may be beneficial to focus on improving functional attributes of the car (for example, acceleration) even if it costs a premium. In this domain (vehicles), it appears that high-performing, high-priced sustainable vehicles appeal to consumers. As a high end-product, at the time of this writing, Tesla has established itself atop the alternative fuel vehicle market by creating sustainable vehicles that excel in functionality [72]. Although it is also considered a well-styled vehicle, it is clear that consumers are attracted to functionality in an environmentally conscious space that has previously lacked high performance [73].

Another way to address sustainable product development is to ensure that a product's sustainable functional features are transparent to users so that their value can be understood. This is not to say that esthetics won't be important in order to enable the product to be accepted into the consumer's lifestyle, but that incorporating functionality into esthetic languages will highlight the important characteristics of the product. Neural activation data showed that participants already automatically think of the social and moral issues regarding sustainability when a product is examined under the lens of sustainability. Cagan and Boatwright present two varying paths by which users can gain an emotional connection with a product: those that are supported (built into the product), and those that are associated (superficial and/or manipulative) [74]. Designing sustainable features that a product can embody (are supported) will help potential consumers forge a positive emotional connection with the product.

6 Conclusion

This work utilized fMRI to better understand how users consider sustainability as part of a multi-attribute product preference decision. Previous research found that including the environmental impact of a product affects preference for that product's disparate product attributes. In particular, functional attributes become more important and esthetic attributes become less important when sustainability is a factor. This work provided validation to these results in the form of both behavioral and neuroimaging data. Behavioral data in this work illustrated the same trends as the prior literature. Neuroimaging data provided a new level of depth in understanding this research question. Empirical neuroimaging evidence indicates that theory of mind and moral reasoning processes are involved in preference judgments involving sustainability. These conclusions were further supported using a meta-analytic approach to examining the empirical data. Furthermore, neuroimaging data supported hypotheses from behavioral results, in that esthetic features become less important when the environmental impact is being considered. This work has implications for how the design community creates and tailors sustainable products to maximize user preference. A larger goal in this work is to use the methods here as a building block to incorporate fMRI and other neuroimaging techniques as tools to answer important questions in the engineering design research community.

Acknowledgment

The authors would like to thank the technologists and research staff at the Scientific Imaging and Brain Research Center at Carnegie Mellon University for their support with data acquisition. As well, the authors thank Chris McComb and Katie Whitefoot for their comments on the paper. Material in this paper builds upon work previously published in the conference proceedings of the International Design Engineering and Technical Conferences [75], as well the Design Computing and Cognition Conference [76]. This material is based upon work supported by the National Science Foundation Graduate Research Fellowship under Grant DGE125252 and the National Science Foundation under Grant CMMI1233864.

References

[1] Ariely, D., and Berns, G. S., 2010, "Neuromarketing: The Hope and Hype of Neuroimaging in Business," Nat. Rev. Neurosci., **11**(4), pp. 284–292.

[2] Alexiou, K., Zamenopoulos, T., Johnson, J. H., and Gilbert, S. J., 2009, "Exploring the Neurological Basis of Design Cognition Using Brain Imaging: Some Preliminary Results," Des. Stud., **30**(6), pp. 623–647.

[3] Sylcott, B., Cagan, J., and Tabibnia, G., 2013, "Understanding Consumer Tradeoffs Between Form and Function Through Metaconjoint and Cognitive Neuroscience Analyses," ASME J. Mech. Des., **135**(10), p. 101002.

[4] Blamey, R. K., Bennett, J. W., Louviere, J. J., and Morrison, M. D., 1999, "Validation of Choice Model Involving Green Product Choice," Choice Modelling Research Reports, Report No. 10, University of New South Wales, Canberra, Australia.

[5] Nederhof, A. J., 1985, "Methods of Coping With Social Desirability Bias: A Review," Eur. J. Soc. Psychol., **15**(3), pp. 263–280.

[6] Spector, P., 2004, "Social Desirability Bias," *The SAGE Encyclopedia of Social Science Research Methods*, M. Lewis-Beck, A. Bryman, and T. Liao, eds., SAGE Publishing, Thousand Oaks, CA. pp. 1045–1046.

[7] Stern, P. C., 2000, "Toward a Coherent Theory of Environmentally Significant Behavior," J. Soc. Issues, **56**(3), pp. 407–424.

[8] Heberlein, T., 1972, "The Land Ethic Realized: Some Social Psychological Explanations for Changing Environmental Attitudes," J. Soc. Issues, **28**(4), pp. 79–87.

[9] Schwartz, S. H., 1973, "Normative Explanations of Helping Behavior: A Critique, Proposal, and Empirical Test," J. Exp. Soc. Psychol., **9**(4), pp. 349–364.

[10] Schwartz, S. H., 1977, "Normative Influences on Altruism," Adv. Exp. Soc. Psychol., **10**(C), pp. 221–279.

[11] Black, J. S., Stern, P. C., and Elworth, J. T., 1985, "Personal and Contextual Influences on Household Energy Adaptations," J. Appl. Psychol., **70**(1), pp. 3–21.

[12] Stern, P. C., Dietz, T., Abel, T., Guagnano, G. A., and Kalof, L., 1999, "A Value-Belief-Norm Theory of Support for Social Movements: The Case of Environmentalism," Hum. Ecol. Rev., **6**(2), pp. 81–97.

[13] Fleming, S. M., Thomas, C. L., and Dolan, R. J., 2010, "Overcoming Status Quo Bias in the Human Brain," Proc. Natl. Acad. Sci. U. S. A., **107**(13), pp. 6005–6009.

[14] Olson, E. L., 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.

[15] She, J., and Macdonald, E. F., 2013, "Trigger Features on Prototypes Increase Preference for Sustainability," ASME Paper No. DETC2013-12973.

[16] Goucher-Lambert, K., and Cagan, J., 2015, "The Impact of Sustainability on Consumer Preference Judgments of Product Attributes," ASME J. Mech. Des., **137**(8), p. 081401.

[17] Huettel, S. A., Song, A. W., and McCarthy, G., 2004, *Functional Magnetic Resonance Imaging*, Sinauer Associates, Sunderland, MA.

[18] Nguyen, T. A., and Zeng, Y., 2010, "Analysis of Design Activities Using EEG Signals," ASME Paper No. DETC2010-28477.

[19] Tovares, N., Boatwright, P., and Cagan, J., 2014, "Experiential Conjoint Analysis: An Experience-Based Method for Eliciting, Capturing, and Modeling Consumer Preference," ASME J. Mech. Des., **136**(10), p. 101404.

[20] Orsborn, S., Cagan, J., and Boatwright, P., 2009, "Quantifying Aesthetic Form Preference in a Utility Function," ASME J. Mech. Des., **131**(6), p. 061001.

[21] MacDonald, E., Gonzalez, R., and Papalambros, P. Y., 2009, "Preference Inconsistency in Multidisciplinary Design Decision Making," ASME J. Mech. Des., **131**(3), p. 031009.

[22] 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.

[23] Turner, H., Orsborn, S., and Grantham, K., 2009, "Quantifying Product Color Preference in a Utility Function," Proceedings of the 2009 American Society of Engineering Management Conference (ASEM), Springfield, MO, Oct. 14–17.

[24] Tseng, I., Cagan, J., and Kotovsky, K., 2012, "Concurrent Optimization of Computationally Learned Stylistic Form and Functional Goals," ASME J. Mech. Des., **134**(11), p. 111006.

[25] She, J., and MacDonald, E., 2013, "Priming Designers to Communicate Sustainability," ASME J. Mech. Des., **136**(1), p. 011001.

[26] 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.

[27] Zysset, S., Wendt, C. S., Volz, K. G., Neumann, J., Huber, O., and von Cramon, D. Y., 2006, "The Neural Implementation of Multi-Attribute Decision Making: A Parametric fMRI Study With Human Subjects," Neuroimage, **31**(3), pp. 1380–1388.

[28] Prabhakaran, V., Narayanan, K., Zhao, Z., and Gabrieli, J. D., 2000, "Integration of Diverse Information in Working Memory Within the Frontal Lobe," Nat. Neurosci., **3**(1), pp. 85–90.

[29] Derrfuss, J., Brass, M., and Yves Von Cramon, D., 2004, "Cognitive Control in the Posterior Frontolateral Cortex: Evidence From Common Activations in Task Coordination, Interference Control, and Working Memory," Neuroimage, **23**(2), pp. 604–612.

[30] Paulus, M. P., Rogalsky, C., Simmons, A., Feinstein, J. S., and Stein, M. B., 2003, "Increased Activation in the Right Insula During Risk-Taking Decision Making is Related to Harm Avoidance and Neuroticism," Neuroimage, **19**(4), pp. 1439–1448.

[31] Vartanian, O., and Goel, V., 2004, "Neuroanatomical Correlates of Aesthetic Preference for Paintings," Neuroreport, **15**(5), pp. 893–897.

[32] Erk, S., Spitzer, M., Wunderlich, A. P., Galley, L., and Walter, H., 2002, "Cultural Objects Modulate Reward Circuitry," Neuroreport, **13**(18), pp. 2499–2503.

[33] Plassmann, H., O'Doherty, J., Shiv, B., and Rangel, A., 2008, "Marketing Actions Can Modulate Neural Representations of Experienced Pleasantness," Proc. Natl. Acad. Sci. U. S. A., **105**(3), pp. 1050–1054.

[34] Winston, J. S., Strange, B. A., O'Doherty, J., and Dolan, R. J., 2002, "Automatic and Intentional Brain Responses During Evaluation of Trustworthiness of Faces," Nat. Neurosci., **5**(3), pp. 277–283.

[35] Morin, C., 2011, "Neuromarketing: The New Science of Consumer Behavior," Society, **48**(2), pp. 131–135.

[36] Reimann, M., Zaichkowsky, J., Neuhaus, C., Bender, T., and Weber, B., 2010, "Aesthetic Package Design: A Behavioral, Neural, and Psychological Investigation," J. Consum. Psychol., **20**(4), pp. 431–441.

[37] Yoon, C., Gutchess, A. H., Feinberg, F., and Polk, T. A., 2006, "A Functional Magnetic Resonance Imaging Study of Neural Dissociations Between Brand and Person Judgments," J. Consum. Res., **33**(1), pp. 31–40.

[38] Knutson, B., Rick, S., Wimmer, G. E., Prelec, D., and Loewenstein, G., 2007, "Neural Predictors of Purchases," Neuron, **53**(1), pp. 147–156.

[39] Plassmann, H., Venkatraman, V., Huettel, S., and Yoon, C., 2015, "Consumer Neuroscience: Applications, Challenges, and Possible Solutions," J. Mark. Res., **52**(4), pp. 427–435.

[40] Grosenick, L., Greer, S., and Knutson, B., 2008, "Interpretable Classifiers for FMRI Improve Prediction of Purchases," IEEE Trans. Neural Syst. Rehabil. Eng., **16**(6), pp. 539–538.

[41] Smidts, A., Hsu, M., Sanfey, A. G., Boksem, M. A. S., Ebstein, R. B., Huettel, S. A., Kable, J. W., Karmarkar, U. R., Kitayama, S., Knutson, B., Liberzon, I., Lohrenz, T., Stallen, M., and Yoon, C., 2014, "Advancing Consumer Neuroscience," Mark. Lett., **25**(3), pp. 257–267.

[42] Berns, G. S., and Moore, S. E., 2012, "A Neural Predictor of Cultural Popularity," J. Consum. Psychol., **22**(1), pp. 154–160.

[43] Berns, G. S., Capra, C. M., Moore, S., and Noussair, C., 2010, "Neural Mechanisms of the Influence of Popularity on Adolescent Ratings of Music," Neuroimage, **49**(3), pp. 2687–2696.

[44] Behrens, T. E. J., Hunt, L. T., Woolrich, M. W., and Rushworth, M. F. S., 2008, "Associative Learning of Social Value," Nature, **456**(7219), pp. 245–249.

[45] Sawe, N., and Knutson, B., 2015, "Neural Valuation of Environmental Resources," Neuroimage, **122**, pp. 87–95.

[46] Greene, J. D., Sommerville, R. B., Nystrom, L. E., Darley, J. M., and Cohen, J. D., 2001, "An fMRI Investigation of Emotional Engagement in Moral Judgment," Science, **293**(5537), pp. 2105–2108.

[47] Sanfey, A. G., 2007, "Social Decision-Making: Insights From Game Theory and Neuroscience," Science, **318**(5850), pp. 598–602.

[48] Greene, J., and Haidt, J., 2002, "How (and Where) Does Moral Judgment Work?," Trends Cognit. Sci., **6**(12), pp. 517–523.

[49] Mumford, J., 2012, "A Power Calculation Guide for FMRI Studies," Soc. Cognit. Affective Neurosci., **7**(6), pp. 738–742.

[50] Consultants, P., 2000, "Eco-Indicator 99 Manual for Designers," Ministry of Housing, Spatial Planning and the Environment, Amersfoort, The Netherlands.

[51] Schneider, W., Eschman, A., and Zuccolotto, A., 2002, "E-Prime Reference Guide," Psychology Software Tools Inc., Pittsburgh, PA.

[52] Rodriguez, R. N., 2011, "SAS," Wiley Interdiscip. Rev.: Comput. Stat., **3**(1), pp. 1–11.

[53] Stark, C. E., and Squire, L. R., 2001, "When Zero is Not Zero: The Problem of Ambiguous Baseline Conditions in fMRI," Proc. Natl. Acad. Sci. U. S. A., **98**(22), pp. 12760–12766.

[54] Cox, R. W., 1996, "AFNI: Software for Analysis and Visualization of Functional Magnetic Resonance Neuroimages," Comput. Biomed. Res., **29**(3), pp. 162–173.

[55] Gorgolewski, K., Burns, C. D., Madison, C., Clark, D., Halchenko, Y. O., Waskom, M. L., and Ghosh, S. S., 2011, "Nipype: A Flexible, Lightweight and Extensible Neuroimaging Data Processing Framework in Python," Front. Neuroinf., **5**, epub.

[56] Jenkinson, M., Beckmann, C. F., Behrens, T. E. J., Woolrich, M. W., and Smith, S. M., 2012, "FSL," Neuroimage, **62**(2), pp. 782–790.

[57] Gauthier, I., Tarr, M. J., Anderson, A. W., Skudlarski, P., and Gore, J. C., 1999, "Activation of the Middle Fusiform 'Face Area' Increases With Expertise in Recognizing Novel Objects," Nat. Neurosci., **2**(6), pp. 568–573.
[58] McCandliss, B. D., Cohen, L., and Dehaene, S., 2003, "The Visual Word Form Area: Expertise for Reading in the Fusiform Gyrus," Trends Cognit. Sci., **7**(7), pp. 293–299.
[59] Gallagher, H. L., and Frith, C. D., 2003, "Functional Imaging of 'Theory of Mind'," Trends Cognit. Sci., **7**(2), pp. 77–83.
[60] Smith, P. L., and Ratcliff, R., 2004, "Psychology and Neurobiology of Simple Decisions," Trends Neurosci., **27**(3), pp. 161–168.
[61] Poldrack, R. A., 2006, "Can Cognitive Processes be Inferred From Neuroimaging Data?," Trends Cognit. Sci., **10**(2), pp. 59–63.
[62] Yarkoni, T., Poldrack, R. A., Nichols, T. E., Van Essen, D. C., and Wager, T. D., 2011, "Large-Scale Automated Synthesis of Human Functional Neuroimaging Data," Nat. Methods, **8**(8), pp. 665–670.
[63] Lieberman, M. D., and Cunningham, W. A., 2009, "Type I and Type II Error Concerns in fMRI Research: Re-Balancing the Scale," Soc. Cognit. Affective Neurosci., **4**(4), pp. 423–428.
[64] Carter, R. M., and Huettel, S. A., 2013, "A Nexus Model of the Temporal-Parietal Junction," Trends Cognit. Sci., **17**(7), pp. 328–336.
[65] Payne, J. W., Bettman, J. R., and Johnson, E. J., 1993, *The Adaptive Decision Maker*, Cambridge University Press, New York.
[66] Moll, J., de Oliveira-Souza, R., Eslinger, P. J., Bramati, I. E., Mourão-Miranda, J., Andreiuolo, P. A., and Pessoa, L., 2002, "The Neural Correlates of Moral Sensitivity: A Functional Magnetic Resonance Imaging Investigation of Basic and Moral Emotions," J. Neurosci., **22**(7), pp. 2730–2736.
[67] Moll, J., de Oliveira-Souza, R., Bramati, I. E., and Grafman, J., 2002, "Functional Networks in Emotional Moral and Nonmoral Social Judgments," Neuroimage, **16**(3), pp. 696–703.
[68] Bzdok, D., Schilbach, L., Vogeley, K., Schneider, K., Laird, A. R., Langner, R., and Eickhoff, S. B., 2012, "Parsing the Neural Correlates of Moral Cognition: ALE Meta-Analysis on Morality, Theory of Mind, and Empathy," Brain Struct. Funct., **217**(4), pp. 783–796.
[69] Young, L., Cushman, F., Hauser, M., and Saxe, R., 2007, "The Neural Basis of the Interaction Between Theory of Mind and Moral Judgment," Proc. Natl. Acad. Sci. U. S. A., **104**(20), pp. 8235–8240.
[70] Ferstl, E. C., and von Cramon, D. Y., 2002, "What Does the Frontomedian Cortex Contribute to Language Processing: Coherence or Theory of Mind?," Neuroimage, **17**(3), pp. 1599–1612.
[71] Yoon, C., Gonzalez, R., Bechara, A., Berns, G. S., Dagher, A. A., Dubé, L., Huettel, S. A., Kable, J. W., Liberzon, I., Plassmann, H., Smidts, A., and Spence, C., 2012, "Decision Neuroscience and Consumer Decision Making," Mark. Lett., **23**(2), pp. 473–485.
[72] Rechtin, M., 2015, "Tesla Model S P85D Earns Top Road Test Score," Consumer Reports Magazine, October 2015.
[73] Good Design Australia, 2015, "Tesla Model S Wins Australia's Most Prestigious Design Accolade," Australian Good Design Awards Program, Edgecliff, Australia, accessed Aug. 7, 2016, http://www.gooddesignaustralia.com/news/entry/tesla-model-s-wins-australias-most-prestigious-design-accolade/
[74] Boatwright, P., and Cagan, J., 2010, *Built to Love: Creating Products That Captivate Customers*, Berrett-Koehler, San Francisco, CA.
[75] Goucher-Lambert, K., Moss, J., and Cagan, J., 2016, "Using Neuroimaging to Understand Moral Product Preference Judgments Involving Sustainability," ASME Paper No. IDETC2016-59406.
[76] Goucher-Lambert, K., Moss, J., and Cagan, J., 2016, "A Meta-Analytic Approach for Uncovering Neural Activation Patterns of Sustainable Product Preference Decisions," Design Computing and Cognition Conference, pp. 1–20.