Understanding Consumer Tradeoffs Between Form and Function Through Metaconjoint and Cognitive Neuroscience Analyses

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This work investigates how consumers make preference judgments when taking into account both product form and function. In prior work, where aesthetic preference is quantified using visual conjoint methods, aesthetic preference and functional preference were handled separately. Here, we introduce a new methodology, metaconjoint analysis, for testing the hypothesis that when consumers make decisions taking into account both a product's form and its function they employ a more complex decision-making strategy than when basing their decisions on form or function alone. We anticipate that this strategy will involve both analytical and emotional processes. When compared with participant ratings of form and function combinations across 28 subjects, the metaconjoint model is shown to have a correlation that was not statistically different from an additive model of form and function. However, unlike the additive model, the metaconjoint model gave additional information about how participants make tradeoffs between form and function. Next, we developed a novel paradigm using functional magnetic resonance imaging (fMRI) to determine what parts of the brain are primarily involved with a given tradeoff between form and function. While in the scanner, study participants were asked to make decisions in trials where only form varied, where only function varied, and where both form and function varied. Results from 14 participants suggest that choices based on products that vary in both form and function involve some unique and some common brain networks as compared to choices based on form or function alone; notably, emotion-related regions are activated during these complex decisions where form and function are in conflict. These results are consistent with the inclusion of emotion in decision-making with regards to product choice and demonstrate the feasibility of using fMRI to address questions about the mental processes underlying consumer decisions. Studying preference decisions together with their accompanying neurological activity will give engineers and designers greater insight into the consumer decision-making process. [DOI: 10.1115/1.4024975]

Introduction

The ability to capture and characterize consumer preference is an important tool for design engineers. When developing a design solution, engineers need useful information about their target users so that they can better tailor their designs. Boatwright and Cagan [1] have argued that emotion is as critical as functionality to captivate the marketplace and increase willingness to pay. Further, as models of consumer behavior have developed over time they have transitioned from focusing primarily on cognition [2,3] to models that balance cognition with affect. Research supports the important role emotion plays in cognitive processes such as perception, decision-making, and memory [4,5]. Additional work has documented some of the ways in which affect can have an impact on decision-making [6–10]. As a result, an effective model of consumer preference needs to take into account both form and function and the fact that emotion can tie into how consumers trade off aesthetics and performance. This model can inform designers on how best to allocate resources during the design process and what features to include in a product.

In this work, we propose a method of modeling consumer preference that combines both the aesthetic and functional aspects of a product into a single function describing overall consumer preference. This method is based on a statistical tool widely used in market research called conjoint analysis [11]. This work is an extension to the work done by Orsborn et al. [12] that introduced a visual conjoint approach that allows for continuously varying choice parameters. In this study, we look at preference for vehicle shape and function specification. For each participant, we first performed conjoint studies to capture their form preference (using visual conjoint) and function preference (using traditional conjoint) separately. In order to derive a preference function that encompassed both form and function, we introduced a second stage to the analysis. An additional conjoint study was performed where subjects were presented with combinations that included both aesthetic and performance information. The previously acquired preference functions were used to vary the levels of form and function presented in the combinations. Participants were also asked to rate combinations of form and function in order to have a comparison for the additive and metaconjoint models. Our hypothesis is that when consumers make decisions taking into

Contributed by the Design Theory and Methodology Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received April 5, 2012; final manuscript received June 28, 2013; published online August 7, 2013. Assoc. Editor: Wei Chen.

account both a product's form and its function they employ a more complex decision-making strategy than when basing their decisions on form or function alone and that emotion plays a large role in the strategy. In other words, preference for the whole product is not simply the sum of preferences for its form and its function.

In trying to better understand consumer preference judgments, we anticipate that the mental processes consumers experience while making judgments may yield useful insight. Having more information about the path consumers take to their decisions can possibly guide designers to solutions that better meet consumer needs. Unfortunately, in some instances, consumers have difficulty explaining the thought processes that lead to their decisions and, further, logical explanation may counter emotional reasoning. In order to gain better insight into the mental processes consumers experience while making preference judgments involving both form and function, we look at the physiological processes occurring in the brain at the time of judgment using neuroimaging. Neuroimaging allows us to identify the brain regions that are active during the decision-making process and some distinct regions that are associated with analytical versus emotional processing.

There are several techniques for collecting brain activity data [13]. Some of the commonly used techniques are electroencephalography, EEG, positron emission tomography, PET, and fMRI. Each technique gives specific physiological information about what is occurring in the brain at a point in time. Brain activity has been previously shown to provide useful information about the design process. For example, Nguyen and Zeng [14] used EEG to study brain activity in designers as they solved design problems. This work found the prefrontal lobe, an area associated with planning, judgment, reasoning and concentration, to be more involved in solution evaluation than in other activities such as solution generation. Additionally, Alexiou et al. [15] used fMRI to show that there is a difference in observed brain activity when solving a well bounded problem versus designing a solution for an open ended problem. Whereas both these studies focus on designers' thinking, in the current study we focus on users' decision-making.

In the past, fMRI has been used to investigate how product characteristics such as price [16] and packaging attractiveness [17] affect consumer decisions. fMRI has also been shown to be able to give insight into the brain activities associated with emotion [13]. As a result, we chose to use this method in our study as a means of gaining further insight into the decision-making process of consumers as they trade off aesthetic form and function.

We anticipate fMRI data, in combination with self-report and behavioral data, will be able to inform the designer about the strategies consumers employ when making preference judgments. In this study, we focused on how consumers use aesthetic and performance information to judge preference with the goal of better informing the product development process.

Previous Work

Conjoint Analysis. Conjoint analysis has been used to model consumer preference since the mid 1960's [11]. In a choice-based conjoint analysis study participants are asked to make choices between multiple options that represent various combinations of the product attribute levels in question. The number of questions and the levels of the attributes in each question are determined by design of experiments [18]. These quantities are chosen to span the design space and are spaced evenly to prevent bias [19]. In this work, we assume that interaction effects are negligible. This allows for use of a main effects model that can be built from a fractional factorial survey design. This assumption was found to be reasonable in previous work with visual conjoint analysis using a design representation similar in complexity to that used in this work [12]. A utility function that describes feature preference can be derived from the participant's responses to these questions.

Although this method of analysis has often been used to characterize consumer preference for the functional attributes of products, extensions to the method have been made. Turner et al. [20] used conjoint analysis to capture color preference. In that study, a survey was designed using three identical backpacks that were colored with different RGB values. Although the method did not predict the favorite colors of all of the study participants, the results suggested some validity in their approach to modeling color preference. Kelly and Papalambros [21] presented a method for capturing aesthetic preference information from subjects. In that work, the shape of a beverage bottle was parameterized and a conjoint study was performed. The shape preference function was then used in conjunction with the engineering performance characteristics of the shapes to create a Pareto front that illustrated the tradeoffs between aesthetic form preference and actual functional performance. Orsborn et al. [12] presented another method for extending traditional conjoint from functional specification to aesthetics. That work showed that aesthetic preference for complex designs such as the front of vehicles could be captured through conjoint analysis. The designs were the composition of several Bézier curves whose control points were varied to create variations in the designs. This technique resulted in a continuous design space.

Reid et al. [22] used a visual conjoint method to quantify the relationship between aesthetics and perceived environmental friendliness. That work had participants rate two-dimensional vehicle silhouettes on environmental friendliness. The results showed that cars with smoother curves were more likely to be thought of as being inspired by nature while boxier cars were less likely. Finally, Tseng et al. presented a method for capturing aesthetic preference and its relationship to actual performance in vehicles using neural networks [23]. The results gave insight into how designers can create designs that meet aesthetic and performance goals.

fMRI. The scanners used in an fMRI study are the same as those used in a traditional MRI study. The major difference is the resolution setting. MRI images are high in spatial resolution and give tremendous detail about the structures of the brain. In contrast, fMRI images are high in temporal resolution and give an indication of blood flow in the brain. Hemoglobin's magnetic properties differ when it is bound with oxygen from when it is not [24]. Because deoxygenated hemoglobin is more magnetic it distorts the magnetic field from the scanner as the field passes through the brain. By measuring the distortion we can determine how much hemoglobin has been deoxygenated and therefore how much oxygen a brain region used. The amount of oxygen used is an indirect measure of activity in that region.

fMRI data have been used to provide interesting insight into preference research. Vartanian and Goel [25] asked study participants to judge paintings based on aesthetics. The results of their study showed that increases in preference were correlated with activity in specific regions of the brain, including the striatum and anterior cingulate cortex. The striatum, particularly the ventral striatum, is important in processing reward, such as anticipation of winning money [26]. The anterior cingulate cortex, a region originally identified as part of the limbic (emotional) circuit, is important for conflict monitoring and error detection in both cognitive and emotional domains [27]. In a different study, Jacobsen et al. [28] asked participants to judge drawings based on their aesthetic and perceptual properties. They found that judgments of aesthetic designs activate multiple regions, including the insula, a part of the brain that receives visceral input from the body and contributes to the generation of visceral responses such as sweating and changes in heart rate; thus, the insula plays an important role in emotional and motivational processes [29]. In another study, participants were scanned while tasting identical wine samples that they believed to be different in type and in price [30]. This work showed that neural activity can be affected by

Table 1 Summary of conjoint analysis designs

	Aesthetic preference	Function preference	Combined preference
Attributes	9	4	2
Levels	3	3	3
Possible profiles	19,683	81	9
Choice trials	36	18	9
D-Efficiency (%)	98.5	98.9	100

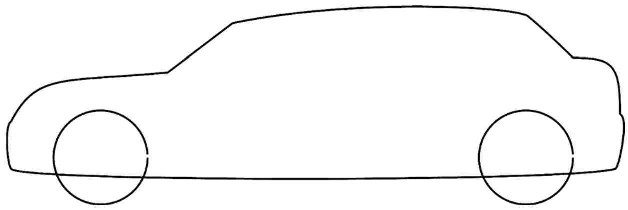


Fig. 1 Example vehicle design

perception as the activation in regions associated with pleasantness were greater for the samples thought to be more expensive. Zysset et al. [31] explored the activation associated with multi-attribute decision-making. It was shown that activation during these types of tasks is distributed over several regions of the brain, including the anterior cingulate and lateral prefrontal cortical areas. The lateral prefrontal cortex, particularly the dorsolateral prefrontal cortex, is especially important for effortful or "executive" cognitive processes, including those involved in analytical thinking and reasoning [32]. In the current study we designed a paradigm that would reveal the brain activity that takes place as the participants make decisions between two options where form and function are in conflict (i.e., where one product has the better form and another has the better functional features).

Methodology

Participants. There were a total of 28 participants in this study (16 female; 12 male; mean age 26.25 yrs). Volunteers for this study were recruited by email. The study participants were divided into two groups of 14. The first group completed only the metaconjoint analysis task while the second completed both the metaconjoint and fMRI tasks.

Procedure—Metaconjoint Analysis. The task was divided into four sections. First, each participant was presented with two separate choice-based conjoint analysis surveys, one designed to assess their individual aesthetic preference and another to assess individual function preference for product attributes. Next, participants were given a personalized validation task where they were asked to make preference decisions in holdout questions in order to test the models developed from the conjoint surveys. This task was also used to gather individual preference for aesthetics and function concurrently. All the conjoint surveys were designed to estimate main effects and were generated in SAS using the *ChoiceEff* macro. Each survey was designed to be balanced and orthogonal using D-Efficiency as the evaluation criteria. The conjoint designs are summarized in Table 1.

Finally, participants were given a ratings task. The results from this task were used to determine how well the choice-based conjoint models could predict combined preference for aesthetic and functional product attributes.

Section 1: Aesthetic Preference Modeling. In Section 1, preference for vehicle shape is assessed. The vehicle designs used in this study are line drawing silhouettes built using a scheme developed by Tseng et al. [23]. An example of the vehicle representation is shown in Fig. 1.

These representations are the composition of eight Bézier curves. The control points of the curves are parameterized in a method that allows the 12 major features of the design—the belt angle, nose angle, ground clearance, body height, roof height, hood length, trunk length, front windshield angle, rear windshield angle, wheel size, front wheel position, and rear wheel position—to be varied between a low and high value. Each parameter can vary from a value of 0 (low) to 100 (high). These values constrain the models to reflect vehicles presently available on the market. All attribute combinations were tried to ensure that each combination would produce a valid design. In this study, we held wheel size and front and rear wheel position constant, leaving only nine attributes.

For each of the nine attributes we used three levels: high, medium, and low. In this vehicle representation scheme, those values are 100, 50, and 0. These levels provide noticeable differences and are spaced evenly throughout the design space. Including three attribute levels will produce three part-worth values and allow a second order curve to be used to describe respondent preference. Nine attributes, each with three levels, leads to 19,683 possible choice profiles. The SAS software package was used to organize a portion of these profiles into a 36-question, 3-option, survey designed to estimate main effects. The survey design is balanced and orthogonal, and its D-efficiency is 98.48%. Using Matlab, the participants were presented each of the 36 trials and instructed to select which of the three designs they preferred. A sample trial is shown in Fig. 2.

To calculate the part-worth utilities for each respondent, we employ the Bradley–Terry–Luce (BTL) equation [33]. This approach has been previously adopted for use with conjoint models [34] and shown to be an effective method for modeling individual preference [12]. As described by Eq. (1), the BTL method states that the probability of a consumer selecting option i from a pool of items j is

$$P(i) = \frac{w_i}{w_j} \tag{1}$$

the number of times that option was chosen, w_i divided by the total number of times that option was presented, w_j. After tallying the subject responses, the normalized probability that low, medium, or high will be chosen for each attribute is plotted. The example in Fig. 3 shows that, for this subject, utility initially increases as hood length increases, but reaches a maximum value after which utility decreases as the hood length further increases. The plot is fit with a second order equation as done by Orsborn et al. [12].

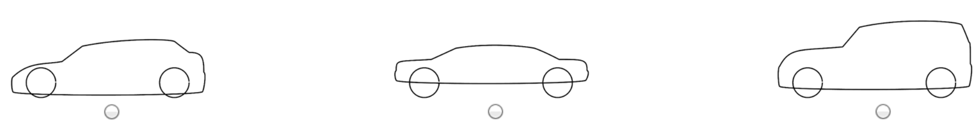


Fig. 2 Screenshot of aesthetic preference trial

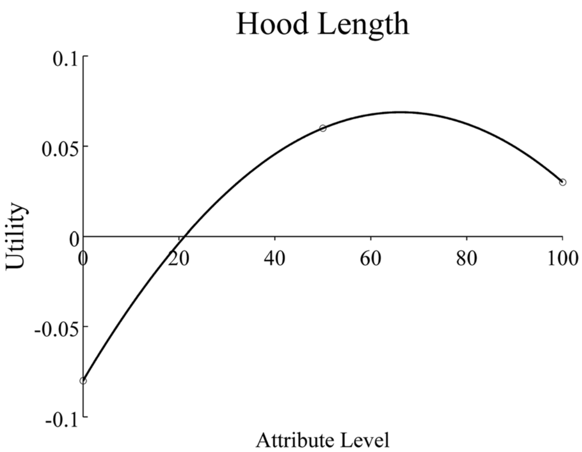
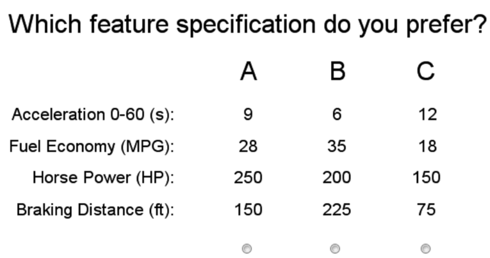


Fig. 3 Hood length preference example plot



Which feature specification do you prefer?

	A	B	C
Acceleration 0-60 (s):	9	6	12
Fuel Economy (MPG):	28	35	18
Horse Power (HP):	250	200	150
Braking Distance (ft):	150	225	75

Fig. 4 Screenshot of function preference trial

The fit takes on the form of the following equation [12]:

$$u_i = \beta_{i1}x_i^2 + \beta_{i2}x_i + \beta_{i3} \tag{2}$$

where u_i is the utility from attribute i, β_i is the regression coefficient, and x_i is the value of the attribute. Equation (2) describes the utility associated with an attribute at any of the levels between 0 and 100. The utility of the entire design is taken to be the sum of the individual attribute utilities as shown in Eq. (3) [12]

$$U(\vec{x}) = \sum_{i=1}^{n} u_i \tag{3}$$

where $U =$ total utility and $u_i = f(\beta_i, x_i)$.

Section 2: Function Preference Modeling. In Section 2 of the study, we modeled the subject's function preference. The function preference is described in terms of four function specifications: 0–60 mph acceleration (6–12 s), fuel economy (18–35 MPG), horsepower (150–250 HP), and 60-0 mph braking distance (75–225 ft). These specifications were chosen based on those used by *Consumer Reports* when providing car-rating data for consumers. 4 attributes, each with 3 levels leads to 81 possible choice profiles. Here, SAS is used to organize a portion of the possible profiles into an 18-question, 3-option, survey designed to estimate main effects. The survey design is balanced and orthogonal, and its D-efficiency is 98.92%. Matlab is used to present each of the 18 trials to the subjects. A sample trial is shown in Fig. 4.

After completing the trials, the subject's function preference equations were derived in the same way as in the aesthetic section. An example plot of a function utility equation is shown in Fig. 5 where utility linearly decreases as acceleration time, measured in seconds taken to get from 0 to 60 miles per hour increases.

The purpose of the first two sections was to develop preference equations describing form and function specific to each subject. In addition to quantifying the preference functions, we also generated and stored example vehicle designs and function specification groups that span the range from low to high utility. With these data, in Section 3, we investigate how the subjects trade off form and function.

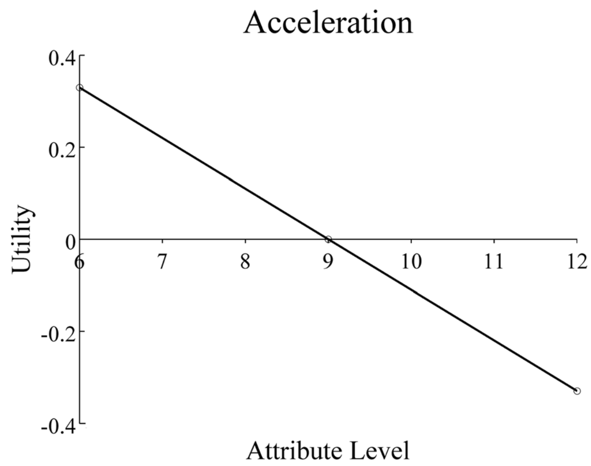


Fig. 5 Acceleration preference example plot

Section 3: Model Validation and Combining Models Through Metaconjoint Analysis. After the initial surveys, participants were presented additional questions in order to validate their aesthetic and function preference models. The validation choice profiles were generated by assigning random values to the attributes and evaluating their utility using Eq. (3). It is possible to find the upper and lower bounds on the utility associated with each of the attributes by finding the maximum and minimum of Eq. (2), respectively, for each attribute. Since the utility of each candidate profile is taken as the sum of the attribute utilities, the upper and lower utility bounds, *Umax* and *Umin*, respectively, for the complete designs were also determined. Each of the designs used in the validation task was classified according to its proximity to *Umax* or *Umin*. Participants were asked to choose between a low utility and a high utility design. Given the difference between *Umax* and *Umin*, low utility is defined as being no more than 20% of that difference above *Umin*, while high utility is defined as no more than 20% of that difference below *Umax*. Mid utility is defined as falling within ±10% of the midpoint between *Umax* and *Umin*. Sensitivity to these values was not addressed in this work.

There were two types of validation questions given in this section, 16 form questions and 16 function questions. The designs presented in this task were different for each subject. For the form validation questions, function information was held constant across the two options while a high versus low utility form decision was made. For the function validation questions, the form information was held constant across the two options while a high versus low utility function decision was made. In addition to the validation questions, this section was also used to present participants with questions designed to gauge their combined preference for both form and function.

Forced choice conjoint analysis allows for developing preference models that characterize the tradeoffs consumers make between the attributes surveyed. As such, it would be ideal to survey both the form and function attributes simultaneously. However, this is often infeasible, as the number of attributes that would need to be included would increase the decision complexity. The added cognitive load from the increased complexity has been shown to have a negative impact on choice consistency [32]. As a result, other methods for dealing with high numbers of attributes have been developed. In adaptive conjoint analysis [35],

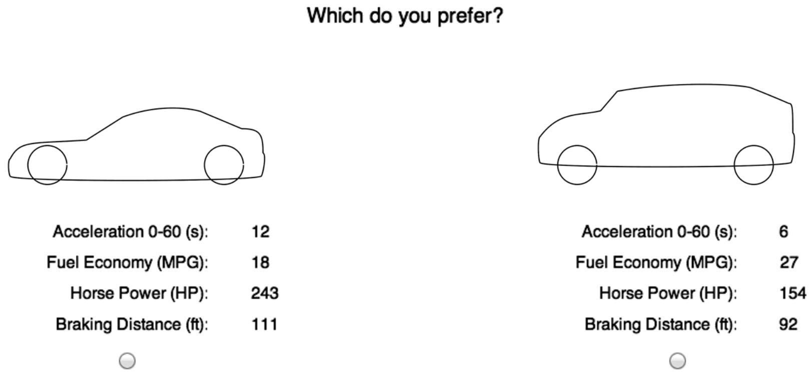


Fig. 6 Screenshot of combined preference trial

questions are asked to gauge how important attributes are to the consumer relative to one another. The survey adapts itself to the individual and weighs preference data for the most important attributes more heavily when constructing the utility model. In other work, large numbers of attributes are handled by holding some of the attributes constant during some of the questions [36]. By reducing the number of attributes that actually vary from question to question an optimal design can be developed. These are not suitable approaches for this situation as holding attributes constant makes differentiating between the visual designs difficult. As an alternative we introduce a multistage conjoint analysis technique called "metaconjoint." Previous work has suggested the use of meta-attributes in cases with large numbers of attributes [37]. Unlike the previous methods our model allows for independently assessing the relative importance of the two sets of attributes (form versus function) to the consumer. This is a major advantage of the method, as the model will take in to account how consumers trade off between form and function. This method is appropriate because forcing choices between low, medium, and high form and low, medium, and high function combinations as described by the individual will capture the tradeoffs they make between form and function.

From this point forward the aesthetic preference equation from Section 1 will be referred to as U_{form}, and the function preference equation from Section 2 will be referred to as U_{func}. Although U_{form} and U_{func} were captured separately, our goal is to capture the combined preference as consumers make their decisions based on available information that includes both form and function. In order to combine U_{form} and U_{func}, we performed a third conjoint study, a metaconjoint study. A metaconjoint analysis differs from a routine conjoint analysis in its attribute definition. The attributes in a traditional conjoint analysis describe a single feature or possibly the relationship between a small number of features. In a metaconjoint analysis, meta-attributes are defined as the aggregation of multiple attributes. In this study, *Mform* and *Mfunc* are meta-attributes that represent the features that describe form and function, respectively. These two meta-attributes (*Mform* and *Mfunc*) each having three levels (low, medium, and high) create a total of nine possible choice profiles. SAS was used to organize all these choice profiles into a nine-question, two-option survey designed to estimate the attribute main effects. The survey design is balanced and orthogonal, and its D-efficiency is 100%. The examples of high, medium, and low utility were taken from those generated in Sections 1 and 2.

In each trial the subject had to make a choice between two different options each with a unique combination of form and function. A sample trial is shown in Fig. 6. Here, a high utility vehicle shape is shown on the left while a low utility vehicle shape is shown on the right. These aesthetic designs were generated based on each respondent's U_{form}. Likewise, the function specifications, high utility on the left and low utility on the right, were generated according to each respondent's U_{func}.

After completing the metaconjoint trials, the same procedure for developing a utility function from Sections 1 and 2 was followed. As before, we were able to construct utility functions for each of the attributes in this conjoint analysis. The key difference here was that the two attributes we tested, *Mform* and *Mfunc*, were not individual attributes but rather meta-attributes, the composition of several different attributes we chose to describe form and function, respectively. In this case, the preference functions developed, U_{mform} and U_{mfunc}, describe preference for *Mform* and *Mfunc* relative to one another. As before, the preference function derived from the conjoint analysis is taken to be the sum of the contributing attributes. In this case, the combined preference U_{comb} is taken to be the sum of the contributing functions as shown in the following equation:

$$U_{\text{comb}} = U_{\text{mform}} + U_{\text{mfunc}} \tag{4}$$

Note $U_{\text{form}} \neq U_{\text{mform}}$ and $U_{\text{func}} \neq U_{\text{mfunc}}$. With Eq. (4), we are able to predict the utility for a given vehicle shape and function specification combination. Figures 7 and 8 show preference for form and preference for function, respectively. For this individual, increasing form utility has a nonlinear effect on overall product preference while increasing function has a linear effect. Judging from the magnitudes of the utility contributions, in this example, improving product form from the lowest to highest level would have a greater impact on overall preference than improving function.

Section 4: Design Rating. In Section 4, we solicited direct information about how subjects trade off form and function. We randomly generated examples of form and function at five different utility levels spaced evenly between the *Umax* and *Umin* values found in the aesthetic and function preference sections. We

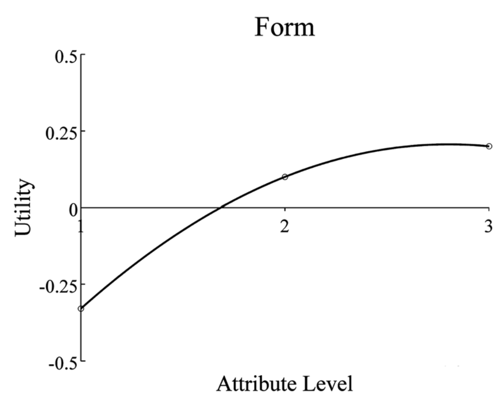


Fig. 7 U_{mform} example plot

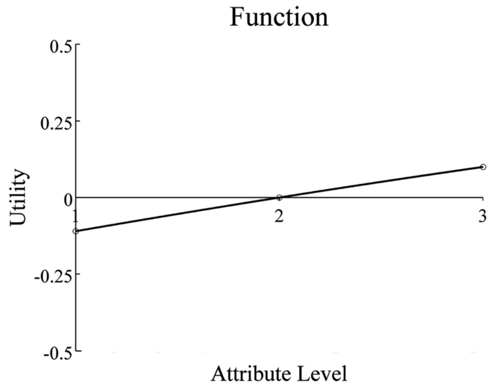


Fig. 8 U_{mfunc} **example plot**

combined these examples into 25 form-function combinations and evaluated each combination with an additive model (one where the total utility is taken to be the sum of the individual contributions of form and function as described by the utility equations found in Sections 1 and 2) and the metaconjoint model (developed from the metaconjoint analysis). Each form-function combination was presented to the subjects and they were asked to rate the combination between 0 (strongly dislike) and 100 (strongly like). A screen shot from this task is shown in Fig. 9.

We calculated the correlation coefficient between the additive model and the ratings as well as between the metaconjoint model and the ratings to determine whether there was a difference between the two models.

Procedure—fMRI Analysis. The metaconjoint analysis task was designed to measure the differences in the predictive capacity of models based on separate versus joint presentation of aesthetic and functional product attributes. Conjoint analysis can be used to understand the ways in which consumer preference can differ based on how information is presented. However, studies such as the one carried out in this work do not provide researchers with much information about why results turn out in a certain way. In order to get a better understanding of why preference decisions differ when based on form, function, or a mix of both, fMRI was employed. By collecting neurological data while consumers make preference decisions, we are able to observe the neural processes that correspond to different choice cases and make inferences about the cognitive strategies employed by consumers.

In order to complete the fMRI task, it was first necessary to develop preference models for each of the participants. Participants completed the same aesthetic, function, and rating tasks from Sections 1, 2, and 4 of the metaconjoint analysis procedure. The utility functions from these surveys were used to generate the trials presented to the participants during the scanner session. This group also completed a variation of the validation and combined preference task from Section 3.

Table 2 Summary of fMRI trials

Trial type	Trials per run	Description
Form only	4	The form varies while function is held constant
Function only	4	The form is held constant while the function varies
Form-function conflict	6	Both form and function vary
Form-function control	4	Two options are either the same or different

After completing the aesthetic preference, function preference, and ratings tasks subjects were prepped for the scanner task. Subjects were taken through a practice run of the task they were to complete inside the scanner. The stimulus presentation software used for the practice run and in the scanner was Macstim. In the practice, run subjects used the computer keyboard to enter their responses to the trials. In the scanner, the subjects had a response glove strapped to their right hand that placed buttons under each of their fingers. The subjects used their index finger to indicate the option on the left and their middle finger to indicate the option on the right.

The fMRI design was structured into 4 runs of 18 trials. The runs were presented in a counterbalanced order across subjects. The trials within each run were presented in pseudorandom order. The average run duration was 362.55 s (~6 min). The task consisted of four distinct trial types, Form Only, Function Only, Form-Function Conflict, and Form-Function Control. These trial types are summarized in Table 2.

For the Form Only, Function Only, and Form-Function Conflict trials the subjects were asked to specify which option they preferred. In the Form Only trials high utility vehicle shapes were pitted against low utility options while function was held constant. In the Function Only trials, high utility function specification groups were pitted against low utility options while form was held constant. These trials are the same format as the validation trials from the metaconjoint task and serve as a validation for the fMRI participants. In the Form-Function Conflict trials, a high utility vehicle shape is paired with a low utility function specification group and pitted against a low utility vehicle shape paired with high utility function specification group. In the final trial type, Form-Function Control, participants were shown two vehicle shape and function specification groups and asked to indicate whether the two options were the same or different. An example trial is shown in Fig. 10.

This trial serves as a control for the Form Only, Function Only, and Form-Function Conflict trials. By asking subjects to decide whether the two options are the same or different, we can subtract out the activation associated with perceptual aspects of the decision and isolate activity specific to preference judgment.

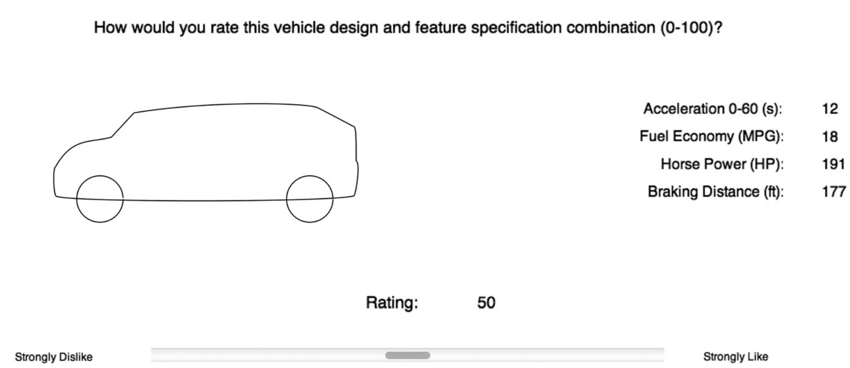


Fig. 9 Screenshot of combination rating task

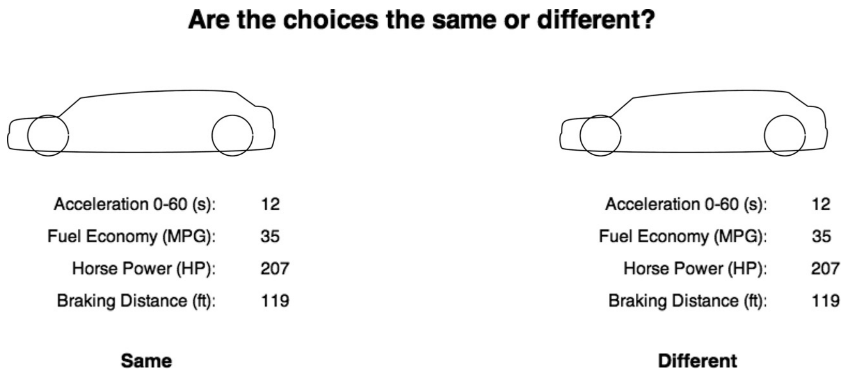


Fig. 10 Screenshot of Form-Function Control trials

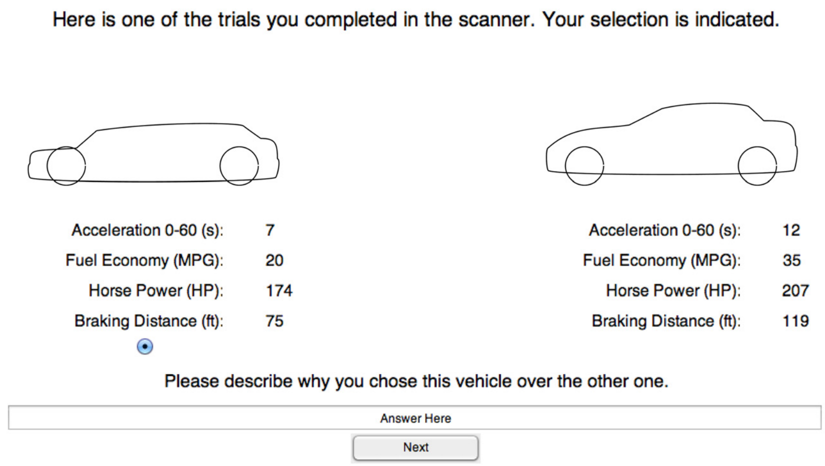


Fig. 11 Screenshot of follow-up question

Participants were presented with a total of 16 Form Only, 16 Function Only, 16 Form-Function Control, and 24 Form-Function Conflict trials.

After completing the scanner task, participants were given a follow-up survey. The survey included the combined preference trials described in Section 3 of the metaconjoint analysis procedure and depicted in Fig. 6, and follow-up questions about the Form-Function conflict trials. We were most interested in the Form-Function Conflict trials because they required the subject to pick either form or function, trading off one for the other. After completing the Form-Function Conflict trials, if the subject chose an option with high form utility or high function utility the subject was shown an answer they gave and asked follow-up questions about how they made their decision. An example is shown in Fig. 11 and the follow-up questions are listed in the Results section.

In order to separate out the activation associated with processing the vehicle designs and function specification groups from the activation associated with decision-making, the trials were presented in a staggered order. First, the vehicle designs were shown alone for 3 s (Design); next the function specifications were added to the screen and shown for 5 s (Specifications); a fixation crosshair was used as a jitter (the pauses between the start of image sampling and the stimulus presentation used when full brain coverage is needed and long scan session are not an issue [38]) for an average of 0.5 s; the question was then added to the screen and the subjects had 8 s to make a decision and enter their response (Choice); finally, a fixation crosshair was used as a jitter for an average of 2.5 s between trials. This design is illustrated in Fig. 12.

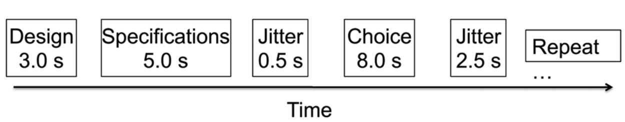


Fig. 12 Experimental design of fMRI trials

fMRI Acquisition. Scans were acquired on a Siemens 3 T Verio Scanner with a 32-channel head coil (Siemens AG, Erlangen, Germany). For each participant, functional scans were acquired using an echo-planar pulse sequence with TR = 2 s, TE = 28 ms, and flip angle = 79 deg. Each pulse recorded 35 oblique-axial slices with slice thickness 3.2 mm and no slice gap (FOV = 205 mm, matrix size 64×64, $3.2 \times 3.2 \times 3.2$ mm, 3 voxels). Four runs were acquired, each comprised of 187 volumes. Extra acquisitions were acquired at the end of the task in every run, in order to allow the hemodynamic response to the final event to return to baseline.

fMRI Data Analysis. The imaging data were analyzed using Statistical Parametric Mapping [39] with SPM'08 (*Wellcome Department of Cognitive Neurology, Institute of Neurology, London, UK*). Data analysis steps included realignment to correct for head motion, direct normalization into a standard stereotactic space as defined by the Montreal Neurological Institute (MNI), and smoothing with a 8 mm Gaussian kernel (FWHM). No participant had sudden head motion greater than 1 mm.

Statistical parametric maps (SPM) were computed using the general linear model, with separate hemodynamic response functions modeled for each of the following six task events: Design (regardless of trial type), Specifications (regardless of trial type), Choice during Form Only trials, Choice during Function Only trials, Choice during Form-Function Conflict trials, and Choice during Control trials. Linear contrasts were computed from the four Choice events as one-way t-contrasts in first level models for each participant, as follows: Form Only versus Control, Function Only versus Control, and Form-Function Conflict versus Control. To identify voxels uniquely activated during Form-Function Conflict decisions, we created a fourth contrast: 2*Form-Function Conflict versus 1*Form Only versus 1*Function Only.

These contrasts were then submitted to a second-level random-effects group analysis. Whole-brain analyses were conducted using significance level of $p < 0.001$ (uncorrected) for magnitude of activation, with an extent threshold of ten voxels, which provides a reasonable balance between Type I and Type II error concerns and is consistent with the false discovery rate in typical behavioral science papers [40,41]. Finally, using the Minimum Statistic compared to the Conjunction Null method [42], we conducted two two-way conjunction analyses to identify activations during the Form-Function Conflict trials that overlapped with activation during the Form Only trials and with activation during the Function Only trials (e.g., the conjunction of areas significantly activated in the Form-Function Conflict versus Control contrast with areas significantly activated in the Form Only versus Control contrast).

Results

Metaconjoint Analysis. As stated previously, each of the study participants responded to 16 form and 16 function validation questions. As a reminder, the high and low utility examples were generated from the preference functions of each individual participant. In this study, hit rate is used to evaluate model performance. Hit rate is determined by dividing the number of correct model predictions, or hits, by the total number of predictions. The hit rate results listed here are from 25 of the 28 participants as data from three of the participants were corrupted. The hit rate in the form validation task was over 90%. In the function validation task, the hit rate was found to be 95%. These hit rate values show that the models are capable of accurately predicting consumer choice.

The next statistic of interest was how well the combined utility function U_{comb} correlated with participant ratings of vehicle shape and function specification group combinations. The goal here was not to predict the participant responses exactly, but rather to capture the general trend of the responses. We found the correlation between the additive utility model and the participant ratings to be 0.54 ($p < 0.001$, $n = 28$) while the correlation between the combined utility model and the participant ratings was found to be 0.49 ($p < 0.001$, $n = 28$). Both of these correlations were found to be statistically significant indicating very reliable and moderately strong positive relationships. However, these correlations were not statistically different from one another. Table 3 describes how the utility predictions (scaled between 0 and 100) from the additive model, the metaconjoint model, and the subject ratings vary with form and function for one of the participants.

Table 3 Utility predictions and subject ratings varying with form and function

M_{form} level	M_{func} level	Additive	Metaconjoint	Rating
1	1	0	0	24
1	2	15	14	9
1	3	37	71	66
2	1	33	14	27
2	2	75	29	76
2	3	77	86	72
3	1	56	29	43
3	2	70	43	62
3	3	100	100	90

The major advantage of using a metaconjoint approach is that it allows for modeling tradeoffs between the meta-attributes. Because this method allows for joint presentation of detailed form and function attributes, it is possible to build models that incorporate how consumers relate form and function. Understanding this relationship will yield insights into how consumers make tradeoffs between form and function. Figure 13 shows trend lines from the additive, metaconjoint, and ratings models that describe how utility predictions and subject ratings vary with form. Each trend line represents how, on average, utility changes with changes in the level of the form meta-attribute independent of the function meta-attribute. These trend lines are computed by averaging the change in utility associated with form at each of the three levels of function.

The slopes of the trend lines in Fig. 13 provide an indication of how much utility is gained by improving form. The slopes of the metaconjoint and subject rating trend lines are similar, 14 and 16, respectively, suggesting a similar gain in utility from improving form. The additive model trend line, however, has a slope of 29 predicting nearly twice the utility gain per form improvement. Figure 14 shows the utility predictions and subject ratings plotted with respect to function.

For this subject, the trend lines from the additive model and subject ratings have similar slopes: 21 and 22, respectively. The slope of the metaconjoint trend line is 36, predicting a larger gain in utility from improving function.

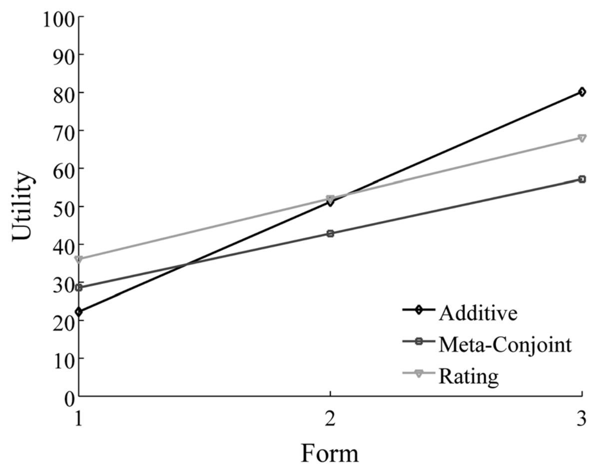


Fig. 13 Additive, metaconjoint, and subject rating trend lines with respect to form

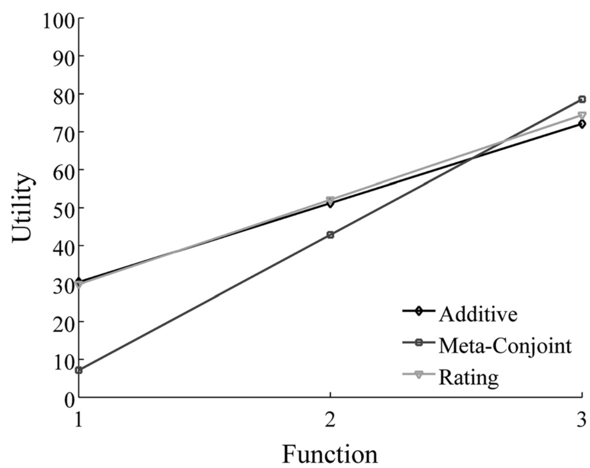


Fig. 14 Additive, metaconjoint, and subject rating trend lines with respect to function

Table 4 Average trend data ($n = 28$)

	Additive	Metaconjoint	Rating
Form	27.68 (0.71)	9.78 (3.11)	8.43 (1.53)
Function	21.63 (0.73)	31.24 (3.32)	13.03 (1.59)

Table 5 Mean fMRI trials reaction times in seconds with standard error

Form only	Function only	Form-function conflict	Control
1.77 (0.12)	1.80 (0.19)	1.87 (0.21)	2.05 (0.16)

The results from the additive and metaconjoint models differ in a meaningful way. The metaconjoint results provide insight into the tradeoffs between form and function that the additive model does not. A summary of the mean slopes for all 28 participants with standard errors is detailed in Table 4.

Because the metaconjoint model accounted for form and function utilities together, the slopes of the trend lines are related and can be compared. The average slope of the form trend line is 9.78 (3.11) compared to an average slope of 31.24 (3.32) for the function line. This indicates that on average participants weighed function far heavier than form in their preference decisions. This trend was seen in the fMRI task as participants most often chose function over form in the conflict trials. In the additive model, the magnitudes of the slopes of the form and function trend lines are much closer together. The trend data indicate that there are comparable gains from improving form and function, which is not consistent with the subject responses. These results illustrate how a metaconjoint approach can be used to aid in understanding how consumers made tradeoffs between form and function.

This study explored using metaconjoint analysis to model consumer preference. The results suggest that there are potential benefits of using this approach. By addressing some of the limitations of this work, those benefits will be more thoroughly explored. For example, in future work conjoint models will be designed to estimate both main and interaction effects. Doing so should improve the resolution of the models and allow for a more precise quantification of the tradeoffs between form and function. However, there is still a lot to learn about underlying processes that lead to the behavior. This is why fMRI is so valuable. Collecting neurological data during these types of decisions will give us more information that can eventually be funneled into preference models making them more reflective of consumer behavior.

fMRI Analysis. Reaction time (RT) was recorded for each of the fMRI trials. The mean RT for the Form Only, Function Only, Form-Function Conflict, and Form-Function Control trials is listed in Table 5. Note the mean RT for the Conflict trials is not statistically different from the Control trials ($p = 0.14$).

As stated previously, in the Form-Function Conflict trials subjects overwhelmingly chose the high utility function specification group option over the high utility vehicle shape option. Each fMRI participant was presented a total of 24 Form-Function Conflict trials. Of the 14 participants, only half chose the high form utility choice over the high function utility choice once or more. The average rate at which those seven participants chose the high form utility option from all 24 options was approximately 18.75%. Their self-reported responses, summarized in Table 6, are consistent with how they chose. When they chose the high form utility option, they indicated that their decision was based more on vehicle shape than function specification; however, this difference did not reach statistical significance ($p = 0.13$). When they chose the high function utility option they indicated their decision was based more on the function specification than the vehicle shape ($p < 0.0001$).

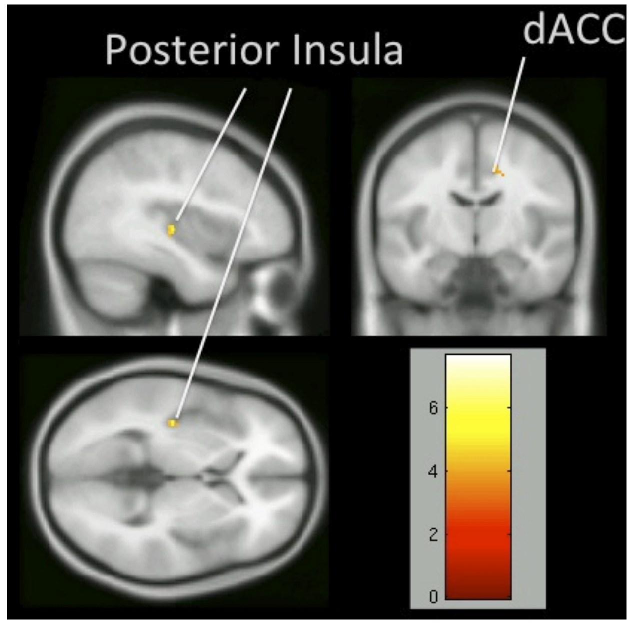


Fig. 15 Neural activity during Form Only versus Control trials

During decisions based on form or function alone, we found activation in both emotion-related and more executive areas. When comparing the Form Only trials to the Control trials, we observed increased activity in multiple areas including the dorsal anterior cingulate (dACC), a region associated with conflict monitoring, error detection, physical and social pain, and induced emotion [43]. Increased activity was also observed in the insula, associated with visceral experience. Experiences that fit into this category include but are not limited to viewing unpleasant faces or disgusting images [44,45]. The activations in the dACC and insula are highlighted in Fig. 15, where the gradient bar indicates t-statistic. It is generally not possible to visually show all activations in only a single slice of the brain (or even in a single slice per plane). For each trial, the authors have chosen slices that depict the activations that are most interesting and relevant to this discussion. Tables detailing an exhaustive list of all activations present during the trials are also provided. The full activation for the Form Only trials is listed in Table 7, where x, y, and z are the spatial coordinates of active regions in the space defined by the MNI, t is the t-statistic, and k is cluster size, the number of active voxels in the cluster.

Table 6 Form-Function Conflict trial follow-up

	Chose form		Chose function	
Question (1–7, not at all—a great deal)	Mean	Standard error	Mean	Standard error
To what extent was your decision influenced by the specifications of the vehicles?	5.00	0.58	6.14	0.29
To what extent was your decision influenced by the designs of the vehicles?	6.17	0.17	2.86	0.48

Table 7 Regions that showed increased activity in Form only versus Control trials

	Region	*x*	*y*	*z*	*t*	*k*
1	Anterior cingulate (BA 24, BA 32)	14	−2	40	4.68	55
2	Anterior cingulate (BA 24, BA 32)	−16	10	36	4.77	26
3	Precentral gyrus	48	0	16	5.23	18
4	Superior and middle frontal gyri	20	30	44	5.16	19
5	Postcentral gyrus	44	−26	34	4.52	18
6	Postcentral gyrus	60	−22	38	4.94	34
7	Precuneus	22	−54	26	7.66	174
8	Insula	−38	−20	2	5.25	18
9	Insula	34	2	20	4.85	17
10	Superior temporal grus/insula	44	−30	16	4.62	44
11	Cerebellum	−20	−38	−26	4.88	70

Notes: MNI coordinates; BA = Brodmann's area

Table 8 Regions that showed increased activity in Function Only versus Control trials

	Region	*x*	*y*	*z*	*t*	*k*
1	Supplementary motor area (BA 6)	8	−12	60	4.98	22
2	Cingulate gyrus (white matter)	24	−2	34	5.58	31
3	Precentral gyrus	44	−16	58	5.92	97
4	Precentral gyrus	40	−20	42	5.07	26
6	Postcentral gyrus	−24	−26	48	4.90	16
7	Postcentral gyrus/precuneus	−14	−42	70	4.24	14
8	Paracentral lobule	20	−44	58	6.70	95
9	Paracentral lobule	24	−30	62	5.54	66
10	Paracentral lobule	8	−40	70	4.62	25
11	Temporal lobe (white matter, L.V.)	34	−50	12	5.86	21

Notes: MNI coordinates; BA = Brodmann's area; L.V. = lateral ventricle

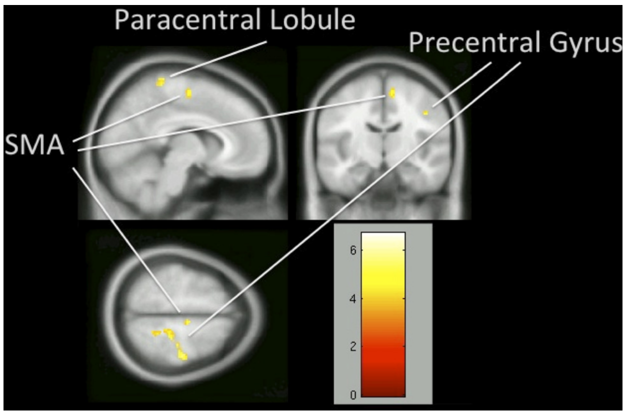


Fig. 16 Neural activity during Function Only versus Control trials

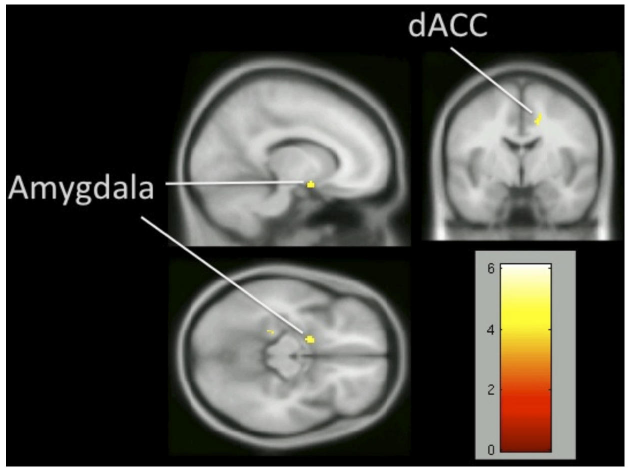


Fig. 17 Neural activity during Form-Function Conflict versus Control trials

The Function Only trials compared to the Control trials isolated activation in the supplementary motor area (SMA) and paracentral lobule (mainly in Brodmann's area 5), among other regions. The SMA has been implicated in planning motor actions and in cognitive control during conflict [46]. SMA activity has also been reported when subjects recall a series of actions to perform from memory [46]. Brodmann's area 5 is involved in higher order somatosensory and proprioceptive processing. These activations may possibly reflect that subjects are imagining themselves driving the cars, as they make their decisions. Figure 16 shows some of the activations from these trials. The full activation is listed in Table 8.

As shown in Fig. 17, the pattern of activation in the Form-Function Conflict trials relative to the Control trials was partly unique and partly similar to the patterns observed in the Form Only and Function Only contrasts. Specifically, as in the previous two contrasts, we observed activity in the SMA, insula, and anterior cingulate. Unlike the other two contrasts, we also saw activity in the amygdala, an area in the limbic system linked with emotional experience and emotional response, particularly fear and arousal, as well as learning and other functions [29]. The full activation is listed in Table 9.

The analyses critical to our hypothesis were those comparing the Form-Function Conflict trials to the Form Only and Function Only trials. In the contrast of Form-Function Conflict versus the Form Only and Function Only trials, we identified a number of regions that showed greater activity level during Conflict decisions. These regions, including the midbrain, orbitofrontal cortex, and a cluster overlapping with the parahippocampal gyrus and amygdala, have links to emotion, arousal, and emotion regulation. Some activation was also observed in the lentiform nucleus, an area that is very close to the limbic region that was activated in the Conflict versus Control contrast. Figure 18 highlights the activity in some of these regions.

Table 9 Regions that showed increased activity in Form-Function Conflict versus Control trials

	Region	*x*	*y*	*z*	*t*	*k*
1	Anterior cingulate	20	−18	30	5.09	36
2	Anterior cingulate (BA 24)	14	−4	42	4.68	18
3	Supplementary motor area (BA 6)	10	−14	60	4.51	23
4	Precentral gyrus	18	−20	66	6.14	42
5	Precentral/postcentral gyri	18	−32	60	4.30	19
6	Precuneus	14	−54	22	4.44	14
7	Insula	34	−18	20	5.14	21
8	Putamen/insula	−30	−8	8	5.13	20
9	Amygdala	−14	0	−14	5.02	23
10	Fusiform/parahippocampal gyrus	−22	−36	−16	4.77	14
11	Superior temporal gyrus/insula	44	−30	14	4.70	23
12	Cerebellum	−20	−34	−24	5.03	17

Notes: MNI coordinates; BA = Brodmann's area

Finally, in order to understand the common activations between the Form-Function Conflict and the Form Only trials and also between the Form-Function Conflict and Function Only trials, two conjunction analyses were performed. Regions active in the conjunction of Form-Function Conflict and Form Only included the insula and the dACC. This activity is highlighted in Fig. 19 and detailed in Table 10.

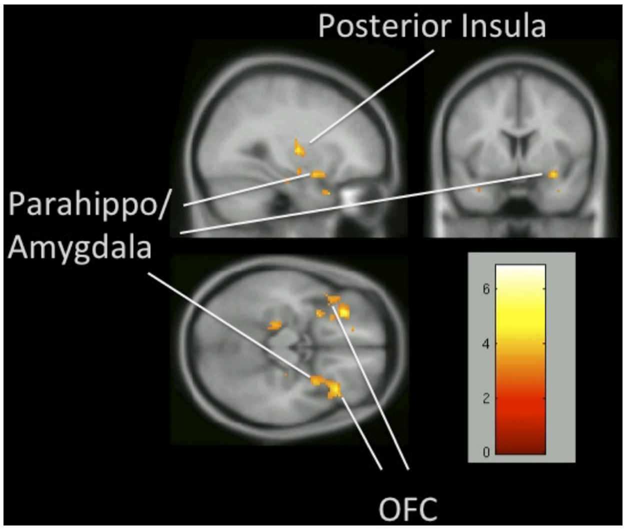


Fig. 18 Difference in neural activity between Form-Function Conflict trials and Form Only and Function Only trials

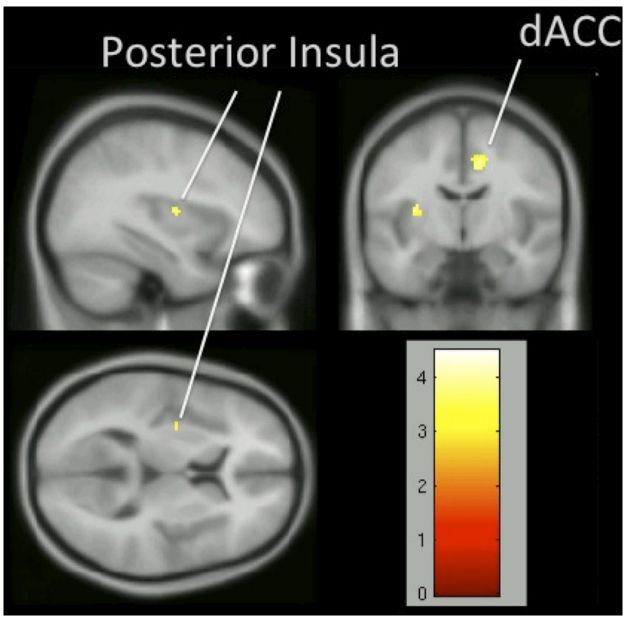


Fig. 19 Regions active in the conjunction of Form-Function Conflict and Form Only

Regions active in the conjunction of Form-Function Conflict and Function Only included the SMA and dACC. This activity is highlighted in Fig. 20 and detailed in Table 11.

Discussion. The beta coefficients in the combined preference functions indicated that subjects weighed function more heavily than form. However, the extent of this preference was not apparent from the betas alone. Most subjects never traded off high function for high form. One of the contributing factors to the high choice of function over form may be the extremely basic representation of the form. This issue will be addressed in future work. Although the low resolution of the form illustrations may have affected its preference, during debriefing several participants mentioned that during the Form-Function Conflict trials they wanted to pick the higher form option but felt they could not ignore the difference in performance specifications. This is consistent with the results of the conjunction analysis. The feedback from

Table 10 Regions active in the conjunction of Form-Function Conflict and form only

	Region	x	y	z	t	k
1	Anterior cingulate (BA 24)	14	−2	40	4.51	120
2	Superior frontal gyrus	18	32	42	3.89	14
3	Precentral gyrus	32	−20	44	3.61	40
4	Precuneus	14	−54	26	4.47	189
5	Precuneus	−14	−56	26	3.84	19
6	Superior temporal grуus/insula	44	−30	14	4.15	85
7	Insula	36	−14	18	3.43	13
8	Insula	−32	−6	10	3.96	16
9	Superior temporal gyrus/insula	−46	−34	16	3.55	18
10	Cerebellum	−18	−36	−24	4.44	35

Notes: MNI coordinates; BA = Brodmann's area

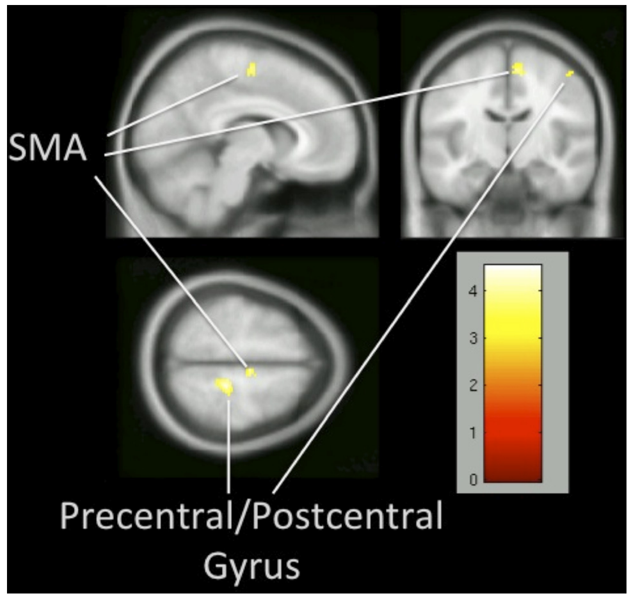


Fig. 20 Regions active in the conjunction of Form-Function Conflict and Function Only

Table 11 Regions active in the conjunction of Form-Function Conflict and Function Only

	Region	x	y	z	t	k
1	Anterior cingulate/supplementary motor area (BA 24)	14	−4	44	4.03	39
2	Supplementary motor area (BA 6)	6	−12	60	4.00	39
3	Precentral and postcentral gyri	18	−32	62	4.53	160
4	Precentral and postcentral gyri	38	−20	40	3.87	32
5	Precentral gyrus	48	−14	56	3.44	12
6	Frontal lobe (white matter/L.V.)	22	−18	30	3.62	12
7	Posterior temporal lobe (white matter/L.V.)	32	−48	10	4.43	29

Notes: MNI coordinates; BA = Brodmann's area; L.V. = lateral ventricle

participants is consistent with our hypothesis that consumer decision-making strategy is more complex when both form and function are taken into account.

Another factor that may have contributed to the overwhelming selection of function over form was the presentation method. Previous work has suggested that joint presentation of alternatives, as opposed to separate presentation, can reduce the role of emotions in evaluation and presumably therefore during choice [47]. This may contribute to the preference reversals that have been observed when switching between joint and separate presentation of form and function. People tend to prefer the "should" alternative (options that are practical or rational) in joint stimulus evaluation but the "want" alternative (options that appeal to emotion) in separate stimulus evaluation [48–50]. In the present study, it is possible that participants viewed the car's performance as a "should" and therefore favored it over the car's aesthetics, a potential "want," during the joint presentations of performance and aesthetics. Another possible reason for function being chosen over form so often has to do with the simplified vehicle representation. The limited detail in the vehicle representations can make it hard for consumers to get excited enough about the designs to choose form over function. These issues will be explored further in future work.

The activation observed during the Form Only trials included the dACC and insula, areas linked with conflict monitoring [43] and visceral experience [29], respectively. Activation in both regions has been reported in previous studies of aesthetic judgment and choice [28,51]. In the Function Only trials, activation was observed in SMA, an area associated with motor planning [46]. One possible explanation is that the participants were imagining themselves driving. Recalling this kind of information while trying to make a preference decision points to a complex decision-making strategy. Consumers are not always conscious of their strategy. When asked how they arrived at their decisions, many participants stated they chose based on the level of the performance characteristic that was most important to them. They were not necessarily aware of the memories that were part of their decisions.

As both form and function varied in the Conflict trials, activation was observed in multiple brain regions, some associated with intuitive feelings and some with analytical thinking. These regions were not the direct sum of those activated during the Form Only and Function Only decisions. Dealing with form and function together can be viewed as a type of multitasking, and the activation in the anterior cingulate may be the result of increased conflict detection [51] rather than just increased emotion during the task. Activation in SMA has also been associated with a bottleneck of information processing during multitasking [52]. This implies some aspect of the conflict decisions may have been more cognitively demanding than the control decisions. However, as previously noted, RT during the Conflict trials was not longer than RT during the Control trials, suggesting that the conflict decisions were not more difficult than the control decisions.

Multiple regions were uniquely more active during the Conflict trials than during the other two trial types, particularly regions linked with emotions, such as the amygdala. This pattern of activation may reflect involvement of emotions in the decision process (i.e., subjects chose based on subjective feelings) or simply reflect experience of negative emotion during the decision (e.g., because subjects did not like having to choose between form and function). In the conjunction analyses of the Form Only, Function Only, and Conflict trials, a greater similarity was seen between the Form Only and Conflict trials than between the Function Only and Conflict trials. This pattern of results may indicate the importance of emotions during the conflict encountered in these decisions.

These findings all have implications on the design process. Acknowledging that consumers employ different and potentially more complex decision-making strategies when faced with choices involving both form and function speaks to the importance of both the individual product aspects and the relationship between them. How designers choose to consider the relationship throughout the design process will have a substantial impact on preference for a product. Additionally, establishing that emotion is an active part the decision-making means that it should also be actively considered during the design process. Being intentional about the emotions associated with a product throughout the design phase allows the designer to guard against negative emotions and capitalize on the positive ones.

One of the major goals of this paper is to introduce the idea that fMRI can be used to study complex consumer decisions relevant to product design. One-way fMRI can help is by showing whether one type of decision (e.g., choice between an option with the better design and an option with the better performance) is similar to or different from another type of decision (e.g., choice between one complete design over another). A second way that fMRI can guide our understanding of consumer decision-making is to provide insight into whether and when emotional versus rational thinking might occur, which might inform the level of confidence for conjoint-based preference modeling. Caution should be exercised with this approach, however, to not engage in faulty reverse inference (e.g., the inference that emotions were involved simply because a limbic region was activated). To help increase confidence in these types of reverse inferences, researchers can collect complementary measures (e.g., self-report of emotion) and report the extent to which the brain activations correlate with these additional measures [53]. fMRI can also help determine if one group of people employs a different strategy during decision-making than another group. Here we provide an illustration of the first way in which fMRI can contribute to understanding of consumer choice to inform product development.

fMRI can also be useful by providing stronger predictors of choice than behavioral measures alone. By matching activation patterns to specific choice states, learning techniques can be applied to neural activity to predict conscious and unconscious choices. Although the combined utility function was reasonably well correlated with participants' responses, clearly more complex decisions are taking place. We believe exploring the relationship between preference decisions and the observed neural activity during those decisions will lead to utility models that are capable of better predictions of choice than models based on conjoint surveys alone. Consistent with this view, previous fMRI research has shown that neural response to persuasive messages can better predict subsequent behavior change than self-reported attitudes and intentions [54].

Conclusion

The results of our study show that when taking both form and function into account, preference judgments are more complex than the sum of the individual judgments. A metaconjoint approach that uses separate conjoint analyses of form and function provides one means to account for the conflicting decisions that are made by consumers. However, this work marks the first time that fMRI was employed to assist in understanding and modeling how consumers trade off form and function in their preference judgments. The conflict between the two different aspects of the product resulted in activation of the emotion-oriented regions of the brain. This work provides preliminary evidence of the importance of the consumer's decision-related emotions in the design process, even if only technological or performance considerations are the focus. In the future we anticipate fMRI data will be a powerful tool in helping to better understand and model complex consumer behavior as a means to inform the product development process.

Acknowledgment

The authors would like to thank the National Science Foundation's Graduate Research Fellowship program and grant (SBE0738058) and Pittsburgh Life Sciences Greenhouse for funding this research. We also thank the Scientific Imaging and Brain Research Center (SIBR) at Carnegie Mellon University, as well as Ian D. Roberts and Thomas Kraynak for helping with analysis of the fMRI data.

References

[1] Boatwright, P., and Cagan, J., 2010, *Built to Love: Creating Products that Captivate Customers*, Berrett-Koehler Publishers, San Francisco, CA.
[2] Payne, J. W., Bettman, J. R., and Johnson, E. J., 1988, "Adaptive Strategy Selection in Decision Making," J. Exp. Psychol. Learn. Mem. Cogn., **14**(3), pp. 534–552.

[3] Payne, J. W., Bettman, J. R., and Johnson, E. J., 1993, *The Adaptive Decision Maker*, Cambridge University Press, Cambridge.

[4] Damasio, A. R., 1994, *Descartes' Error: Emotion, Reason, and the Human Brain*, Putnam, New York.

[5] Loewenstein, G. F., Weber, E. U., Hsee, C. K., and Welch, N., 2001, "Risk as Feelings," Psycholog. Bull., **127**(2), pp. 267–286.

[6] Bettman, J., Luce, M., and Payne, J., 1998, "Constructive Consumer Choice Processes," J. Consum. Res., **25**(3), pp. 187–217.

[7] Shiv, B., and Fedorikhin, A., 1999, "Heart and Mind in Conflict: The Interplay of Affect and Cognition in Consumer Decision Making," J. Consum. Res., **26**(3), pp. 278–292.

[8] Isen, A. M., 2001, "An Influence of Positive Affect on Decision Making in Complex Situations: Theoretical Issues With Practical Implications," J. Consum. Psychol., **11**(2), pp. 75–85.

[9] Coricelli, G., Dolan, R. J., and Sirigu, A., 2007, "Brain, Emotion and Decision Making: The Paradigmatic Example of Regret," Trends Cogn. Sci., **11**(6), pp. 258–265.

[10] Slovic, P., Finucane, M., Peters E., and Macgregor, D., 2007, "The Affect Heuristic," Eur. J. Oper. Res., **177**(3), pp. 1333–1352.

[11] Luce, D. R., and Tukey, J. W., 1964, "Simultaneous Conjoint Measurement: A New Type of Fundamental Measurement," J. Math. Psychol., **1**(1), pp. 1–27.

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

[13] Phan, K. L., Wager, T., Taylor, S. F., and Liberzon, I., 2002, "Functional Neuroanatomy of Emotion: A Meta-Analysis of Emotion Activation Studies in PET and fMRI," NeuroImage, **16**(2), pp. 331–348.

[14] Nguyen, T. A., and Zeng, Y., 2010, "Analysis of Design Activities Using EEG Signals," Proceedings of the ASME 2010 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE), Montreal, Quebec, Canada.

[15] 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.

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

[17] Stoll, M., Baecke, S., and Kenning, P., 2008, "What They See is What They Get? An fMRI-Study on Neural Correlates of Attractive Packaging," J. Consum. Behav., **7**(4-5), pp. 342–359.

[18] Green, P. E., and Srinivasan, V., 1978, "Conjoint Analysis in Consumer Research: Issues and Outlook," J. Consum. Res., **5**(2), pp. 103–123.

[19] Zwerina, K., Huber, J., and Kuhfeld, W., 1996, *A General Method for Constructing Efficient Choice Designs*, Fuqua School of Business, Duke University, Durham, NC.

[20] Turner, H., Orsborn, S., and Lough, K. G., 2009, "Quantifying Product Color Preference in a Utility Function," Proceedings of 2009 American Society of Engineering Management, Springfield, MO.

[21] Kelly, J., and Papalambros, P. Y., 2007, "Use Of Shape Preference Information in Product Design," International Conference on Engineering Design, ICED'07, Paris, France.

[22] 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.

[23] Tseng, I., Cagan, J., and Kotovsky, K., 2011, "Learning Stylistic Desires and Generating Preferred Designs of Consumers Using Neural Networks and Genetic Algorithms," Proceedings of the ASME 2011 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE), Washington, DC.

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

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

[26] Knutson, B., Adams, C. M., Fong, G. W., and Hommer, D., 2001, "Anticipation of Increasing Monetary Reward Selectively Recruits Nucleus Accumbens," J. Neurosci., **21**(16), p. RC159.

[27] Bush, G., Luu, P., and Posner, M., 2000, "Cognitive and Emotional Influences in Anterior Cingulate Cortex," Trends Cogn. Sci., **4**(6), pp. 215–222.

[28] Jacobsen, T., Schubotz, R. I., Höfel, L., and Von Cramon, D. Y., 2006, "Brain Correlates of Aesthetic Judgment of Beauty," NeuroImage, **29**(1), pp. 276–285.

[29] Ernst, M., and Paulus, M. P., 2005, "Neurobiology of Decision Making: A Selective Review From A Neurocognitive and Clinical Perspective," Biol. Psychiatry, **58**(8), pp. 597–604.

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

[31] 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.

[32] Goel, V., and Dolan, R. J., 2003, "Reciprocal Neural Response Within Lateral and Ventral Medial Prefrontal Cortex During Hot and Cold Reasoning.," NeuroImage, **20**(4), pp. 2314–2321.

[33] Luce, R. D., 1977, "The Choice Axiom After Twenty Years," J. Math. Psychol., **15**(3), pp. 215–233.

[34] Green, P. E., Carroll, J. D., and DeSarbo, W. S., 1981, "Estimating Choice Probabilities in Multiattribute Decision Making," J. Consum. Res., **8**(1), pp. 76–84.

[35] Johnson, R. M., 1987, "Adaptive Conjoint Analysis," Sawtooth Software Conference Proceedings, pp. 253–265.

[36] Kessels, R., Goos, P., and Vandebroek, M., 2010, "Optimal Two-Level Conjoint Designs With Constant Attributes in the Profile Sets," J. Stat. Plann. Inference, **140**(11), pp. 3035–3046.

[37] Netzer, O., Toubia, O., Bradlow, E. T., Dahan, E., Evgeniou, T., Feinberg, F. M., Feit, E. M., Hui, S. K., Johnson, J., Liechty, J. C., Orlin, J. B., and Rao, V. R., 2008, "Beyond Conjoint Analysis: Advances in Preference Measurement," Mark. Lett., **19**(3–4), pp. 337–354.

[38] Amaro, E., and Barker, G. J., 2006, "Study Design in fMRI: Basic Principles," Brain Cogn., **60**(3), pp. 220–232.

[39] Friston, K. J., Penny, W. D., Ashburner, J., Kiebel, S. J., and Nichols, T. E., 2006, *Statistical Parametric Mapping: The Analysis of Functional Brain Images*, Academic Press, New York.

[40] Forman, S. D., Cohen, J. D., Fitzgerald, M., Eddy, W. F., Mintun, M. A., and Noll, D. C., 1995, "Improved Assessment of Significant Activation in Functional Magnetic Resonance Imaging (fMRI): Use of a Cluster-Size Threshold," Magn. Reson. Med., **33**(5), pp. 636–647.

[41] Lieberman, M. D., and Cunningham, W. A., 2009, "Type I and Type II Error Concerns in Fmri Research: Re-Balancing the Scale," Soc. Cogn. Affect. Neurosci., **4**(4), pp. 423–428.

[42] Nichols, T., Brett, M., Andersson, J., Wager, T., and Poline, J.-B., 2005, "Valid Conjunction Inference With the Minimum Statistic," NeuroImage, **25**(3), pp. 653–660.

[43] Eisenberger, N. I., and Lieberman, M. D., 2004, "Why Rejection Hurts: A Common Neural Alarm System For Physical and Social Pain," Trends Cogn. Sci., **8**(7), pp. 294–300.

[44] Craig, A. D., 2002, "How Do You Feel? Interoception: The Sense of the Physiological Condition of the Body," Nat. Rev. Neurosci., **3**(8), pp. 655–666.

[45] Critchley, H. D., Wiens, S., Rotshtein, P., Ohman, A., and Dolan, R. J., 2004, "Neural Systems Supporting Interoceptive Awareness," Nat. Neurosci., **7**(2), pp. 189–195.

[46] Nachev, P., Kennard, C., and Husain, M., 2008, "Functional Role of the Supplementary and Pre-Supplementary Motor Areas.," Nat. Rev. Neurosci., **9**(11), pp. 856–869.

[47] Ritov, I., and Baron, J., 2011, "Joint Presentation Reduces the Effect of Emotion On Evaluation of Public Actions," Cogn. Emotion, **25**(4), pp. 657–675.

[48] Hsee, C. K., 1996, "The Evaluability Hypothesis: An Explanation for Preference Reversals Between Joint and Separate Evaluations of Alternatives," Org. Behav. Human Decis. Process., **67**(3), pp. 247–257.

[49] Bazerman, M. H., Tenbrunsel, A. E., and Wade-Benzoni, K., 1998, "Negotiating With Yourself and Losing: Making Decisions With Competing Internal Preferences," Acad. Manage. Rev., **23**(2), pp. 225–241.

[50] Kahneman, D., and Ritov, I., 1994, "Determinants of Stated Willingness to Pay for Public Goods: A Study in the Headline Method," J. Risk Uncertainty, **9**(1), pp. 5–37.

[51] Pochon, J.-B., Riis, J., Sanfey, A. G., Nystrom, L. E., and Cohen, J. D., 2008, "Functional Imaging of Decision Conflict," J. Neurosci., **28**(13), pp. 3468–3473.

[52] Dux, P. E., Ivanoff, J., Asplund, C. L., and Marois, R., 2006, "Isolation of a Central Bottleneck of Information Processing With Time-Resolved FMRI," Neuron, **52**(6), pp. 1109–1120.

[53] Poldrack, R. A., 2006, "Can Cognitive Processes be Inferred From Neuroimaging Data?," Trends Cogn. Sci., **10**(2), pp. 59–63.

[54] Falk, E. B., Berkman, E. T., Mann, T., Harrison, B., and Lieberman, M. D., 2010, "Predicting Persuasion-Induced Behavior Change From the Brain," J. Neurosci., **30**(25), pp. 8421–8424.