Modeling Aggregate Choice for Form and Function Through Metaconjoint Analysis

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In the previous work, meta-attributes have been used to model the relationship between two groups of disparate product attributes. There, preference for form, function, and the relationship between the two were modeled for individual consumers. However, this approach is limited as designers are often called on to choose a design that best appeals to a group of consumers, not individuals. This work expands on the concept and makes it more generally applicable by adapting metaconjoint to model aggregate choice for consumer groups. The results from this work show that a metaconjoint approach can be used to model aggregate choice for form and function and can yield better results on holdout sample predictions than form or function alone. [DOI: 10.1115/1.4028274]

Introduction

One of the most popular methods for constructing consumer preference models is conjoint analysis [1]. In conjoint analysis, direct feedback is solicited from consumers in the form of product surveys. These surveys present participants with multiple product profiles chosen to span the design space without conflating the effects of attributes [2]. In the past decade, conjoint analysis has been applied in a variety of engineering design contexts [3–5]. The work presented here focuses on the metaconjoint methodology initially developed by Sylcott et al. [6] to model combined preference for disparate groups of product attributes. Here, modifications are presented that overcome limitations in the original methodology, allowing the method to be used to model the aggregate response of a group resulting from individual preferences. This extension is valuable because designers typically need to develop a single best solution for a group as opposed to a unique solution for each individual consumer.

Previous Work

A variety of approaches have been followed when modeling aesthetic preference [7–12]. Methods have also been proposed for modeling aesthetic preference in conjunction with functional considerations [13,14]. However, unlike the metaconjoint approach, these methods have not directly captured how consumers make tradeoffs between form and function in a single utility function. In a metaconjoint study, each participant initially completes surveys that capture their form preference and function preference separately. In an additional conjoint study, participants are presented with combinations that include both aesthetic and performance information. The previously acquired choice models are used to vary the levels of form and function presented in the combinations. This methodology results in a single utility function capable of modeling preference tradeoffs between aesthetic and functional product attributes [6].

The work presented here addresses two limitations of the initial metaconjoint approach. The first limitation is a focus on individual consumers. Although there is value in predicting how individual consumers respond to product designs, it is potentially more advantageous to model aggregate response when designing products for a target population. Second, interaction effects were not considered in the previous work. By studying the relationship between form and function, interaction effects will describe how information about each aspect can influence preference for the other and give insight into how to allocate design resources. This work demonstrates how the metaconjoint approach can be adapted to overcome both of these limitations making the method more versatile and useful to designers.

Modeling and Evaluation

In this work, discrete choice models are used to describe consumer preference. These models relate the utility of a design and its alternatives to the probability of the focal design being chosen [15]. In order to model choice for the consumer group, we treat all conjoint data as though they come from the same consumer. This common assumption results in an aggregate model that treats all respondents as being drawn from the same group. The models are fit following the maximum likelihood estimation method as described by Train [16]. For a deeper explanation, see Ref. [17]. This work does not seek to determine a group choice through group decision making, but rather through aggregated analysis of the individual preferences.

One of the most common metrics used to describe a choice model's predictive accuracy, hit rate (HR) [18], is calculated by comparing observed choices with the alternative of highest observable utility in each choice set. Each time the observed selection matches the alternative with highest observable utility counts as a hit—otherwise it is a miss. HR is calculated as $\sum_t \sum_{j\in M_t} n_{jt}/N$, where for product j from a set of products J_t in choice situation (conjoint question) t, $N = \sum_t \sum_{j\in J_t} n_{jt}$ is the total number of conjoint questions answered, and M_t is the alternative with the largest observable utility in choice set t, so that $M_t \in \{v_{jt}: v_{jt} > v_{kt}\ \forall k \in J_t\}$. When $\{v_{jt}: v_{jt} > v_{kt}\ \forall k \in J_t\}$ contains more than one element, the element M_t is selected at random from among those elements. Another metric, mean absolute share error (MASE) is used to evaluate how well the observed share of choices matches the predicted share of choices. It is calculated by taking the average of the absolute difference between the observed and predicted share for each design alternative, $\sum_t \sum_{j\in J_t} \left|p_{jt} - s_{jt}\right| / |J_t|$, where p_{jt} is the predicted share of choices and s_{jt} is the observed share of choices for product j in choice set t. These metrics are used to evaluate performance both within sample and on a holdout sample. The in-sample responses are those used to construct the model while the holdout sample refers to additional questions that are included in the survey to be used for model validation.

Study Methodology

Overview. There were a total of 104 participants in this study (48 female, 56 male, mean age 28.8 yr). Volunteers for this study were recruited online using Amazon.com's Mechanical Turk system. Consent was obtained from each participant prior to starting the survey. Participants were required to be 18 yrs or older. Participants were compensated with \$2.00.

The task consisted of three conjoint analysis surveys. First, each participant was presented with a survey designed to assess aesthetic preference for vehicle shape. Next, participants completed a survey that assessed preference for some of the functional

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attributes of a vehicle. Finally, participants were given a survey that assessed preference for aesthetic and functional attributes concurrently. Each of the study's participants completed the surveys in the same order, aesthetic, function, and combined. The survey order was not counterbalanced because the combined survey needed to take place after the aesthetic and function surveys so the initial choice models would be independent. As the initial surveys were relatively short and as evaluation of aesthetic and function requires separate processing, visual and verbal, respectively, carry-over effects were not expected to be significant.

One of the major departures from the previous metaconjoint work was the use of random instead of fixed survey designs. In the previous approach, a single survey was used to develop individual utility functions for each participant. In a random design scheme, each participant takes a different randomly designed survey. After specifying the permissible values of each attribute, surveys are constructed by randomly assigning attribute combinations to each question. The participant responses all contribute to a single model and the resulting utility function describes the aggregate choice for the group.

One potential concern when aggregating individual preferences to make a decision for a group is Arrow's Impossibility Theorem. The theorem states that there is no decision procedure that converts individual preferences into collective choice while still satisfying several minimally reasonable conditions [19]. Although there is discussion in the literature of how this can negatively impact the design process [20,21], the approach taken in this work is more analogous to an evaluation by a single decision maker than a social choice. As a result, Arrow's Theorem is not directly applicable [22].

Random designs have been employed in a variety studies to model group choice [23–29] and have been shown to be robust in situations where the importance of interactions is not known beforehand [30]. Treating all responses as coming from a single participant allows large enough sample sizes to sufficiently cover the design space. Such designs are capable of estimating both main and interaction effects. Unlike traditional conjoint analysis, metaconjoint analysis combines independently obtained choice models into a single function that characterizes how consumers make tradeoffs between two groups of attributes, leading to insight into preference tradeoff between the groups. Take form and function, for example. For a given product, it is possible to determine whether consumers will gain more utility from improvements in the attributes that contribute to form or those that contribute to function. This sort of insight helps designers and engineers know how best to allocate limited resources (to appearance or functionality). Here, the use of a random design scheme to develop meta-attributes allows for the incorporation of responses from a large group into a single utility function that describes how, on average, the group values form and function relative to one another. This relationship is likely to vary between products and it is valuable for designers to understand how consumers make tradeoffs between the two. Doing so allows designers to focus their attention on the product aspects that yield the highest gains in consumer utility. Each of the participant's unique, randomly designed surveys was developed and administered using the Sawtooth Software SSI Web tool. After completing the conjoint analysis tasks, participants answered some follow up questions about their product experience and demographics.

Eliciting Aesthetic Preference. The aesthetic in this study are vehicle designs depicted by line drawing silhouettes developed by Tseng et al. [14]. An example of the vehicle representation is shown in Fig. 1.

As 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 12 major features of the design to be varied continuously.

In this study, wheel size and front and rear wheel position were held constant, leaving only nine attributes, belt angle, nose angle, ground clearance, body height, roof height, hood length, trunk length, front windshield angle, and rear windshield angle. For each of the nine attributes, there were three levels: low, medium, and high. Each aesthetic preference survey consisted of 18 preference trials, 6 holdout trials, and 1 repeat trial used to check for consistency. The holdout trials were mixed in with the preference trials. The same six holdout trials were used for each participant. In each trial, participants were asked to select the design they preferred most. A sample trial is shown in Fig. 2.

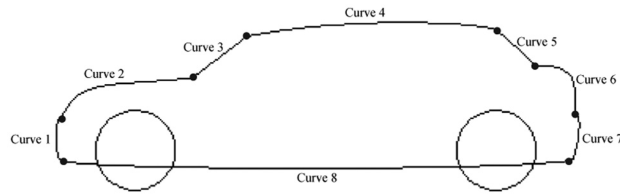

Fig. 1 Example vehicle

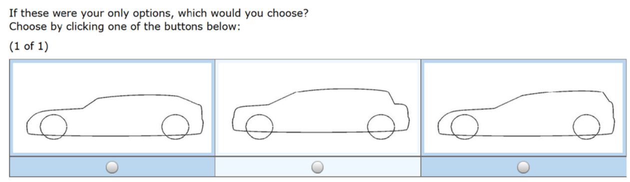

Fig. 2 Sample aesthetic preference trial

Eliciting Function Preference. In the next survey, preference for functional attributes was elicited. The vehicle function is described in terms of three function specifications: fuel economy (18, 28, or 35 MPG), 0–60 mph acceleration (6, 8.5, or 11 s), and 60–0 mph braking distance (120, 135, or 150 ft). These specifications were chosen based on those used by *Consumer Reports* when providing car-rating data for consumers. Each function preference survey consisted of 9 preference trials, 6 holdout trials, and 1 repeat trial used to check for consistency. In each trial, participants were asked to select the group they preferred most. A sample trial is shown in Fig. 3.

Eliciting Combined Preference. The third and final survey included all the form and function attributes. Each combined preference survey consisted of 18 preference trials, 6 holdout trials, and 1 repeat trial used to check for consistency. In each trial, participants were asked to select the vehicle and specification group combination they preferred most. A sample trial is shown in Fig. 4.

Results

For each discrete choice model, the script developed by Train [31] was used to solve for the regression coefficients, β. The performance results from a part-worth model with first order interactions for the aesthetic attributes are presented in Table 1.

The form model scored better on each of the performance metrics than the null model both in and out of sample. Additionally, the β values (not shown here) indicate that participants preferred

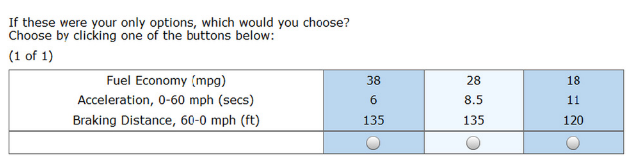

Fig. 3 Sample function preference trial

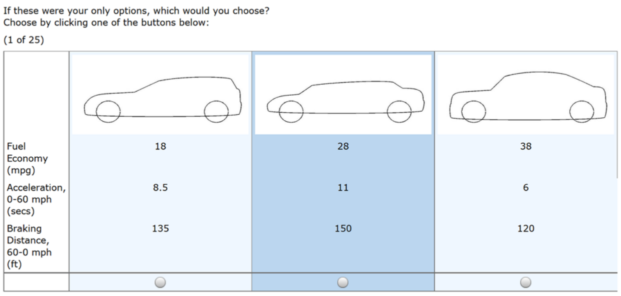

Fig. 4 Sample combined preference trial

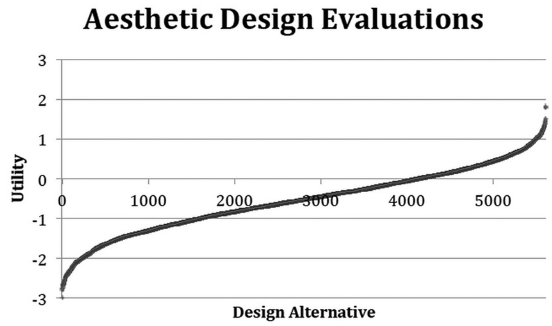

Fig. 5 Plot of aesthetic design evaluations in combined survey

Table 1 Aesthetic choice model performance

		Null model	Form
In sample	LL	−2056.60	−1762.90
	HR	34%	56%
	MASE	—	—
Hold out	LL	−685.53	−619.99
	HR	37%	54%
	MASE	17%	10%

Table 2 Function choice model performance

		Null model	Function
In sample	LL	−1028.30	−638.15
	HR	32%	74%
	MASE	—	—
Hold out	LL	−685.53	−829.16
	HR	23%	52%
	MASE	29%	23%

longer hood lengths and steeper rear windshield angles. For a detailed list of all coefficients, see Ref. [17].

The performance results from the function survey are detailed in Table 2. The function model outperformed the null model on each of the metrics both in and out of sample. Values for β indicate participants prefer high gas mileage and short acceleration times.

Table 3 summarizes the performance results from the combined form and function survey. The combined model scored better than the null model on each of the performance metrics both in and out of sample.

Next, a metaconjoint approach is used to characterize the relationship between form and function. The first step in developing a single meta-attribute that describes overall form is to use the model developed from the aesthetic preference survey to evaluate each of the aesthetic designs presented in the combined survey. In the combined survey, each of the 104 participants faced 18 decisions with three alternatives per choice for a total of 5616 design alternatives presented to the group. Figure 5 shows a scatter plot of the utilities of each of the design alternatives sorted from low to high.

The utility varies between a minimum of −3 and a maximum of 2. The designs were then divided into three groups based on their utility. These groups, for low, medium, and high utility were defined so that there would be a comparable number of designs in each group as shown in Fig. 6.

There are approximately 1870 design alternatives in each group. The design groupings of low, medium, and high correspond to the meta-attribute levels of 1, 2, and 3. Next, the design matrices for the combined surveys are recoded. The nine form attributes are replaced with the single form meta-attribute. The meta-attribute is coded at level 1, 2, or 3 based on the utility evaluation of the form attributes. The same procedure is followed to develop a meta-attribute that describes function. The new design matrix is used to solve for beta coefficients that describe aggregate response to the meta-attributes of form and function. The results from this model are shown in Table 4, while Table 5 shows the results of treating each alternative in the combined survey as the sum of form and function evaluated with the coefficients from the independent surveys.

Table 3 Combined form–function choice model performance

		Null model	Combined
In sample	LL	−2056.60	−1314.77
	HR	33%	71%
	MASE	—	—
Hold out	LL	−685.53	−484.59
	HR	48%	69%
	MASE	29%	10%

Discussion

The results listed in Tables 1 and 2 show both the form and function models performed moderately well on the holdout sample predictions and much better than the null model, which is equivalent to random guessing. The accuracy of the prediction made by the model validates this approach. However, these results are not sufficient to understand how these consumers view form and function in relation to one another. Since the combined survey solicited choices based on both form and function, consumers had to take both into consideration when making decisions. The results in Table 3 are from a model developed by treating each of the form and function attributes independently. The results from this combined model differ from the form only and function only models in two interesting ways. First, several of the form attributes that were found to be insignificant in the form only survey,

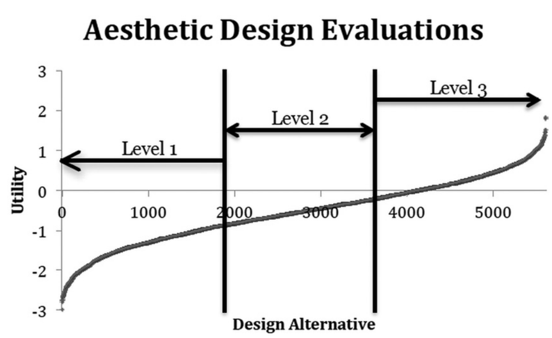

Fig. 6 Division of aesthetic design evaluations in combined survey

Table 4 Metaconjoint choice model performance [*** $p \le 0.01$, ** $p \le 0.05$, * $p \le 0.1$]

	β	Null model	Metaconjoint
	$Form_1$	0	−0.18 (0.13)
	$Form_3$	0	0.52 (0.13) ***
	$Function_1$	0	−1.46 (0.17) ***
	$Function_3$	0	1.22 (0.13) ***
	$Form_1$*$Function_1$	0	−0.21 (0.24)
	$Form_1$*$Function_3$	0	−0.14 (0.18)
	$Form_3$*$Function_1$	0	−0.12 (0.22)
	$Form_3$*$Function_3$	0	−0.08 (0.18)
In sample	LL	−2056.60	−1532.84
	HR	33%	65%
	MASE	—	—
Hold out	LL	−685.53	−433.01
	HR	48%	77%
	MASE	29%	6%

such as body height, were significant in the combined survey. Trunk length was found to be significant in the form only survey but insignificant in the combined survey. Likewise acceleration and braking distance were found to be significant in the function only survey but insignificant in the combined survey. This suggests that consumers may adjust their decision-making strategy when presented with form and function information simultaneously. Second, the combined model performs much better on holdout sample prediction (HR = 69%) than either of the form (HR = 54%), or function (HR = 52%) models. Despite having more attributes for consumers to consider, the model that included both form and function was found to be a better predictor than form or function alone.

The results from the metaconjoint approach listed in Table 4 show that there was a significant positive response to form being at a high level, a negative response to function being at a low level, and a positive response to function being at a high level. There was not a significant response to form being at a low level. The magnitudes of the function betas were also relatively higher than those for form suggesting function had a higher impact on consumer decision making. This is supported by self-report responses. Participants were asked to indicate the extent to which they based purchasing decisions on form and function. A 5-point scale was used: 1 being not at all and 5 being entirely. The mean for form was found to be 3.4 (standard error = 0.1), while the mean for function was found to be 4.1 (standard error = 0.1). This difference is statistically significant ($p < 0.001$). The interactions between form and function were not significant. This suggests neither form nor function moderated response to the other. Interestingly, the holdout predictions based on the meta-attributes (HR = 77%) outperformed predictions from the combined model (HR = 69%). The meta-attribute results were comparable to results listed in Table 5 from the model where the form and function coefficients were assumed to be the same as those found in the form only and function only model. However, that formulation included no information about the relationship between form and function highlighting a major advantage of the metaconjoint approach.

One limitation of this work has to do with the designs the model will predict as high utility. If the group likes sleek sporty vehicles as well as large boxy sport utility vehicles (SUVs), the model makes no distinction and they will have the same utility level at the meta-attribute level. This is a potential pitfall in this method as treating two very different designs as identical introduces error to the model. This issue can be addressed in future work by restricting the vehicle model to just cars or SUVs, for example. Another limitation comes from the potential for consumers to make inferences about the attribute combinations. In developing the preference trials, no constraints were placed on the attribute combinations. As a result, combinations where all the attributes were at the highest levels were permitted. Consumers may infer that such combinations would be infeasible or prohibitively expensive and alter their decisions. To minimize these effects, participants were instructed to choose the combination they preferred based only on the information provided and as if those were the only choices available.

Table 5 Summary of additive model results

		Null model	Additive
In sample	LL	−2056.60	−1532.84
	HR	33%	65%
	MASE	—	—
Hold out	LL	−685.53	−433.01
	HR	48%	77%
	MASE	29%	6%

Conclusion

This work presents an extension to the previous metaconjoint methodology that allows for characterizing how groups of consumers relate form and function with meta-attributes, based on aggregated individual data. This is an important distinction, as designers often need to find solutions that appeal best to a group and not just individuals. The results from this approach are shown to have higher predictive accuracy on the holdout sample than either the form or function models alone or a combined model that includes both. Here, metaconjoint provided an easily interpreted description of how consumers relate form and function. Understanding this relationship is useful as consumers often make decision based on both form and function. However, the approach can also be extended to other disparate groups of product attributes.

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