# Quantifying Aesthetic Form Preference in a Utility Function

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*One of the greatest challenges in product development is creating a form that is aesthetically attractive to an intended market audience. Market research tools, such as consumer surveys, are well established for functional product features, but aesthetic preferences are as varied as the people that respond to them. Additionally, and possibly even more challenging, user feedback requires objective measurement and quantification of aesthetics and aesthetic preference. The common methods for quantifying aesthetics present respondents with metric scales over dimensions with abstract semantic labels like "strong" and "sexy." Even if researchers choose the correct semantics to test, and even if respondents accurately record their responses on these semantic scales, the results on the semantic scales must be translated back into a product shape, where the designer must take the consumers' numerical scores for a set of semantics and translate that into a form which consumers will find desirable. This translation presents a potential gap in understanding between the supply and demand sides of the marketplace. This gap between designer and user can be closed through objective methods to understand and quantify aesthetic preferences because the designer would have concrete directions to use as a foundation for development of the product form. Additionally, the quantification of aesthetic preference could be used by the designer as evidence to support certain product forms when engineering and manufacturing decisions are made that might adversely affect the aesthetics of the product form. This paper demonstrates how the qualitative attribute, form, cannot only be represented quantitatively, but also how customer preferences can be estimated as utility functions over the aesthetic space, so that new higher utility product forms can be proposed and explored. To do so, the form is summarized with underlying latent form characteristics, and these underlying characteristics are specified to be attributes in a utility function. Consumer surveys, created using design of experiments, are then used to capture an individual's preference for the indicated attributes and thus the form. Once preference is summarized in the utility function, the utility function can be used as the basis for form generation and modification or design verification.* [DOI: 10.1115/1.3116260]

*Keywords: utility function, form preference, consumer preference, discrete choice analysis, product design*

## 1 Introduction

**1.1 Motivation for Form Preference.** In light of the importance of new products to corporate growth, much research has been done in the area of new product development. A key focus has been to understand consumer preference so that new products address the needs and desires of the potential consumers. For many product categories, exterior styling and other aesthetic elements are measured to be critical to the buying decision or to customer satisfaction. This research creates and discusses a method to map customer utility of complex product shapes, providing a method for product designers to conduct early market research in a continuous design space to find high utility product shapes.

Engineering design research has produced models for understanding consumer preference for product features and functionality related to creating new products that match consumer *needs*. Methods, such as quality function deployment through the house of quality [1] and mapping customer preferences onto fuzzy sets [2,3], only consider consumer preference for features and functionality. Emotional product characteristics, especially shape, cannot be ignored during the design process because they have considerable influence on consumer purchase decisions [4–8]. While some methods have been created to account for emotional responses to consumer products during design [9,10], these methods are still limited due to their dependence on subjective scales [11,12], such as semantics [13]. Product form has been considered with respect to functionality and manufacturing [14], but the aesthetic considerations were neglected by not taking them into account directly. Aesthetic preference for an individual product feature has been determined using shape morphing [15], but does not account for multiple features or indicate how to create a set of design concepts that would be preferred.

These results from past research indicate the importance of formal study of emotive product characteristics such as aesthetics. By directly quantifying a consumer's preference for form within a class of products, the work presented in this paper circumvents the subjective limitations of semantics, both in terms of the variation in the meanings of the words and in terms of the mapping of the words to forms. Our approach does not require a priori sets of descriptors of products (e.g. sportiness and luxuriousness) on which respondents score the product shapes, nor does our approach require the analyst to specify important product details to include as potential constructs (e.g. size of headlight). Rather than asking consumers to translate forms into ratings on semantic descriptors, this work allows consumers to see the forms and to simply indicate which forms are preferred. There are important advantages of our approach relative to those that require respon-

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dent scoring. First, our approach does not require the researcher to know the potential subjective characteristics a priori. Second, our approach does not prime respondents with a set of criteria on which the analysts expect them to measure the product. Third, our approach does not present respondents and designers with the challenge of translating back and forth between visual and verbal languages.

Although past research shows the importance of and interest in consumer preferences for product aesthetics, extant research in this area has been limited due to the challenge of quantifying subjective preferences. But recent work has yielded a method to map the continuous space of numerous curves to a smaller set of dimensions that can be feasibly used as a basis for experimental design [16]. We build on that method to develop and analyze consumer preferences within a quantified aesthetic space, taking away the subjectivity of understanding preferences for a complex space of product aesthetics. Along with automatic design generation, the process presented in this work provides a stable foundation for developing new products that not only meet utilitarian consumer needs, but also their aesthetic preferences.

## 2 Methodology for Quantifying Form Preference

In this section we introduce the general methodology used for quantifying consumer aesthetic form preference. The rest of this paper then goes through the details of the methodology in the context of an example application.

The first step is to choose a product design space. Since what is being determined is a consumer's preference for a consumer product form, a set of products that are all in the same competitive market are chosen. For example, if a company wants to determine the form preference for travel coffee mugs, a sample of coffee mugs from this product class should be chosen. Ideally, this sample will represent all, or close to all, the parametric variations within the product class. There are instances where some features may not be included on all the products, such as handles on a coffee mug. If the feature does not exist, its parametric value can be reduced to zero, essentially eliminating the feature's form. This product design space defines the generic form of the product.

The generic form of these products then needs to be atomized. The product form is broken into characteristics, like the coffee mug handle, and each characteristic is represented using Bezier curves. Each Bezier curve is then represented using atomic attributes. Once the atomization is done, then the parametric ranges for the atomic attributes are derived from the product sample by representing each product form in the sample set within the atomized product space. The atomic form attributes then translates directly into the attributes of the descriptive utility function.

We employ utility functions to relate product shape to customer preferences. A utility function is a tool used by economists to describe a person's utility, a measure of happiness, or satisfaction gained by using a certain good or service [17,18]. Utility functions have been used quite successfully in engineering design research [19–24].

A benefit of a utility function is that it can represent a complex space where many different attributes each account for a dimension. A utility function offers a means to describe the relationship of all these attributes and then the space can be explored to maximize a person's utility. Utility functions can be used in optimization to determine an optimal set of trade-offs [25–27]. This utility function can then be used to automatically generate new designs according to the derived preference.

Discrete choice conjoint analysis allows estimation of utility weights in a relatively realistic task, wherein respondents select their most preferred item out of a set [28,29]. Additional motivation for this research is that quantifiable performance measures are not independent of qualitative issues for product designers have not found or agreed on an objective measure for quantifying aesthetics [30].

While the typical conjoint survey requires respondents to read and evaluate verbal descriptions of products, where varying attributes are described using text, the conjoint in this study is pictorial. It has been demonstrated that pictorial representations have an advantage over text in that they reduce fatigue, are more interesting [29], and produce better results [31,32].

Respondents answer two surveys, an initial calibration/estimation survey, and a follow-up validation survey. To accommodate heterogeneity of the aesthetic preferences of respondents, the respondent's results from the initial survey are analyzed individually, and a utility function is created for each individual. This utility function is then used to create a respondent-specific set of product concept designs to verify the validity of the individual's utility function, where these product concept designs are presented to the individual respondent in the follow-up validation survey.

In summary, utility functions have been used in engineering design research to quantify preference for quantitative attributes. The work presented here takes the qualitative attribute of form and captures preference for it in a utility function. This utility function is then used to generate new designs that match consumer preference.

## 3 Determining Attributes

As with any discrete choice study, the choice of attributes is fundamental to the understanding of the design space. There are two theories of product form considered. The first considers products to have drama [33]. Drama is described as the stages of anticipation, anxiety, and integration. This is contrary to the second theory that states that the viewing of art is linear, not holistic [34]. Tension is created in three ways: anticipation, conflict/contrast, and complexity. This suggests that product designers separate their products into discrete elements and ask the consumers to rank order them with respect to their expressing the product's personality. Then, the source of the tension is known and can be used in the marketing of the product. In this work, it can be used in the designing (or redesigning) of product form. By atomizing the form of a product [33], it can be determined which attributes truly affect the consumer response and how. Utility theory states that it is necessary to choose attributes that represent the consumer interest. This choice of appropriate attributes is not trivial. The technique in this research is one approach to choosing attributes, and the proof of concept reveals it to be reasonably effective in the end result of assessing and predicting customer preferences for form.

**3.1 Parametrizing the Design Space.** The current state of the art for discrete choice conjoint analysis is limited to about 30 variables for effective survey techniques using design of experiments [35]. With a larger attribute space, the survey respondent is likely to fatigue from the large number of questions required. Therefore, it is necessary to minimize the number of attributes needed to initially describe a product's form.

For the sample data set, 20 sports utility vehicles (SUVs) were chosen from the 2003 model year. Fifty-three traditional SUV models were produced in 2003. Of these, ten were identical in form to other SUVs due to rebadging, e.g. the GMC Yukon and the Chevrolet Tahoe. The true population size, with respect to form, was 43 SUVs. Of these, 20 were included in the sample, accounting for 47% of the population. The selection requirements were that each vehicle have an available blueprint that included the front and side views. Each of the views must be isometric (or as parametrically close as possible) and the two views should complement each other parametrically, i.e. the proportions in each view of the drawing is consistent with the actual vehicle. Table 1 lists the sample vehicles.

Seven atomic attributes were selected from the full representation of the SUV form (Fig. 1). These were chosen because they provided an interesting design space while keeping the number of

Table 1 SUV sample (2003 model year)

| | SUVs |
|---|---|
| 1 | Acura MDX |
| 2 | BMW X3 |
| 3 | BMW X5 |
| 4 | Chevrolet Suburban |
| 5 | Ford Escape |
| 6 | Ford Excursion |
| 7 | Ford Expedition |
| 8 | Ford Explorer |
| 9 | Hyundai Santa Fe |
| 10 | Kia Sportage |
| 11 | Land Rover Free Lander |
| 12 | Land Rover Range Rover |
| 13 | Mazda Tribute |
| 14 | Mercedes Benz ML |
| 15 | Mitsubishi Montero |
| 16 | Mitsubishi Montero Sport |
| 17 | Porsche Cayenne |
| 18 | Suzuki Grand Vitara |
| 19 | Toyota Land Cruiser |
| 20 | Toyota RAV4 |

variables manageable. Atomic attributes Hcowlx and Hcowlz position the cowl with respect to the coordinate axis, which is located on the ground just below the middle of the front axle. V1hoodx and V1hoodz position the top of the grill with respect to the cowl. V1grllz indicates the height of the grill. V1hdltz positions the headlight with respect to the cowl. V4hdltz is the height of the headlight.

In summary, the representation of a complex form with lesser features is called atomization [33]. The form of an automobile has first been broken in characteristics, i.e. headlight and grill. Then each characteristic has been subdivided into the curves needed to represent that characteristic. The representation of the curve is then divided into its atomic attributes (Fig. 2). These atomic attributes can be modified to change the overall form of the vehicle, the gestalt. The consumer sees only a change in product form. Meanwhile, the designer is manipulating the form atomically.

**3.2 Form of Utility Function.** Now that the attributes have been determined, they must be composed into a utility function. The true functional form of individual's utility for aesthetics being unknown, we employ a combination of linear and quadratic specifications. We assume the utility for the latent attributes to be separable, using a linear model for each attribute $u_i$

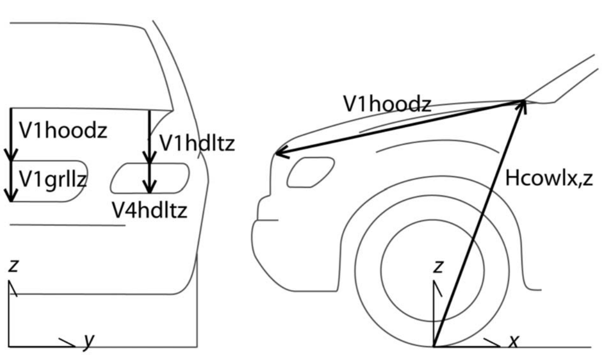


Fig. 1 Seven SUV atomic attributes

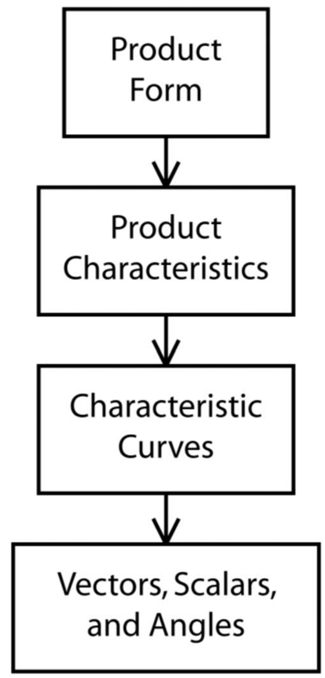


Fig. 2 Atomization of product form

$$U(\bar{x}) = \sum_{i=0}^{n} u_i: \quad u_i = f(\beta_i, x_i) \tag{1}$$

where $u_i$ is some function representing the utility of an individual attribute $x_i$ from the vector of attributes $\bar{x}$, where $n$ is the total number of attributes. This function also includes the attribute weights, $\beta$, which vary depending on the functional form. For each attribute $u_i$, we assume quadratic utility. Each attribute has a squared, a linear, and a constant term with a separate weight, $\beta_{ij}$, for each term of the function where $x_i$ is the parametric value of the atomic attribute (Eq. (2)). While the quadratic form allows for interior solutions, a linear individual attribute utility would be limiting in that it would force "corner solutions," where maximum utility is assumed to be at either the constrained maximum or minimum of the parametric range. The quadratic form for individual attribute utility is sufficient for most representations in that it can approximate a maximum within a range, but can also be linear if the preference is truly linear [36]

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

Because the individual utility function is quadratic, its 2D space (attribute versus weight) can be searched for a maximum and minimum utility using any number of optimization techniques, such as pattern search. While a maximum would be easy to find using a derivative, this method is not applicable in every situation. A nonlinear general utility function would require optimization techniques, and is the subject of future research. If a user's preference for an individual attribute is linear, it can still be captured using a quadratic, then $\beta_{i1}$ is simply zero. Some quadratics are convex and some are concave. Some quadratics do not reach their maximum or minimum within the constrained space. This complexity and its implication on product design generation will be demonstrated later.

In summary of the modeling approach, the overall gestalt of the vehicle is described through an atomization of the form: separating the form into characteristics, describing each characteristic with a set of curves, and representing each curve with a set of atomic attributes. The preference for these attributes is then represented in a utility function that assumes a linear relationship between the atomic attributes with quadratic utility over the levels of the attribute. While the overall gestalt of the product may change through the atomic manipulation of attributes, the consumer's preference can still be capture for the form as a whole.

## 4 Estimating Utility Weights

Section 3 demonstrated what the $x_i$ in the utility function represents: a value in the parametric range of the attribute. It was shown that the "best" value can be found by optimizing according to the utility function. But, what was not stated was how the attribute weights, $\beta_{ij}$, are estimated.

**4.1 Design of Experiments.** Discrete choice analysis is used to determine the attribute weights for the utility function. Rank ordering, an alternative to discrete choice, has been shown to be effective in understanding preference [29], though it is questioned due to its dissimilarity with the actual choice process consumers use when choosing products. Utilizing SAS, a pre-existing survey creation and analysis tool, a fractional factorial design can be created [29], using a modified Fedorov algorithm to build the survey design based on a multinomial logit model [37]. This algorithm is based on the null hypothesis that the attribute weights are zero, i.e. zero prior parameter values. Initially, what is required is the number of attributes to be tested and the levels that those attributes should be tested at. Attribute levels chosen for testing should span the desired range and be evenly spaced to prevent biases [37]. For example, if the rim diameter attribute is to be tested with its maximum at 20 in. and minimum at 10 in. Then three discrete attribute levels should be 10 in., 15 in., and 20 in. The number of attribute levels to test is determined by the form of the individual utility function. If the individual utility function is linear, a minimum of two attribute levels is necessary. As is the case here, a minimum of three attribute levels is necessary for a quadratic. In general, it is not necessary for each attribute to have the same number of levels. Because the overall utility function is linear (Eq. (1)), it does not require that $u_i$ be of the same form for each attribute. In this work, $u_i$ is always a quadratic.

Once the number of attributes and their levels are determined, a fractional factorial experiment design can be created. It is important to consider several criteria when choosing an experiment design option [38]. First, the experiment design should be balanced. A balanced design presents the consumer each level of each attribute the same number of times. Second, the experiment design should be orthogonal. An orthogonal design presents the consumer each pair of each level of each attribute in the same number of times. For example, two attributes $x_1$ and $x_2$ would be tested at each combination of their three levels, the same number of times in an orthogonal design, totaling in eight combinations: $2^3$. While 100% efficiency is not an exclusionary criterion for good experiment designs, it was sought in all of the design choices. The more efficient a design, the more precise the estimation of the coefficient for each attribute level, which is the weight on the attribute in the utility function. Additionally, the experimental design impacts which weights are identified, such as main effects and interactions. The only way to completely account for all main effects, two-way interactions, and higher-order interactions is to have a full factorial. By ensuring that the fractional factorial experiment design is an orthogonal array (both orthogonal and balanced), all estimable main effects are uncorrelated [39]. Third, experiment designs vary depending on the number of choices per question. But, the number of choices per question can affect the number of questions required for an efficient design. In each of the experiment designs chosen, three options were presented for each question. This was found to be the best for minimizing the number of questions needed while keeping the task simple. This was due to the mathematical implication that each attribute had three levels, which were required for fitting a quadratic, as will be seen in Sec. 4.2. The fourth criterion is to minimize fatigue [40]. The more complex the choices, the more distorted the estimates become [41]. With form, the complexity of the multitude of variables is in a sense "hidden;" though there are many attributes, the consumer only sees a changing picture. It has been suggested to use simplified strategies to prevent fatigue or boredom, such as making the study as short as possible, because as people get more tired, they simplify their decision making [40]. For example, in the beginning consumers may choose a vehicle based on the whole design, toward the end they may be choosing based on one or two key features, such as track width or the front view of the grill. Simplification can be done through minimizing the number of questions and minimizing the number of choices per question. For example, consider that one is looking for an experiment with 7 attributes at 3 levels each. The first experiment option may be 36 questions, each with 3 choices. The second experiment option may be only nine questions, but with nine choices per question. While the first experiment design is much longer, the individual task complexity is much less (choosing one-of-three versus one-of-nine), and therefore a less fatiguing experiment.

Once the design is chosen, the experiment must be constructed. It is common in marketing to include a no-choice option, or a constant. This is done especially in empirical modeling in order to specify a model, which more closely reflects the actual choice process, because in the empirical data set of actual purchases, consumers truly have the option to forgo all of the focal products. Our laboratory experiment did not include the no-choice for two reasons, beyond simply the fact that the laboratory controlled the set of available options, unlike empirical data. The first is that what is being attempted to be understood is preference. Most marketing studies seek to find out what preference *at what price*. In this study, price is not an issue and was purposely left out. Only the understanding of which form is preferred over another is of interest. Second, adding a no-choice option degrades the precision of the estimates [37]. When an experiment is designed it assumes that there will be a response for each question. For each no-choice option selected, the efficiency of the experiment design decreases and, thereby, the estimation of the part worth is more likely to be imprecise. If the part worth is incorrect, its error will propagate through the methodology; the utility function is less likely to truly match the consumer and therefore product designs created or analyzed based on the utility function will also not match the consumer's preference.

**4.2 Discrete Choice Analysis.** Once the survey has been constructed and administered, the respondent's results need to be analyzed to determine the part-worth estimates. A part-worth is the estimated preference for a single choice instance. Since the experiment was designed to be both orthogonal and balanced, and because part-worth parameters are estimated by the individual, estimates for the discrete choice logit model are a one-to-one transformation of those using the simple the Luce method [42], often now referred to as the Bradley–Terri–Luce (BTL) equation [43], since Bradley and Terry had earlier proposed Luce's choice axiom in binary choice sets [44]. In the BTL method, the probability that a consumer will select option $i$ from a pool of items $j$ is

$$P(i) = \frac{w_i}{w_j} \tag{3}$$

In this work, $w_i$ is simply the number of times that option was chosen divided by the total number of times that option was offered, $w_j$.

Since there are three levels for each attribute, there are three part-worth values that need to be estimated. For example (Table 2), the horizontal position of the cowl may be offered at three levels covering its parametric range: level 1 at 71.958 in. (maximum), level 2 at 63.883 in. (mean), and level 3 at 55.808 in. (minimum). A consumer chooses designs with level 1 13 times, level 2 14 times, and level 3 9 times out of 36 questions.

Then the probability of that person preferring each level is just

Table 2 Part-worth estimation example

| Level | Parametric value | Times chosen | % chosen (%) | Centered |
|---|---|---|---|---|
| 1 | 71.958 | 13 | 36.1 | 0.028 |
| 2 | 63.883 | 14 | 38.9 | 0.056 |
| 3 | 55.808 | 9 | 25.0 | −0.083 |

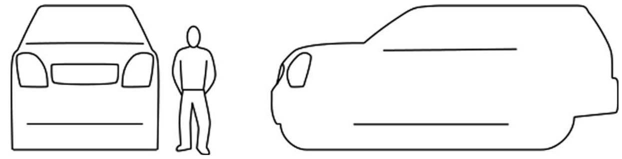

Fig. 5 Option designs 1 and 2

the percentage of times that they chose it: 36.1%, 38.9%, and 25.0%, respectively. These values are then centered around zero by subtracting the average percentage of the set, thus the magnitude of the estimates reflects the importance or weight of that attribute in the overall utility function, $U_i$.

These centered values are then the part-worth values. Example part-worth values are plotted versus the attribute range (Fig. 3). Since the intention is to estimate the weights for the utility function based on a quadratic function, a quadratic curve is fit to the three part-worth values (Fig. 4). This function is of the parametric range for the attribute versus its utility and easily converts from $y=-0.0013x^2+0.1702x-5.5996$ to $u_i=\beta_{i1}x_i^2+\beta_{i2}x_i+\beta_{i3}$ (Eq. (2)), where $\beta_{i1}=-0.0013$, $\beta_{i2}=0.1702$, and $\beta_{i3}=-5.5996$. This attribute's utility function is then combined with the other attributes' utility functions to form the full utility function for that individual consumer. Once all attribute weights for the utility function have been determined, the utility function can be used in designing new products forms or confirming existing designs.

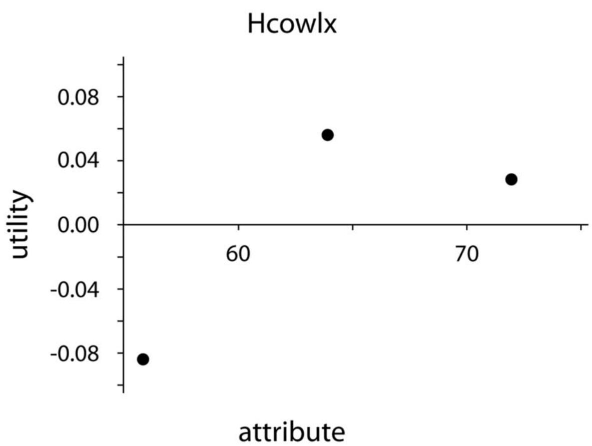


Fig. 3 Part-worth value example

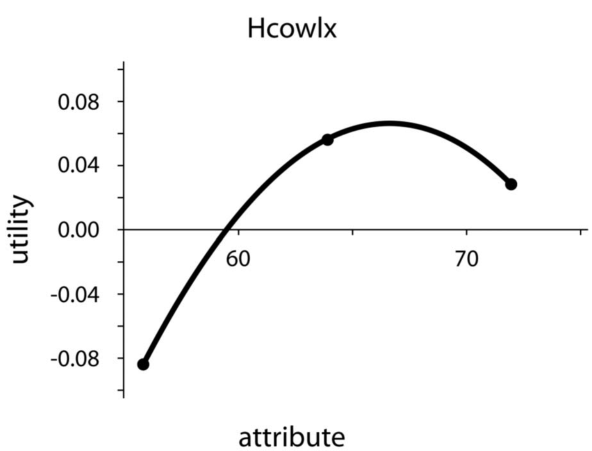


Fig. 4 Quadratic function example

## 5 Consumer Study

The following is a study conducted as a validity check, to determine if the process developed is predictive of consumer preferences of vehicle forms outside of the set presented in the initial calibration and estimation set. An initial vehicle survey was used to determine the weights for a respondent's utility function. The initial survey was the same for each respondent. Then, a follow-up survey, individualized for each respondent, validated the utility functions through designs created according to the respondent's utility function. Both studies were provided online to ensure each respondent could take the survey in a comfortable setting and to facilitate data collection.

**5.1 Initial Survey Design.** An initial sample study using all 55 of the atomic attributes from the headlight and grill characteristics needed to describe the curves in detail had several problems that could not be addressed directly. The issues that could be addressed, fatigue and attribute interaction, were both able to be minimized by reducing the number of attributes included in the utility function. The number of attributes chosen was based on the need to keep the experiment length as short as possible while still being able to change the appearance of the vehicle significantly. Since a quadratic function is being used to describe preference for each attribute, each attribute must have three levels. As stated previously, these attribute levels were set at maximum, average, and minimum for the parametric ranges found in the product sample. Through an iterative process using SAS software, it was found that a reasonably sized orthogonal array (orthogonal and balanced design) of 36 questions could be determined from 7 attributes. This experiment is composed of 18 different product designs. Four of the questions are asked multiple times (with the options in different orders) to verify choice consistency.

The seven attributes chosen to be included in the utility function are shown in Fig. 1: Hcowlx, Hcowlz, V1hoodx, V1hoodz, V1grllz, V1hdltz, and V4hdltz. Fifty-one other attributes are needed to create a completed vehicle form. The 51 attributes are each kept constant at a neutral parametric value, so as to minimize their interaction with the seven attributes included in the utility function and thus to minimize their influence on the survey respondents design choices. The seven explored attributes, while few, provide a large variation in the form of the vehicles, as can be seen in Figs. 5–7. Table 3 lists these attributes and the parametric values for their three levels for the initial vehicle survey. Each parametric value is in inches.

**5.2 Vehicle Survey.** A publicly available web-based survey host was used to build the survey structure and to administer all surveys. This pre-existing software was used for the sake of quickly conducting the experiment. The first page of the online vehicle survey introduced the survey and provided some general information. This second page provided instructions on how the

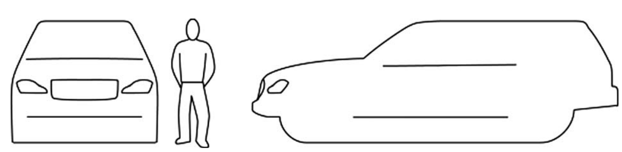

Fig. 6 Option designs 11 and 12

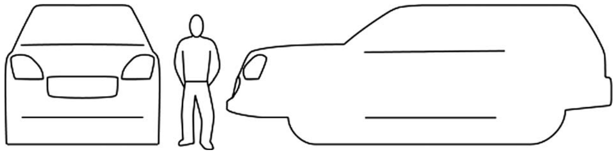

Fig. 7 Option designs 31 and 32

survey would work and gave an example drawing to familiarize the respondent with the forms that would need to be assessed. The third (Fig. 8), and each consecutive page, showed three vehicle forms created according to the design of experiments. Next to each form was a radio button. The respondent was required to choose an option before the next question would become available. This proceeded as such through all 36 questions. After 18 questions, the half-way point, the respondent was reminded that taking a break was encouraged if needed.

Upon completion of the survey, the respondent's answers were downloaded and analyzed (in Microsoft Excel) using the BTL method. Once the attribute weights, $\beta_{ij}$, were determined, the resulting utility function was then ready to be used to create respondent specific designs.

**5.3 Verification Survey.** To verify that the utility function captures the respondent's preference, a second survey was administered. Where the first survey was general and given to the respondents universally, the verification survey is based on an individual's utility function and was thus customized for each respondent.

The verification survey was composed of ten questions each with three options, in the same layout as the first vehicle survey. In this case, the options are not orthogonal designs intended to be analyzed for attribute weights. Each option represented one of three types of designs: high utility, neutral utility, or low utility. The order of these options was randomized for each verification survey question.

For a design to be included in the verification survey, its utility must be within 10% of its respective target. Included high utility designs must be greater than

$$U_{\max} - (0.1 * (U_{\max} - U_{\min})) \quad (4)$$

Likewise, low utility designs must be less than

$$U_{\min} + (0.1 * (U_{\max} - U_{\min})) \quad (5)$$

The constraint for the neutral utility designs is

$$[U_{\min} + (0.5 * (U_{\max} - U_{\min}))] \pm (0.05 * (U_{\max} - U_{\min})) \quad (6)$$

By applying these constraints, it could be ensured that the designs were visually distinct and were separate enough in utility to not be accidentally convoluted.

The verification survey had a similar opening survey page and the instructions page was the same, except the number of questions was changed from 36 to 10, and the estimated time was reduced to 5 min. The questions, from the perspective of the respondent, were essentially the same. It is interesting to note that one respondent even delayed taking the verification survey until prodded because he was convinced he had already taken it.

Table 3 Attributes and their levels

| Attributes | | Levels 1 | Levels 2 | Levels 3 |
|---|---|---|---|---|
| 1 | Hcowlx | 71.958 | 63.883 | 55.808 |
| 2 | Hcowlz | 55.908 | 49.920 | 43.931 |
| 3 | V1hoodx | −43.344 | −48.272 | −53.201 |
| 4 | V1hoodz | −6.024 | −11.087 | −16.149 |
| 5 | V1grllz | −5.684 | −10.485 | −15.286 |
| 6 | V1hdltz | 11.199 | 8.193 | 5.187 |
| 7 | V4hdltz | −4.485 | −9.970 | −15.455 |

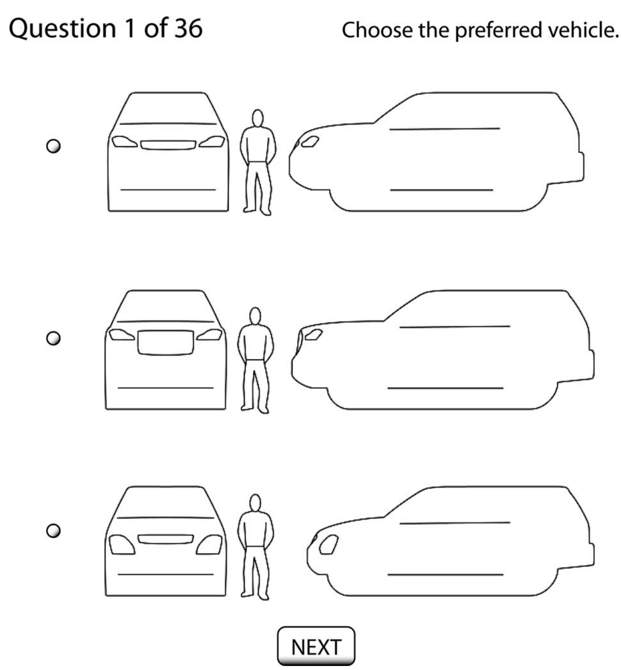


Fig. 8 Vehicle survey example question

## 6 Results

The sample population for this experiment consisted of 30 individuals ranging from 23 years old to 61 years old, with an average of 37 years old. The experiment was intentionally directed at a population over the age of 25, with the expectation that persons of an automotive purchasing age would be more conscious of product form design. The sample population was almost evenly split according to gender (16 males versus 14 females) though there were considerably more married persons than nonmarried persons (23 versus 7).

Each respondent was contacted via an online message board or email announcement. The respondent then contacted the experiment coordinator and was assigned a numeric identifier for anonymity. An email was sent to the respondent that contained a hyperlink to the first survey. Upon completion of that survey, the respondent's results were downloaded and processed as discussed in Sec. 5. Upon creation of the individualized verification survey, a second email was sent to the respondent with a hyperlink to their verification survey. Upon completion of the verification survey, the results were downloaded and compared with expected results.

**6.1 Individual Utility Functions.** An individual's utility function was found by analyzing the results from the vehicle survey using the BTL method described earlier. The resulting utility function, $U_i$, was composed of a utility function for each atomic attribute, $u_i$ shown in Fig. 1. Each attribute utility function could be plotted against its parametric range. These came in one of four forms: sloped linear, convex, concave, or flat. All the examples used in this section are actual attribute utility functions from the experiment. Respondent 30 was chosen for these examples because the attribute utility functions span the entire spectrum (Figs. 9–15) of functional forms.

The utility function for attribute Hcowlx (the horizontal position of the cowl relative to the global coordinate axis) was determined to be linear with a preference for the horizontal position of

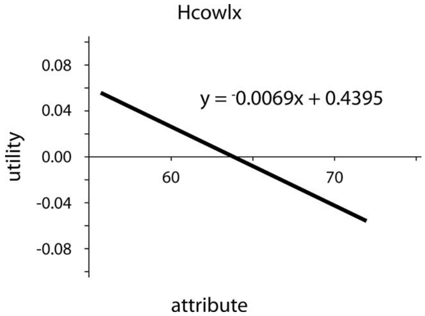


Fig. 9 Respondent 30 Hcowlx

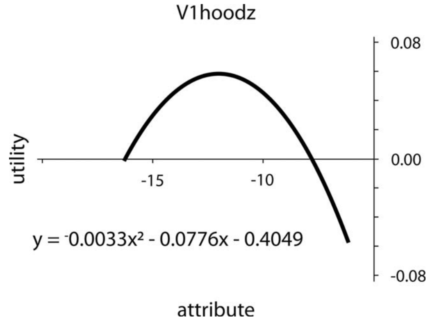


Fig. 12 Respondent 30 V1hoodz

the cowl to be as close to the front axle as possible (Fig. 9) at 55.80 in. A linear attribute utility function shows a maximum preference at one of the parametric constraints.

A convex utility function (Fig. 10) shows that an attribute has a particular parametric value range that is preferred. (It is specifically not stated that the exact parametric value for the attribute could be determined. As in all utility theory, where models are approximations of true preferences, the parametric estimates reflect approximate preferences rather than exact preferences.) Attribute Hcowlz (the vertical position of the cowl relative to the global coordinate axis (Fig. 10) is symmetric and concave. For Hcowlz, the utility function estimate indicates the highest utility for the vertical height of the cowl is close to 50 in., with a rapid decrease in utility if the cowl is raised or lowered.

An unusual form of an attribute utility function is flat (Fig. 11). If the respondent chooses each level of an attribute an equal number of times during the vehicle survey, the BTL method produces part-worth values of zero. What can be inferred is that the respondent does not consider the attribute of importance in their choices among the presented options. For product design generation, a flat utility function gives the greatest flexibility to the designer, in that a design may fall anywhere within an attribute's parametric range without affecting customer preferences. Respondent 30 showed no preference for the length of the hood (V1hoodx, Fig. 11), providing flexibility in hood length when designing form concepts.

The preference for the height of the hood (V1hoodz, Fig. 12) is similar to that for the height of the cowl, though here the concave function is not symmetric. It has a highest estimated preference at 11.75 in. below the height of the cowl. The utility for the height of the grill is linear (V1grillz, Fig. 13), with greater preference to-

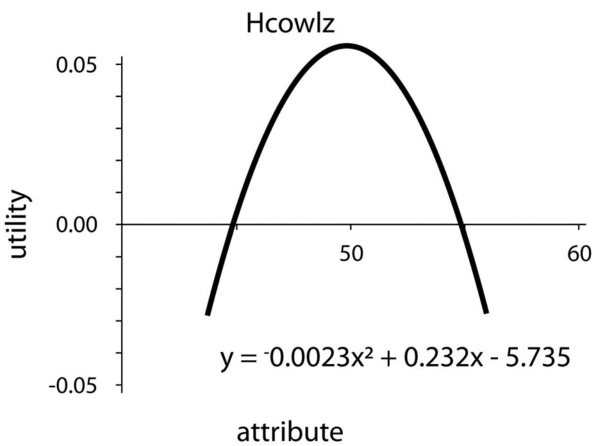


Fig. 10 Respondent 30 Hcowlz

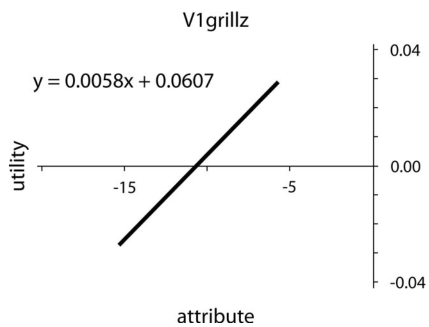


Fig. 13 Respondent 30 V1grllz

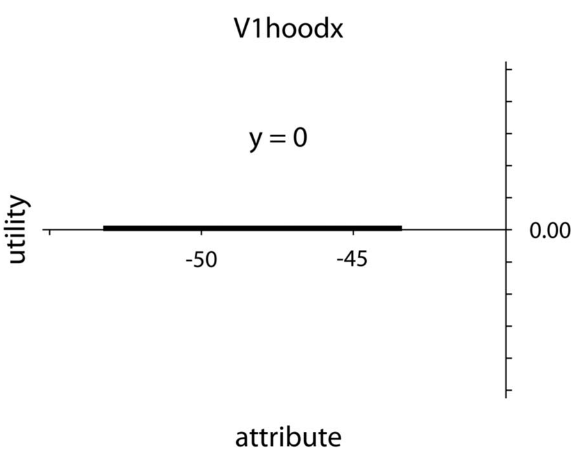


Fig. 11 Respondent 30 V1hoodx

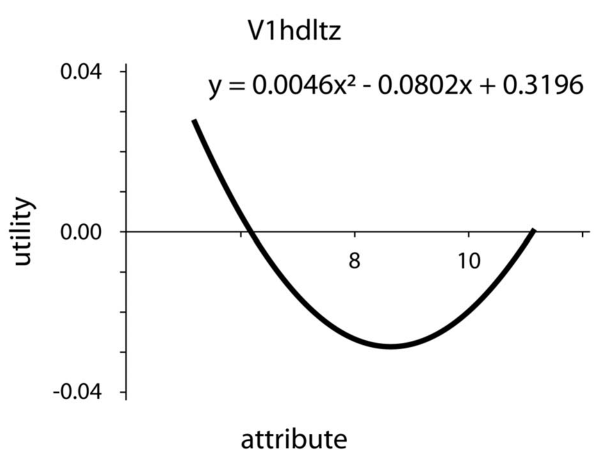


Fig. 14 Respondent 30 V1hdltz

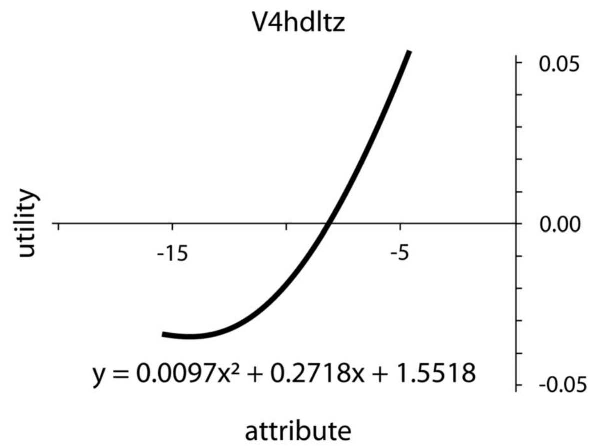


Fig. 15 Respondent 30 V4hdltz

ward the shortest grill, 5.68 in. tall.

A concave utility function (Figs. 14) has a clear parametric range that is not preferred. The shape of this function allows for distinct designs with a higher utility for this attribute, either the minimum or maximum in the parametric range. This allows for compromise in the design and distinctive forms that the individual still prefers. The distance from the cowl to the top of the headlight (V1hdltz, Fig. 14) also has a maximum utility at the lower constraint, 5.19 in. But, since it is concave, large and small distances are preferable to those in between.

The final attribute, the height of the headlight (Fig. 15), also has a constrained preference at the shortest value, 4.50 in. These functions map out the space of preferred forms for Respondent 30, and the functions can be used to compare designs or to create new designs that fit Respondent 30s quantified preference.

The respondent's utility function is then used to create concept designs. Figure 16 shows one of the high utility concept designs created according to Respondent 30s utility function. This design has a utility value of 0.802, where the maximum possible utility for Respondent 30 is 0.804. Just as the attribute utility plots suggest, it was designed with small headlights and grill. The hood is relatively long, the positioning of the cowl is at its minimum.

While this design is high utility for Respondent 30, it is not necessarily high utility for everyone. As a contrast, Fig. 17 shows a low utility design for Respondent 15, one that is similar to the high utility design for Respondent 30, with the headlight and grill both quite short in the two designs. Designers would need to take preference heterogeneity into consideration as the conceptual design process moves forward. One way to accommodate the difference would be to see if various respondents' utility functions cluster into distinct market segments [32].

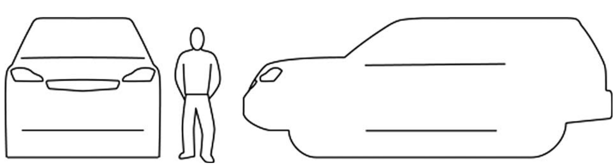

Fig. 16 Respondent 30 high utility design 1

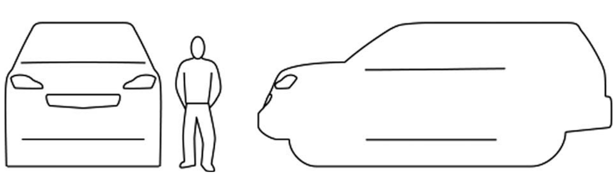

Fig. 17 Respondent 15 low utility design 2

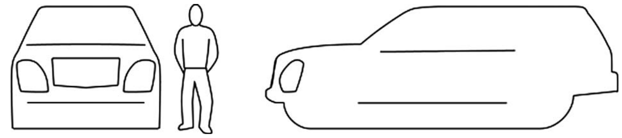

Fig. 18 Respondent 30 low utility design 6

Figure 18 shows one of the low utility concept designs for Respondent 30. This design has a utility of $-0.43$, where the lowest possible utility is $-0.51$. This form concept has many obvious differences from the maximum utility design in Fig. 14, all of which reflect the utility functions presented for Respondent 30. Both the headlight and grill are taller, and the cowl height is shorter and farther back. It is important to note that the length of the hood has changed, but does not affect the design preference, as indicated in Fig. 11. The positioning of the headlight and grill with respect to the cowl has changed dramatically.

Figure 19 shows a neutral utility design for Respondent 30. For respondents, this set of designs was the most diverse. Linear (Figs. 9 and 13), or nonpeaking quadratic (Fig. 15), functions only have a short parametric range for neutral designs. But, convex and concave functions (Figs. 10, 12, and 14) all have two separate parametric ranges, where the utility function crosses the horizontal axis, which offer attribute values for neutral designs. These values, while seemingly unimportant, should be considered carefully. As a product's form is refined, it needs to account for many individual preferences in a single target market. While a single form design may not be high utility for every individual, if the design can be kept at neutral utility, or above, it is more likely to be preferred over a low utility design. The aggregation of individual utility functions has shown to be effective for determining market segments [32]. Its potential for application to product form is quite clear, but is left for future research.

**6.2 Results From Individual Verification Surveys.** Not all respondents had such a mix of utility functions as Respondent 30. For certain respondents, many of the attribute utility functions were flat. For others, all attribute utility functions had an interior maximum or minimum. As stated previously, the purpose in the verification survey is to assess the degree to which the utility function accurately reflects form preference. Respondents were presented with ten questions, where each question had three options: one that was generated from what was estimated to be the high utility portion of the design space, one from the low utility design space, and one neutral utility design. The respondent was required to choose one of the three options. If the estimated utility functions are relevant, one would expect respondents to choose the forms that were estimated to have higher utility. The order that the design options were presented was randomized for each respondent, to eliminate any ordering effects. Unlike the first survey, which was identical for each respondent, each set of designs for the verification survey was created specifically for the respondent, totaling 900 designs for the 30 respondents.

The results from the verification surveys are summarized in Fig. 20. High utility designs were chosen 78.33% of the time on average, with a standard deviation of 23.06%. The neutral utility designs were chosen at an average of 19.33% of the time, with a

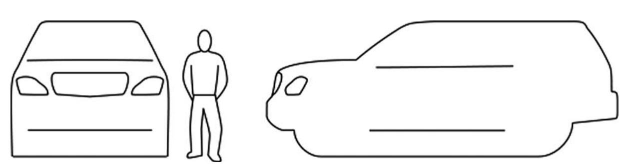

Fig. 19 Respondent 30 neutral utility design 2

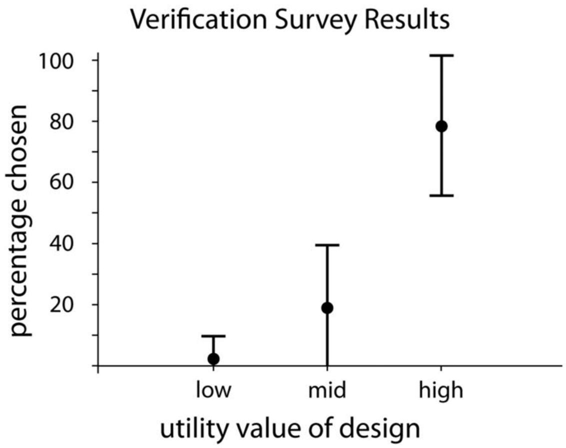


**Fig. 20 Summary of verification survey results**

standard deviation of 19.82%. It should be noted that this crosses the 0% value. Finally, on average the low utility designs were chosen 2.33% of the time, with a standard deviation of 7.74%.

The results clearly show that respondents tended to prefer high utility designs. There is no overlap between the standard deviation bars for the high and neutral utility designs, showing that the difference in choice probabilities of the high and the neutral designs is statistically significant. Although the difference in the choice probabilities of the low and neutral designs are not statistically significant, the observed choice probability for the low utility designs is lower than that of the neutral designs, giving directional support to the utility function estimates. Overall, the results of the verification survey show that the methodology developed here successfully elicits aesthetic form preferences of the respondents even at an individual level.

## 7 Conclusions

When a new product is designed, it is necessary to account for factors that influence the choice of product and purchase decision of the consumer. Engineering design has developed methods for accurately ascertaining engineering parameters for new products, such as which features should be included in a product. However, a product is also composed of other parameters that have not been formally incorporated into new product design analyses, but which may be influential for certain product categories. In certain product categories, for example, consumer choices may be influenced by the visual appeal of the product. This paper introduced a method for quantifying a consumer's form preference in a utility function. Through design of experiments an initial survey is created that tests the consumer's preference for specific product forms. An analysis of the initial survey results produces a utility function that can then be used to create product form designs that match the consumer's preference.

Future research could address ways to reduce the number of designs evaluated by respondents for complex products, such as vehicles, possibly using techniques such as adaptive conjoint. Additionally, the BTL method is appropriate for balanced orthogonal designs, such as was utilized here; although for our data the BTL yielded the same results as would the logit function, future research can directly incorporate functional forms such as logit and probit. The example provided demonstrated an interesting, but simplified, design space. As more product form detail is captured and more complex products are analyzed, the number of attributes needed to describe the design space will increase significantly. The next challenge is how to represent the design space with the least number of attributes while still capturing the fundamental form changes that consumers find important. This will require a reparametrization of the design space that may include or combine previously used methods, such as key product ratios. As the product complexity increases, the traditional utility function representation may not be sufficient. New representations may need to be developed that quantify the design space in a more concise format.

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