**Ian Tseng**
Graduate Student
Integrated Design Innovation Group,
Department of Mechanical Engineering,
Carnegie Mellon University,
Pittsburg, PA 15213
e-mail: ian.h.tseng@gmail.com

**Jonathan Cagan**
George Tallman & Florence Barrett Ladd,
Professor,
Integrated Design Innovation Group,
Department of Mechanical Engineering,
Pittsburgh, PA 15213
e-mail: cagan@cmu.edu

**Kenneth Kotovsky**
Professor
e-mail: kotovsky@cmu.edu

**Matthew Wood**
Graduate Student and DoD SMART Scholar

Integrated Design Innovation Group,
Department of Psychology,
Carnegie Mellon University,
Pittsburgh, PA 15213

# Form Function Fidelity

*Engineering goals are typically rooted in addressing the functional needs of a product. While these engineering goals and specifications can be important in consumers' buying decisions, many times the first impression of the product comes from judgments of the product's aesthetic form. For this reason, this paper set out to study how well human judgment of performance based on a car's shape correlates with the actual measured performance of the car's shape, and what features of the car's shape most influence this judgment. More specifically, participants were asked to rate how aerodynamic, sporty, fuel efficient, and rugged a computer generated car design appeared to them, and these ratings were analyzed against the actual aerodynamics of the vehicle as well as key indicators of sportiness and cornering stability such as center of gravity and wheel stance. The inter-rater consistency of human judgments was also studied. Using this human judgment data, the attributes in car design with the greatest effect on participant judgment of vehicle performance were identified, and were compared against their importance and effect in actual vehicle performance. Analysis of this data gives key insights about how car designers can create designs that better convey the desired goals of a car to consumers while also meeting those performance goals. The results of this study provide evidence that consumers are reasonably accurate at determining certain functional performance traits, such as aerodynamics, but are insensitive to other traits, such as the wheelbase of the vehicle design. It was also determined that the stylistic and functional performance judgments of the consumers surveyed may have been influenced by social norms and conventions learned from past experiences with vehicle designs.*
[DOI: 10.1115/1.4007933]

## Introduction

The form and function of product shape are highly interrelated. When people are asked to make form based shape judgments, their reasoning is informed by a wide range of considerations. A number of these considerations may be judged on implied functional performance based on the shape of the product. An example of this implied functionality is how people may perceive a car with thicker doors to be safer in collisions, regardless of whether the design is actually safer. The authors and contributors of a number of books [1–4] have also reasoned that a source of form-based shape reasoning is rooted in stylistic norms. These stylistic norms include adherence to cultural and social fashions, as well as correlations with the media, society, and products they may have encountered before. Some of these correlations may have also originated from functional reasons and implications, but often have been largely confounded by stylistic norms. An example of the effect of stylistic norms might be a boxy car that appears safer to a consumer because past designs have correlated boxy vehicle design with safety. In order to properly integrate these human product perceptions into the design process, the relationship between these perceptions and actual product performance must be understood.

The goal of this research is to understand how designers can better use product shape to communicate to consumers, whether it is due to stylistic reasons or because it implies functional performance. A better understanding of how people formulate stylistic and functional judgments and how these judgments correlate with functional goals will lead to a better understanding of how functional performance goals can be communicated to the consumer, and will allow potential synergies to be exploited and tradeoffs to be better understood, revealing optimal tradeoff decisions. To follow the previous example, in addition to the importance of creating a safe vehicle design, it may also be important to communicate this feeling of safety to the consumer using functional form language.

Contributed by Design Theory and Methodology Committee of ASME for publication in the Journal of Mechanical Design. Manuscript received September 13, 2012; final manuscript received October 8, 2012; published online November 21, 2012. Assoc. Editor: Panos Y. Papalambros.

## Related Work

Much work has been done to examine, measure, and model consumer preference computationally [5–8]. Many of these methods use well-developed theories and methods from economics, operations research, decision sciences, and other disciplines, such as discrete choice modeling and logistic regression, and apply them to engineering design. While these methods can be useful in determining the utility of product attributes and features, they do not consider the stylistic form of the product, or the implied performance this form conveys to the consumer.

In order to incorporate stylistic form, a method must be employed for generating shape in a controlled deterministic manner that allows for a connection between the shape being generated and the measured preference. One such possible computational design tool is the use of shape grammars [9]. A shape grammar is a set of shape replacement rules that allows for an initial shape to be altered in constrained ways to generate a desired shape. Over the years shape grammars have been developed to generate designs ranging from architectural floorplans [10] and row houses [11], to coffeemakers [12]. Shape grammars have also been used to define branding cues of Harley Davidson motorcycles [13] and Buick cars [14]. Orsborn et al. [15,16] also built a shape grammar for designing cars, which he pared down to create a simpler seven-parameter model to design the front end of sport utility vehicles (SUVs). This model was used to run a discrete choice consumer survey to gauge aesthetic preference [16,17].

Morphing is a less computationally intense alternative to shape grammars for shape generation [18,19]. Morphing starts with a population of known designs that are parametrically created, and by taking linear averages between the parameter values between two or more designs, a new linear recombination of the parent designs can be created. Since all parameter values lie within the range of the parent designs, the system is stable, meaning that all possible morphed combinations will be geometrically valid. A downside to this stability is that designs outside of the realm of the parent population cannot be created. Morphing has been used with a grey theory predictor to model consumer preference of aesthetic designs of liquid-crystal display (LCD) monitors [18]. Smith et al. [19] used morphing methods and an original population of 30 production cars to explore the design space of car shapes. Using this morphing model, it was possible for them to approximate the curb weight of vehicles based on known curb weights of the original population. A number of designs were self-scored for "sportiness," which allowed a transformation vector to be derived that could be added to the parameter values of any design to make that vehicle appear more "sporty". This method of adding a transformation vector allows these morphed models to leave the safe boundaries of the original population of car designs, but opened the door to possibly invalid solutions and model instability.

The literature discussed thus far in this paper has only examined the blanket issue of preference, but in reality preference is made up of a number of lower-level judgments and feelings. The decomposition and separate treatment of these reasons for why consumers prefer a product may allow for a more powerful and universal grasp of preference as a whole. As a result, it may be useful to model these more specific judgments separately first, so that they can be recombined later to target specific combinations of consumer needs and desires. For instance, if a customer would prefer that a product appear rugged and not modern, their preference can be modeled as a composite of those two more specific judgments. One method that can be used to decompose product goals is Kansei engineering [20,21]. Kansei engineering is a tool developed by Nagamachi where the desired emotional feelings that result from interacting with the product can be extracted, decomposed, and used to define tangible product functions and design goals. These desired emotions are often measured using surveys that employ the semantic differential or the Likert scale.

The semantic differential [22] is a way to measure the meaning of concepts and break them down into multiple dimensions of opposing adjectives using factor analysis. Due to the semantic differential's capability with abstract concepts, a common recent use is on surveys where consumers are asked to rate a product on a linear scale that ranges between two opposing words. Similarly, the Likert Scale [23] can also be used to give survey-takers a means to quantitatively report emotional responses towards products. Unlike the semantic differential, the Likert Scale presents survey-takers with only one word, and the survey taker responds with how well that word describes the product.

In the examination of brand by Chen et al. [24], six commonly occurring adjectives were selected from shampoo advertisements to represent common brand goals for shampoo. They then measured participants' ratings using the semantic differential on how well these adjectives described eighteen different hair care product bottles, which were stripped of all labels and all painted the same color. Using the resulting survey data, a shape grammar was developed describing the different needs of shampoo bottle shaping and targeted brand goals. The semantic differential was also used [25] to model shape perception. Based on simple geometric relationships and survey data, a fuzzy logic system was implemented that could predict whether a variety of shapes appeared aggressive or soft. One criticism of this research is that the shapes used were designed specifically to be either extremely aggressive or soft with no middle ground. Other research that examined survey concerns in design [26] tracked the differences between participants of different age groups on their product form perceptions, and [27] studied the effects of viewpoint shifts and latent sensitivity of customers when evaluating shape aesthetics.

In 2009, Reid et al. [28] presented a methodology for quantifying the perceived environmental friendliness of vehicle silhouettes. In this paper, participants rated computer generated vehicle designs on how environmentally friendly the design appeared, or how likely the designs were inspired by nature. These data were correlated with the actual physical positions used in each vehicle design. This work found that vehicles with shape discontinuities, leading to a boxier shape, were less likely to be perceived as inspired by nature, and that vehicles with more raked front and rear windscreens, and more gently transitions into the roofline, in turn are more likely to be perceived as environmentally friendly.

The work presented in this paper builds on the findings of Reid et al. by studying the effects of performance criteria such as actual aerodynamics, the height of the vehicle and wheelbase, on consumer perceptions. This work also extends Reid's work by studying a wider range of consumer perceptions, and by relating them to more elements of vehicle design, which is afforded by a more dynamic vehicle shape model.

## Overview

This paper attempts to better understand how people judge functional performance of products, and how well these judgments compare to indicators of actual performance. More specifically, participants were asked to rate how aerodynamic, sporty, fuel efficient, and rugged a computer generated car design appeared to them, and these ratings were analyzed against the actual aerodynamics of the vehicle as well as intuitive engineering indicators of sportiness and cornering stability such as the height, volume, and center of gravity of the vehicle and the vehicle's wheelbase. The inter-rater consistency of human judgments was also studied. Using this human judgment data, the attributes of car design with the greatest effect on participant judgment of vehicle performance were identified, and were compared against their importance and effect in actual vehicle performance.

## Methods

A computer-administered survey was set up in a booth at the 2009 Pittsburgh Vintage Grand Prix car show. Thirty-four attendees of the car show volunteered for this study. The data from eight participants, who were younger than the legal driving age, or who did not successfully complete the survey, were removed from the data pool, resulting in twenty-six participants, eighteen male, and eight female.

**Survey Data.** In order to measure participants' judgments of each vehicle design, a computer administered semantic differential survey was used. The computer program showed each participant thirty computer-generated car designs in succession. The car designs were generated using a parametric generation model described later in this paper. The first five cars shown to each participant were the same across all participants to allow for inter-rater reliability tests, and to ensure the same range of examples is initially shown to each participant to calibrate their responses for the remaining vehicles. The remaining twenty-five cars shown were randomly generated by the computer and differed across all participants. Each participant was asked to rate each car design on four criteria on a five-level Likert scale. The four criteria used were selected as traits that can be used to describe a vehicle's appearance, but also extend to how a vehicle design is expected to perform based on its appearance. In specific, the four criteria are how sporty, rugged, aerodynamic, and fuel-efficient the car looked. These four criteria were consistently presented in this order to participants to reduce confusion and mental processing time. In pilot studies it was found that the order of presentation did not significantly affect ratings from participants. A screenshot of the survey program interface is shown in Fig. 1.

**Parametric Design Generation.** In order to consistently and deterministically generate a large variety of car designs, a parametric car model was created. This model consists of eight cubic Bezier curves and two circles. These eight curves are defined by twelve design parameters that can vary in integer steps between 0 and 99. The range of each design parameter was calibrated to extremes as historically seen in car designs. The twelve design parameters and their definitions are shown in Table 1. All curves are labeled in Fig. 2 on a sample vehicle design. Curve 1 defines the

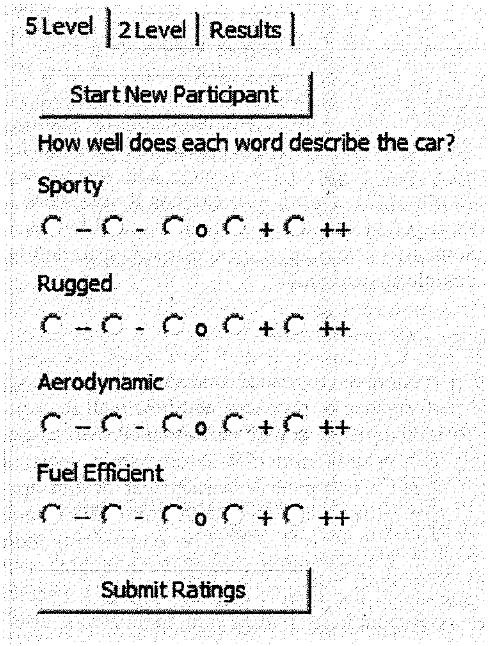


**Fig. 1 Survey program interface**

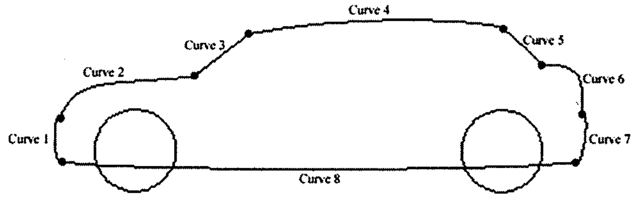


**Fig. 2 Curves in vehicle design model**

**Fig. 3 Vehicle design in line with high ratings in aerodynamics**

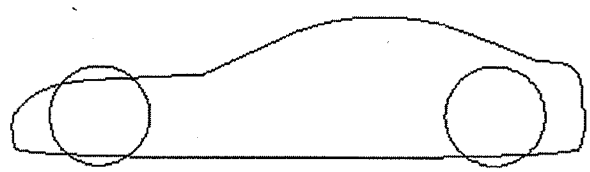

**Fig. 4 Vehicle design in line with high ratings in sportiness**

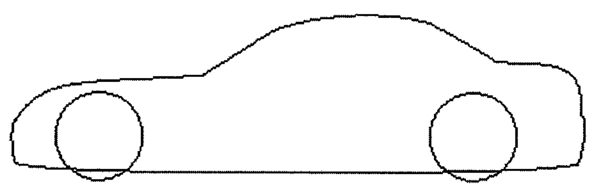

**Fig. 5 Vehicle design in line with high ratings in fuel efficiency**

front bumper, the position of its control points are defined by parameter values for ground clearance and trim height. Curve 2 defines the front grille and hood, the position of its control points are defined by continuity with Curve 1 and by parameter values for cowl height and hood length. Curve 3 defines the front windshield, the position of its control points are defined by continuity with Curve 2 and by parameter values for roof height and windshield angle. Curve 4 defines the roof, the position of its control points are defined by continuity with Curves 3 and 4 and by the parameter value for roof height. Curve 5 defines the rear window, the position of its endpoints are defined by continuity with Curve 6 and by parameter values for rear window angle and roof height. Curve 6 defines the trunk lid, the position of its endpoints are defined by continuity with Curve 7, and with the parameter values for trunk length, cowl height, and belt angle. Curve 7 defines the rear bumper, the position of its endpoints are defined by the parameter values for belt angle and trim height. Curve 8 defines the under-pan of the car, the position of its endpoints are defined by continuity with Curves 1 and 7. The circles defining the wheels are defined by the parameters for front and rear wheel position, and the parameter for wheel size.

It is worth noting at this point that the range of values in the chromosome are designed such that most normally existing classes and vintages of vehicles can be generated, from sports cars, SUVS, sedans, and minivans, to hot rods of the 1920s. Many combinations of these traits result in vehicles that are shaped like nothing ever produced, and allow this model to create unique and innovative designs. Some examples of vehicles that were generated by this model are shown in Figs. 3–6. For more information about this parametric vehicle design model, please see Ref. [29].

**Aerodynamic Model.** In order to assess the accuracy of participant judgments, a method for determining the aerodynamic drag properties of a vehicle's geometry was needed. In current production vehicles, this task is typically performed two ways, wind tunnel testing, and computational fluid dynamics analysis. Due to the

**Table 1 Twelve car design parameters**

| Parameter | Description |
|---|---|
| 1 | Belt angle—The angle of rise of the belt line from nose to tail. |
| 2 | Ground clearance—The distance from the floor-pan to the ground. |
| 3 | Trim height—The top height of the bumper at the nose. |
| 4 | Cowl height—The height where the hood meets the windshield. |
| 5 | Roof height—The height of the top of the windshield. |
| 6 | Hood length—The length from the back of the bumper to the windshield |
| 7 | Trunk length—The length from the back of the rear windshield to the front of the rear bumper. |
| 8 | Windshield angle—The angle the windshield leans back. |
| 9 | Rear window angle—The angle the rear windshield leans forward. |
| 10 | Wheel size—The diameter of the wheels. |
| 11 | Front wheel position—The length distance of the front wheel from the origin. |
| 12 | Rear wheel position—The length distance of the rear wheel from the origin. |

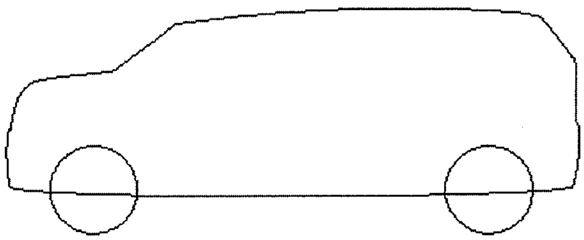

**Fig. 6 Vehicle design in line with high ratings in ruggedness**

quantity of models that needed to be assessed, neither of these methods were deemed efficient. Instead, a feature based aerodynamic drag coefficient metamodel called CDaero by Guan, Chan, and Calkins [30–32] was adapted for use with our parametric vehicle model.

Guan's model was based on work by Carr and Stapleford [33], who developed 13 discrete parametric equations that modeled the primary contributions of aerodynamic drag. This model was updated by Guan in 1995 for use with modern vehicle shapes. Guan's model uses 51 parameters to define vehicle shape and to calculate 13 primary contributions to drag coefficient, and in test cases was reportedly able to predict vehicle drag coefficient to within $+8.2\%$ to $-15.2\%$ of actual wind tunnel results. This model was further refined by Chan [32] to yield $\pm 6\%$ accuracy on the same test cases.

The parameters used in CDaero define areas, ratios, and angles in the vehicle design that most affect vehicle aerodynamic performance, and do not contain enough information to draw a complete vehicle shape. In contrast, the parameters used in the parametric vehicle design model define the Bezier curves needed to draw the complete shape of the vehicle, and do not directly relate to the mathematical equations used to approximate aerodynamic performance. Similarly, CDaero uses more parameters than our parametric vehicle design model, and using all of its parameters to generate survey stimuli would have required significantly more survey data to account for the additional degrees of freedom. As a result, it was beneficial to use both representations of vehicle form, which necessitated the method for transposing between the two models described in the next paragraph.

Six of the 13 primary contributions, wheel wells, external mirrors, drip-rails, window recesses, mudflaps, and the cooling system were deemed extraneous to our needs since they modeled vehicle traits that did not exist in our model. Modeling only the seven remaining relevant contributions reduces the list of 51 necessary parameters to only 32 parameters. The vehicle model used in CDaero is three-dimensional, while our model is two-dimensional. Of the 32 parameters, 14 pertain only to width, or details that are irrelevant in our model, and thus were assumed to equal a constant average value, resulting in a simplified CDaero model with only 18 parameters. In essence the code for CDaero is still being run in three-dimensions but with all parameters in the third dimension held constant as an average value as prescribed by the authors of CDaero.

In order to convert our 12-parameter model into the 18 required parameters, analytical solutions for a number of heights, positions, and points were used. Remaining points that could not be ascertained analytically were found by computationally searching along various vehicle curves for maximum curvature, points of inflection, and maximum and minimum height. The results from these searches at extreme parameter values allowed values to be approximated using interpolation. The resulting model allows us to assign an aerodynamic drag coefficient to each vehicle design generated by our parametric model. While this aerodynamic drag coefficient is not absolute, the trends of improved or worsened aerodynamic performance between different vehicle designs should be accurately captured. It should be noted that since this model outputs an estimated coefficient of drag, a lower value would normally correspond to better aerodynamic performance. But for consistency with the results of human judgments of aerodynamics, the output of the model was inverted such that a better aerodynamic performance is indicated with a higher number. For further detail of the methods used to transpose between the parametric vehicle model and CDaero, please see Ref. [29]. The performance of the adapted CDaero model is shown to agree with engineering intuition in a later section of this paper.

**Center of Gravity and Volumetric Assessment.** We anticipated that participants might base functional judgments on the center of gravity and total volume of the vehicle shape, so a program was also developed to calculate these properties of each car shape. Since this assessment is compared with human form judgments, which are determined solely from the visible silhouette of the vehicle shape, this method determines the center of gravity of the vehicle shape, assuming uniform density, and not the actual center of gravity of a constructed vehicle. The program parses each of the eight Bezier curves used to draw the vehicle shape into 100 line segments, and uses these segments to form triangles around a central point known to be within the vehicle shape. The resulting 800 triangles, which approximate the volume of the vehicle shape, can then also be used to find the x and y coordinates of the center of gravity by summing a volumetrically weighted average of the coordinates of each individual triangle.

**Inter-Rater Reliability.** In order to assess the reliability and consistency of ratings between different raters on judging the same car, the first five vehicles presented to each participant were the same. To measure this inter-rater reliability, we chose to use intraclass correlations as documented by Shrout and Fleiss [34,35]. Specifically, we used a two-way random effects model with relative agreement because both the rater evaluating any given design and the properties of that design vary, and the primary interest of the research was to investigate properties of designs, and not of raters, which give rise to aesthetic judgments. In addition, we were interested in extrapolating similarities in rater evaluations for the four judgment criteria (sportiness, aerodynamics, fuel efficiency, and ruggedness) across all designs. Inter-rater agreement (Cronbach's Alpha) was between 0.856 and 0.975, well above the typical threshold of 0.7 for all criteria [34], indicating that reliability was highly consistent across judges. See Table 2 for the actual alpha values and 95% confidence intervals for each of the four criteria. It is also interesting to note that raters were most consistent across judgments of aerodynamics, followed by the sportiness, ruggedness, and were the least consistent in judging the apparent fuel efficiency of a car design. Since inter-rater reliability was good to excellent across raters on this subset of cases, and our interest is in understanding the properties of car designs (and not individual preferences) that give rise to aesthetic valuations, rater evaluations were aggregated across all participants. Aggregating evaluations across judges with good inter-rater agreement on a subset of designs is a common procedure when evaluating designs in product design and related domains [36–38].

## Results and Discussion

Pearson's product-moment correlation coefficients were calculated to measure the linear dependence between the human aesthetic judgment data, functional performance data, and the 12

**Table 2 Interrater reliability measured by intraclass correlation**

| Criteria | Cronbach's alpha | Confidence interval (95%) |
|---|---|---|
| Aerodynamic | 0.975 | 0.926–0.997 |
| Sporty | 0.962 | 0.889–0.995 |
| Fuel Efficient | 0.856 | 0.580–0.983 |
| Rugged | 0.908 | 0.732–0.989 |

vehicle design parameters. The resulting correlation matrices of this survey experiment can be found in Tables 3 and 4, and are discussed below. Table 3 is a correlation table comparing the twelve vehicle design parameters against measures of human judgments of these vehicle designs. Similarly, Table 4 is a correlation table comparing the measures of functional performance and human judgments against each other. In both tables, the correlation data are from twenty-six participants, each seeing thirty vehicle designs, resulting in 780 data points ($N = 780$). Due to the high level of consistency across raters when shown the same five car designs, as measured in the previous section using Cronbach's Alpha, and the random assignment of the remaining 25 vehicle designs shown to each participant, the effects of between-participant patterns were deemed negligible.

Our interest is in understanding the visual features of designs that give rise to aesthetic judgments across individuals, and not within any one individual. This approach ignores any participant-level effects. Although in some cases this could raise concerns about increased Type I error associated with ignoring nesting effects in regression and related analyses [39,40], asking individuals to evaluate each of the designs generated by our parametric design approach would have been intractable given participant time constraints and concerns about evaluation fatigue. We used the Bonferroni correction to handle Type I error concerns associated with multiple correlation analyses. This approach is conservative compared to other alternatives (e.g., Sidak correction) [41], and was chosen to account for Type I error related to nesting directly.

For the following results, a familywise alpha level of $\alpha_{FW} = 0.10$ (or a 10% chance of falsely rejecting the null hypothesis) was used across all correlations, which is appropriate in exploratory analyses with large families [42]. A Bonferroni correction was applied to reduce the likelihood of Type I error from the large number of comparisons (95). Bonferroni correction is generally agreed to be a very conservative approach for controlling Type I error. As a result, the threshold for accepting any one correlation as significant for these analyses was an alpha level of $\alpha = 0.001$. In Tables 3 and 4, cells containing significant correlations per this criteria are bolded and shaded in grey.

**Verification of the Aerodynamics Model.** Studying the correlations between the vehicle design parameters and the parametric aerodynamics model yields give insights about what vehicle design parameters are most important to improving vehicle aerodynamics, as well as to help verify the accuracy of the aerodynamics model by comparing these correlations with trends expected with engineering intuition. In the first row of Table 3, it can be seen that actual aerodynamics is highly correlated with the first five vehicle design parameters, which pertain to vehicle height. The aerodynamics model correlates a lower ground clearance, a lower trim height, a lower cowl height, and a lower roof height with improved aerodynamic performance. This agrees with engineering intuition, since a car with these traits would displace less air in motion and thus should have a lower coefficient of drag. Table 4 confirms this further by showing strong correlations between good aerodynamics and low center of gravity, low overall height, and low volume. The model also correlates a steeper belt angle and more rearward horizontal center of gravity with improved aerodynamic performance. These two traits both yield a more wedgelike shape to the car.

**Human Judgment of Vehicle Design Parameters.** Significant correlations between human judgments and vehicle design parameters are presented in Table 3. These correlations indicate that vehicles with lower trim height, lower cowl height, a longer hood, and more steeply raked front and rear windscreens were judged more aerodynamic by participants. This follows common sense of what people commonly attribute to good aerodynamics. An example of a vehicle design with parameters in line with good aerodynamic judgments can be seen in Fig. 3.

Similarly, cars with lower ground clearance, lower trim height, longer hoods, more steeply raked front and rear windscreens, and larger wheels were deemed to appear more sporty to participants. This also follows in line with traits common to sports cars, and is highly similar to the set of traits that communicate good aerodynamics. An example of a vehicle design in line with high marks in sportiness can be seen in Fig. 4.

When judging fuel efficiency, participants prefer designs with higher roof heights. This finding agrees with Reid et al. [28] who found that smoother roof transitions, which is how the parametric model used in this paper draws higher roof heights, would be perceived as more environmentally friendly. An example of a vehicle design in line with high marks in fuel efficiency can be seen in Fig. 5.

Lastly, it was found that higher ground clearance, and higher cowl heights led to higher scores in perceived ruggedness. These traits are common in rugged off-road type vehicles, which tend to ride higher off the ground and have taller body proportions afforded by a higher cowl height as shown in Fig. 6.

**Human Judgment of Aerodynamics and Other Performance Criteria.** Table 4 describes correlations between human judgment and measures of performance criteria. Participants appeared to be good at judging the aerodynamic performance of vehicle designs. There was a strong positive correlation between the better aerodynamic performance and participant judgments of good aerodynamics. Similarly, vehicles that were rated as more sporty also tended to have better actual aerodynamic performance. Conversely, vehicles that were judged to be more rugged tended to exhibit poorer actual aerodynamic performance. Surprisingly, there was no measured correlation between judgments of fuel efficiency and actual aerodynamic performance.

In agreement with the correlations with aerodynamics, it can be seen that low vehicle height and low center of gravity are strongly correlated with high judgments in sportiness and aerodynamics, while high vehicle height and high center of gravity are strongly correlated with high judgments of ruggedness. This agrees with general engineering knowledge where lower vehicles have a lower center of gravity, which can translate into higher cornering stability, characteristic of a sports car, and cutting through less air when moving, which translates to better aerodynamics. Similarly, a taller vehicle design may afford improved ground clearance and interior volume, useful for rugged vehicle applications. It was also found that smaller car designs, or cars with lower volume, were found to correlate with high judgments in aerodynamics and sportiness, while larger volumes were found to correlate with high judgments in ruggedness.

On the other hand, neither the wheelbase of the vehicle designs, which is the distance between the wheels in the side view of the vehicle, nor the horizontal center of gravity of the vehicle designs appear to have any significant effect on human judgments of aerodynamics, sportiness, fuel efficiency, or ruggedness. This suggests that participants were either insensitive to the wheelbase and horizontal center of gravity of the vehicles in forming their judgments, or the effect of these factors were too complex or inconsistent to be measured using a correlation table.

**Relationships Between Different Human Judgments.** In order to better understand how people create form judgments of cars, the relationship between different human judgments must also be studied. Given the real-world correlations between a car's aerodynamics and its fuel efficiency, the strong positive correlations between the perceived aerodynamics and the perceived fuel efficiency are unsurprising. More surprising, perhaps, is a strong positive correlation between the perceived sportiness and perceived fuel efficiency given that high levels of sportiness might not traditionally be associated with good fuel efficiency. There

Table 3 Correlations between human judgment and vehicle design parameters

| | | Parameter 1 (belt angle) | Parameter 2 (ground clearance) | Parameter 3 (trim height) | Parameter 4 (cowl height) | Parameter 5 (roof height) | Parameter 6 (hood length) | Parameter 7 (trunk length) | Parameter 8 (windshield angle) | Parameter 9 (rear window angle) | Parameter 10 (wheel size) | Parameter 11 (front wheel position) | Parameter 12 (rear wheel position |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjusted actual aerodynamics (higher=better) | Correlation | **0.149** | **−0.675** | **−0.320** | **−0.318** | **−0.279** | 0.018 | 0.015 | 0.035 | −0.024 | −0.040 | −0.024 | −0.028 |
| | Significance | **<0.001** | **<0.001** | **<0.001** | **<0.001** | **<0.001** | 0.641 | 0.705 | 0.372 | 0.528 | 0.301 | 0.527 | 0.471 |
| Judgment of aerodynamics (higher=better) | Correlation | 0.005 | −0.094 | **−0.191** | **−0.125** | −0.008 | **0.134** | 0.001 | **0.142** | **0.154** | 0.002 | 0.016 | −0.043 |
| | Significance | 0.896 | 0.015 | **<0.001** | **0.001** | 0.841 | **0.001** | 0.982 | **<0.001** | **<0.001** | 0.961 | 0.680 | 0.263 |
| Judgment of sportiness (higher=better) | Correlation | 0.042 | **−0.136** | **−0.191** | −0.062 | −0.043 | **0.231** | 0.034 | **0.141** | **0.131** | **0.136** | 0.047 | −0.036 |
| | Significance | 0.280 | **<0.001** | **<0.001** | 0.109 | 0.264 | **<0.001** | 0.386 | **<0.001** | **0.001** | **<0.001** | 0.229 | 0.356 |
| Judgment of fuel efficiency (higher=better) | Correlation | 0.039 | −0.003 | −0.106 | −0.002 | **0.152** | 0.046 | 0.079 | 0.085 | 0.106 | −0.006 | −0.016 | −0.082 |
| | Significance | 0.316 | 0.947 | 0.006 | 0.960 | **<0.001** | 0.238 | 0.041 | 0.028 | 0.006 | 0.883 | 0.681 | 0.034 |
| Judgment of ruggedness (higher=better) | Correlation | 0.012 | **0.203** | 0.100 | **0.142** | 0.024 | −0.098 | −0.110 | −0.026 | −0.022 | 0.007 | −0.001 | −0.023 |
| | Significance | 0.761 | **<0.001** | 0.010 | **<0.001** | 0.529 | 0.011 | 0.005 | 0.496 | 0.565 | 0.853 | 0.987 | 0.556 |

**Table 4 Correlations between human judgment and performance factors**

| | | Overall height (higher=taller) | Wheelbase (higher=longer) | Adjusted actual aerodynamics (higher=better) | Center of gravity x (higher=rear) | Center of gravity y (higher=top) | Volume (higher=bigger) | Judgment of aerodynamics (higher=better) | Judgment of sportiness (higher=better) | Judgment of fuel efficiency (higher=better) | Judgment of ruggedness (higher=better) |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Adjusted actual aerodynamics (higher=better) | Correlation<br>Significance | −0.776<br><0.001 | −0.002<br>0.965 | 1<br>— | 0.229<br><0.001 | −0.758<br><0.001 | −0.717<br><0.001 | 0.205<br><0.001 | 0.226<br><0.001 | 0.000<br>0.995 | −0.194<br><0.001 |
| Judgment of aerodynamics (higher=better) | Correlation<br>Significance | −0.202<br><0.001 | −0.041<br>0.290 | 0.205<br><0.001 | 0.003<br>0.942 | −0.238<br><0.001 | −0.225<br><0.001 | 1<br>— | 0.568<br><0.001 | 0.359<br><0.001 | −0.027<br>0.485 |
| Judgment of sportiness (higher=better) | Correlation<br>Significance | −0.210<br><0.001 | −0.058<br>0.137 | 0.226<br><0.001 | 0.065<br>0.095 | −0.261<br><0.001 | −0.241<br><0.001 | 0.568<br><0.001 | 1<br>— | 0.163<br><0.001 | 0.059<br>0.129 |
| Judgment of fuel efficiency (higher=better) | Correlation<br>Significance | 0.019<br>0.616 | −0.045<br>0.248 | 0.000<br>0.995 | −0.047<br>0.226 | −0.056<br>0.147 | −0.019<br>0.621 | 0.359<br><0.001 | 0.163<br><0.001 | 1<br>— | 0.090<br>0.020 |
| Judgment of ruggedness (higher=better) | Correlation<br>Significance | 0.229<br><0.001 | −0.015<br>0.695 | −0.194<br><0.001 | 0.001<br>0.989 | 0.260<br><0.001 | 0.282<br><0.001 | −0.027<br>0.485 | 0.059<br>0.129 | 0.090<br>0.020 | 1<br>— |

**Table 5 Two principal components**

| Component matrix (2 components extracted) | | |
|---|---|---|
| | Components | |
| | 1 | 2 |
| Judgment of aerodynamics | 0.874 | −0.174 |
| Judgment of sportiness | 0.792 | −0.116 |
| Judgment of fuel efficiency | 0.596 | 0.246 |
| Judgment of ruggedness | 0.101 | 0.958 |

Note: Extraction method: principal component analysis.

appears to be no correlation between judgments of ruggedness and judgments of aerodynamics, sportiness, or fuel efficiency.

**Principal Component Analysis.** Principal component analysis is a mathematical technique that can be used to reduce the number of dimensions needed to describe a data set in which there are a large number of interrelated variables [43]. In this case it is a useful tool to determine the interrelations between different stylistic form judgments, and to analyze whether participants are actually bringing different judgment criteria to the table. A look at the correlations between different stylistic form judgments in Table 4 indicates strong positive correlations between judgments of aerodynamics, sportiness, and fuel efficiency. There is also a weak positive correlation between judgments of ruggedness and fuel efficiency. Using principal component analysis, two principal components with positive eigenvalues were identified and are shown in Table 5. These two principal components alone are able to explain 69.4% of the variation between the four judgment variables. The first principal component is comprised mostly of linear combinations of ratings of sportiness, aerodynamics, and fuel efficiency, and the second principal component is comprised almost entirely of ratings of ruggedness. What this means is that judgments of aerodynamics, sportiness, and fuel efficiency are highly interrelated and likely dependent on the same factors, and are highly independent to judgments of ruggedness. It is important to make the distinction that what is shown here does not indicate that ruggedness is the opposite of the other dimensions, but rather a wholly independent judgment that is not correlated with the trends of the others.

## Conclusions

Whether it is due to years of product experience, advertising, or an innate ability to judge performance, it appears that the participants in this study were able to accurately judge certain aspects in a car design's performance. Participants were able to reliably and accurately gauge the aerodynamic performance of a variety of car designs. They also tended to agree about the properties of vehicle designs that gave rise to different aesthetics. Specifically, participants agreed that car designs which are smaller, lower to the ground, and have a lower center of gravity to be sportier and more aerodynamic, while larger and taller vehicles with a higher center of gravity were perceived to be more rugged. Perhaps this can all be explained by the literature, which suggests that consumers often judge the functionality of a product using social norms and conventions of other products that the consumer is familiar with. As expected, it was found that the vehicle traits that best communicate specific perceptions of aerodynamics, sportiness, fuel efficiency, and ruggedness were generally in line with current vehicle classes that perform best in each of those criteria. The vehicle designs rated sportiest and most aerodynamic follow industry norms for sports car design, while designs rated most fuel efficient had more curvaceous roof lines, and designs rated more rugged were high riding vehicles with tall bodies. On the other hand, consumer judgments appear not to be affected by the wheelbase or horizontal center of gravity of a vehicle design. It is worth noting at this point that these norms and conventions may be strongly rooted in specific, regions, cultures, and demographics, so caution must be exercised before extending findings from this study, or any similar study, to other consumer groups, or a general consumer base. This study, for instance, relied on people in Pittsburgh attending a car show.

Principal component analysis helped to shed light on the relationships between different rated consumer judgments. It appears that out of the four categories of ratings that were surveyed, judgments of aerodynamics, sportiness, and fuel efficiency were highly interrelated, and ratings of ruggedness were largely independent. This lends insights by suggesting that it may not be necessary to survey all three of the interrelated categories. This finding also suggests that participants are not strictly rating preference with these vehicles, and possess at least two totally separate representations in these judgments.

A potential warning against the intentional or unintentional use of social norms and conventions to educate consumers about the performance characteristics of a product is best illustrated by the lack of correlation between participant judgments of fuel efficiency and actual aerodynamics—two characteristics that engineering logic would expect to be strongly and positively correlated. Further examination revealed that vehicles rated as more fuel-efficient tended to have profiles that resembled several popular hybrid vehicle models with higher roof heights and more gradual roof shape transitions. These shapes are selected for these hybrid vehicles due to a variety of utility, safety, comfort, and packaging reasons, but are not actually as aerodynamic as many lower-slung sports car shapes. In reality many of these sports car shapes, while very aerodynamic and thus having great potential to be fuel efficient, are often equipped with high power engines that negate any potential fuel savings. It is hypothesized that participants have been trained by the market to favor slightly taller rooflines as fuel-efficient over low-slung sports car like shapes, despite the latter vehicle design's aerodynamic advantage. Further work needs to be done to examine this hypothesis and to better understand the lack of correlation between judgments of fuel efficiency and actual aerodynamic performance.

In conclusion, this study indicates that consumers form product judgments based on their perceptions of performance, but that these perceptions, while often accurate, can be manipulated and thus are not always accurate. For example, simply designing a fuel-efficient car to perform well aerodynamically might not be sufficient to communicate the vehicle's fuel efficiency to consumers. As a result, product designers might be well heeded to investigate ways to better communicate a product's design and performance intentions and capabilities using form language that is appropriate and desirable for the product being designed.

## Acknowledgment

This work was supported by the National Science Foundation under Grant Nos. BCS0717957 and SBE0738058.

## References

[1] Parsons, G., and Carlson, A., 2009, *Functional Beauty*, Oxford University, Oxford, UK.
[2] Ewen, S., 1990, *All Consuming Images: The Politics of Style in Contemporary Culture*, Basic Books, NY.
[3] Morgan, G., 1998, *Images of Organization: The Executive Edition [Abridged]*, Berrett-Koehler Publishers, Thousand Oaks, CA.
[4] Harrison, L. E., and Huntington, S. P., eds., 2001, *Culture Matters: How Values Shape Human Progress*, Basic Books, NY.
[5] Hazelrigg, G. A., 1998, "A Framework for Decision-Based Engineering Design," J. Mech. Des., **120**(4), pp. 653–659.
[6] Li, H., and Azarm, S., 2000, "Product Design Selection Under Uncertainty and With Competitive Advantage," J. Mech. Des., **122**(4), pp. 411–418.
[7] Wassenaar, H. J., Chen, W., Cheng, J., and Sudjianto, A., 2005, "Enhancing Discrete Choice Demand Modeling for Decision-Based Design," ASME J. Mech. Des., **127**(4), pp. 514–523.

[8] Michalek, J. J., Ceryan, O., Papalambros, P. Y., and Koren, Y., 2006, "Balancing Marketing and Manufacturing Objectives in Product Line Design," ASME J. Mech. Des., **128**(6), pp. 1196–1204.
[9] Stiny, G., 1980, "Introduction to Shape and Shape Grammars," Environ. Plann. B, 7(3), pp. 343–351.
[10] Stiny, G., and Mitchell, W. J., 1978, "The Palladian Grammar," Environ. Plann. B, **5**(1), pp. 5–18.
[11] Cagdas, G., 1996, "A Shape Grammar: The Language of Traditional Turkish Houses," Environ. Plann. B, **23**(4), pp. 443–464.
[12] Agarwal, M., and Cagan, J., 1998, "A Blend of Different Tastes: The Language of Coffee Makers," Environ. Plan. B: Plan. Des., **25**(2), pp. 205–226.
[13] Pugliese, M., and Cagan, J., 2002, "Capturing a Rebel: Modeling the Harley-Davidson Brand Through a Motorcycle Shape Grammar," Res. Eng. Des., **13**(3), pp. 139–156.
[14] McCormack, J. P., Cagan, J., and Vogel, C. M., 2004, "Speaking the Buick Language: Capturing, Understanding, and Exploring Brand Identity With Shape Grammars," Des. Stud., **25**, pp. 1–29.
[15] Orsborn, S., Cagan, J., Pawlicki, R., and Smith, R. C., 2006, "Creating Cross-Over Vehicles: Defining and Combining Vehicle Classes Using Shape Grammars," Artif. Intell. Eng. Des. Anal. Manuf., **20**, pp. 217–246.
[16] Orsborn, S., Cagan, J., and Boatwright, P., 2008, "Quantifying Aesthetic Form Preference in a Utility Function," ASME Design Engineering Technical Conferences: Design Theory and Methodology Conference, Aug. 3–6, Brooklyn, NY.
[17] Swamy, S., Orsborn, S., Michalek, J., and Cagan, J., 2007, "Measurement of Headlight Form Preference Using Choice-Based Conjoint Analysis," Proceedings of ASME IDETC/CIE 2007, Sept. 4–7, Las Vegas, NV.
[18] Hsiao, S. W., and Liu, M. C., 2002, "A Morphing Method for Shape Generation and Image Prediction in Product Design," Des. Stud., **23**(5), pp. 533–556.
[19] Smith, R. C., Pawlicki, R., Kokai, I., Finger, J., and Vetter, T., 2007, "Navigating in a Shape Space of Registered Models," IEEE Trans. Vis. Comput. Graph., **13**(6), pp. 1552–1559.
[20] Nagamachi, M., 2002, "Kansei Engineering as a Powerful Consumer-Oriented Technology for Product Development," Appl. Ergon., **33**, pp. 289–294.
[21] Bouchard, C., Lim, D., and Aoussat, A., 2003, "Development of a Kansei Engineering System for Industrial Design: Identification of Input Data for KES," 6th Asian Design International Conference, ADC, Tsukuba.
[22] Osgood, C., Suci, G., and Tannenbaum, P., 1957, *The Measurement of Meaning*, University of Illinois Press, Urbana, Il.
[23] Likert, R., 1932, "A Technique for the Measurement of Attitudes," Arch. Psychol., **140**, pp. 1–55.
[24] Chen, X., McKay, A., de Pennington, A., and Chau, H. H., 2004, "Package Shape Design Principles to Support Brand Identity," 14th IAPRI World Conference on Packaging, 14th IAPRI World Conference on Packaging.
[25] Achiche, S., and Ahmed, S., 2008, "Mapping Shape Geometry and Emotions Using Fuzzy Logic," Proceedings from ASME 2008 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.
[26] Chang, C. C., and Shih, Y. Y., 2003, "A Differential Study on the Product Form Perceptions of Different Age Group Users," Proceedings of the 6th Asian Design International *Conference*.
[27] Yanagisawa, H., and Murakami, T., 2008, "Factors Affecting Viewpoint Shifts When Evaluating Shape Aesthetics Towards Extracting Customer's Latent Needs of Emotional Quality," Proceedings of the ASME 2008 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.
[28] Reid, T., Gonzalez, R., and Papalambros, P., 2009, "A Methodology for Quantifying the Perceived Environmental Friendliness of Vehicle Silhouettes in Engineering Design," Proceedings of the ASME 2009 International Design Engineering Technical Conferences & Computers and Information in Engineering Conference.
[29] Tseng, I. H., 2011, "The Unification of Stylistic Form and Function," Ph.D. thesis, Carnegie Mellon University, Pittsburg, PA.
[30] Calkins, D. E., and Chan, W. T., 1998, "CDaero—A Parametric Aerodynamic Drag Prediction Tool," International Congress and Exposition, Feb., Detroit, MI, SAE Technical Paper No. 980398.
[31] Guan, L., 1995, "Feature Based Aerodynamic Drag Coefficient Metamodel," M.S. thesis, University of Washington, Seattle, WA.
[32] Chan, W. T., 1997, "Empirical Prediction of Automobile Drag Coefficient," M.S. thesis, University of Washington, Seattle, WA.
[33] Carr, G. W., and Stapleford, W. R., 1981, "A Proposed Empirical Method for Predicting the Aerodynamic Drag of Cars," Motor Industry Research Association (MIRA), England.
[34] Shrout, P., and Fleiss, J., 1979, "Intraclass Correlations: Uses in Assessing Rater Reliability," Psychol. Bull., **86**(2), pp. 420–428.
[35] McGraw, K. O., and Wong, S. P., 1996, "Forming Inferences About Some Intraclass Correlation Coefficients," Psychol. Methods, **1**(1), pp. 30–46.
[36] Lonergan, D. C., Scott, G. M., and Mumford, M. D., 2004, "Evaluative Aspects of Creative Thought: Effects of Appraisal and Revision Standards," Creativity Res. J., **16**(2&3), pp. 231–246.
[37] Redmond, M. R., Mumford, M. D., and Teach, R., 1993, "Putting Creativity to Work: Effects of Leader Behavior on Subordinate Creativity," Org. Behav. Hum. Decis. Process., **55**, pp. 120–151.
[38] Robinson, M. A., Sparrow, P. R., Clegg, C., and Birdi, K., 2005, "Design Engineering Competencies: Future Requirements and Predicted Changes in the Forthcoming Decade," Des. Stud., **26**(2), pp. 123–153.
[39] Gelman, A., and Hill, J., 2006, "Data Analysis Using Regression and Multilevel/Hierarchical Models," Cambridge University, Cambridge, New York.
[40] Seltzman, H., 2012, "Experimental Design and Analysis," http://www.stat.cmu.edu/~hseltman/309/Book/Book.pdf
[41] Field, A., 2005, *Discovering Statistics Using SPSS*, Sage Publications, Inc., Thousand Oaks, CA.
[42] Keppel, G., and Wickens, T. D., 2004, *Design and Analysis a Researcher's Handbook*, 4th ed., Pearson Prentice Hall, New Jersey.
[43] Jolliffe, I. T., 2002, *Principal Component Analysis*, 2nd ed., Springer, New York.