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A METHODOLOGY FOR QUANTIFYING THE PERCEIVED ENVIRONMENTAL FRIENDLINESS OF VEHICLE SILHOUETTES IN ENGINEERING DESIGN

Tahira Reid*
PhD Candidate
Design Science Program

Richard Gonzalez
Professor
Department of Psychology

Panos Papalambros
Professor
Department of Mechanical Engineering

University of Michigan
Ann Arbor, MI,USA
*Corresponding author email: tnreid@umich.edu

ABSTRACT

Methods from psychology and engineering are used to quantify subjective, or perceptual, design attributes of artifacts. A modeling framework of perceptual attributes suitable for inclusion in design optimization is presented. The framework includes stimuli development based on design of experiments, survey design, and statistical analysis of data. The proposed modeling method is demonstrated on a subjective attribute we call 'perceived environmental friendliness' using vehicle silhouettes as a case study.

Keywords: Design science, perceptions, perception-based attributes, subjective attributes, environmental friendliness, design methodology, decision making

1. INTRODUCTION

Engineering functionality attributes have long been used in design optimization of artifacts and systems. Our ability to quantify the values of engineering attributes, such as, say, weight or stress, as functions of the design variables, allows their inclusion in a mathematical design optimization model. We do not possess the same ability to quantify subjective design attributes, specifically those that are based primarily on people's perception, henceforth called perception-based or perceptual attributes. Perceptual attributes are design properties that can influence people's judgments about objective qualities such as safety and weight. People make judgments on these attributes with little or no quantitative information. For example, a vehicle is perceived as safe without knowing safety metrics such as crash test ratings and number of airbags; or an object is perceived as heavy without knowing its actual weight. People often use heuristics to make decisions when they do not have enough information to make those decisions [1]**.** Heuristics refer to mental shortcuts or rules of thumb that people use to make subjective judgments when information or time is limited.

Quantifying subjective attributes and the attendant user preferences for them are important in product design. Functionality and usability seem no longer sufficient in a product's success [2]. As product variety and maturity increase in the marketplace, the emerging product differentiators are the subjective responses to the product as experienced by the customer [3]. It is now well accepted that, to make appealing designs, designers should include characteristics that are visceral or engage the senses [4]. Likewise, the inclusion of semantic functions in the design process helps to produce designs that "signal, indicate, express, and describe" [5].

The automotive industry, vehicle users, and governments have become increasingly concerned about environmental issues in the production and use of automobiles. There is increased interest not only in making more eco-friendly vehicles, but also in making them visually appealing in a "green" way [6]. It is expected that by 2011, there will be 75 hybrid powertrain models available in the US market [7]. Depending on market conditions and government regulations, fuel economy may not be the only driver for the purchase of hybrid or electric vehicles when the price premium paid for the new technology does not result in a timely payback in fuel cost savings. There may be additional factors that motivate people to purchase eco-friendly vehicles.

Some motivators were identified in a semiotic study conducted by Heffner et al. [8] on early adopters of hybrid vehicles. The study showed that many of them purchased hybrid vehicles for reasons beyond fuel economy, including ethics, concern for others, personal or national independence, and individuality. Many adopters did not perform "rational" analyses such as breakeven time or annual fuel savings. Rather, purchase decisions were driven by subjective preferences. Some early adopters specifically identified the distinct styling of their hybrid vehicle being among the drivers for their choice and enjoyed the attention that driving such a unique-looking car attracted. The specific design factors (i.e., visual cues) were not identified. Nonetheless, the literature shows that people's own reasoning about their behavior and choices are not always in sync with what actually drives their behavior and choice [9]. People may want to drive a car that conveys to the world that they are eco-friendly and are proud of it. Design attributes have meaning to the consumer beyond their objective value.

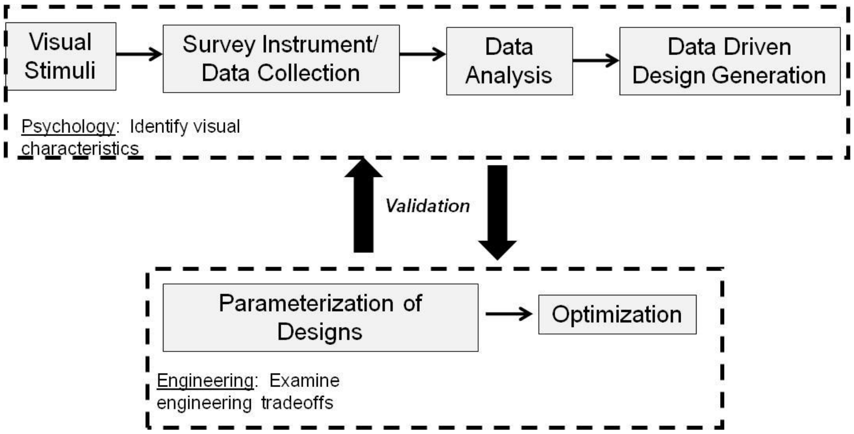


Figure 1: Design science approach for quantifying perception-based attributes

This paper examines design features that influence people's judgments about the perceived environmental friendliness of a vehicle, and how to use that information to develop new designs in the context of engineering design. Section 2 reviews the literature; Section 3 discusses the methodology; Section 4 presents results with interpretation; and Section 5 summarizes the results and discusses future work.

2. LITERATURE REVIEW

A number of methods have been developed to assess subjective attributes. They include semantic differential methods [10], Kansei engineering [11], the Kano method [12] and numerous others [2]. These methods typically involve the selection of words, phrases or word-pairs to describe the subjective attribute of interest. Consumers rate or choose a word or phrase that best characterizes the subjective aspects of the artifact in question.

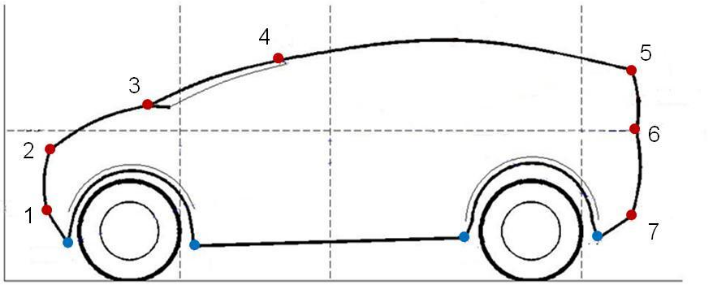


Figure 2: Sample silhouette (not from DOE). Points 1 – 7 were varied; all other points were held fixed.

The engineering design research community is familiar with demand, choice and preference models, such as the general class of utility models to represent consumer choice. There is an analogous literature in psychology and marketing that has developed quantitative models for measuring attitudes, subjective dimensions, and perceptual attributes. Such models include factor analysis, multidimensional scaling, and various clustering models. These models have been shown to be good predictors of demand and choice, and so are relevant to decision-making models in engineering design. Methods for relating perceptual attributes to choice include conjoint analysis and preference maps. Dagher and Petiot [13] used concepts from Kansei engineering, conjoint analysis and PREFMAP to assess user preference for the front-end design of cars. These techniques identified the factors influencing preference, which in turn aided in the formation of relevant categories to characterize vehicles. Swamy et al. [14] used conjoint analysis to quantify consumer preference about the form of headlights on two-dimensional representations of a vehicle front end. Kelly et al. [15] used interactive genetic algorithms to examine the visual aesthetic preferences for a variety of shapes. This method allows users to choose shapes from a large set and eventually converge to a most-preferred shape. MacDonald et al. [16] used conjoint analysis and methods from psychology to identify crux and sentinel attributes, where crux attributes are those attributes that people want but cannot readily articulate (e.g., ability of paper towel to absorb water, crashworthiness of a vehicle) and sentinel attributes are those that people perceive will provide the desired crux attribute (e.g., quilt pattern on paper towel, inclusion of airbags in vehicle). Lai et al. [17] demonstrated the use of robust design techniques to assess the "feeling" quality of a product in order to enhance its design. Osborn et al. [18] used principal component analysis to systematically examine vehicle characteristics that most readily identify the form of several vehicle classes from three perspectives.

Table 1: List of binary codes in a Taguchi design of experiments and their corresponding (x, y) points on Figure 2 as coded by the first 14 factors. The 15th factor called 'cur' controls the curvature of the overall vehicle.

Vehicles	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	cur
1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
2	2	2	1	1	1	2	1	1	1	1	2	2	2	2	2
3	1	2	2	2	2	1	1	1	1	2	1	1	2	2	2
4	2	1	2	2	2	2	1	1	1	2	2	2	1	1	1
5	2	1	1	2	2	1	1	2	2	1	1	2	1	2	2
6	1	2	1	2	2	2	1	2	2	1	2	1	2	1	1
7	2	2	2	1	1	1	1	2	2	2	1	2	2	1	1
8	1	1	2	1	1	2	1	2	2	2	2	1	1	2	2
9	2	1	2	1	2	1	2	1	2	1	2	1	2	1	2
10	1	2	2	1	2	2	2	1	2	1	1	2	1	2	1
11	2	2	1	2	1	1	2	1	2	2	2	1	1	2	1
12	1	1	1	2	1	2	2	1	2	2	1	2	2	1	2
13	1	1	2	2	1	1	2	2	1	1	2	2	2	2	1
14	2	2	2	2	1	2	2	2	1	1	1	1	1	1	2
15	1	2	1	1	2	1	2	2	1	2	2	2	1	1	2
16	2	1	1	1	2	2	2	2	1	2	1	1	2	2	1

Table 2: Question wording in the survey for each of the major dependent measures

Dependent Measure	Wording of questions
PEF (rating)	Based on the visual content, please rate how environmentally friendly the vehicle appears to be.
PREF (choice)	Please select 2 vehicles you like the best.
FAMT (rating)	Please rate how much this design shape looks like a vehicle you may encounter in your daily life.
IBN (rating)	Using the scale below, please rate how much you think the vehicle shape below was inspired by shapes found in nature.
IBN (sorting)	**Online subjects (select from screen):** Please select all the vehicle shapes you think were LIKELY to be inspired by nature (Just try your best. There are no wrong or right answers.) **In-person subjects stated orally (using a stack of 17 cards):** In front of you are a stack of cards showing the vehicles that you just saw. Similar to the last section of the survey, please sort the cards into two stacks where one is "Likely Inspired by Nature" and the other is "Not Likely Inspired by nature"

Table 3: Demographic information of survey respondents

Gender			Age Groups			
F	M	N/A	18-30	31-50	51-70	> 70
50%	49%	1%	32%	32%	29%	7%

Thus, engineering researchers have demonstrated that methods from psychology can be used successfully in the engineering decision-making process. In this spirit, the present paper examines the role that consumer perception has in influencing design decisions, particularly in the context of the perceived environmental friendliness of products. The methodology presented is generic and can be used in other perceived preference domains.

3. METHODOLOGY

Figure 1 illustrates the proposed method; visual stimuli created through design of experiments (DOE) and data collected through a survey instrument lead to creation of new designs, which can be validated with additional survey data collection. Validated designs are parameterized and integrated into a design optimization model that includes typical engineering attributes. The latter optimization is not part of the discussion in the present paper.

Visual Stimuli

A key starting point is to develop stimuli that have minimal extraneous detail in order to have greater control over the factors that may influence judgment. A number of methods for creating automotive shapes have been proposed. Kokai et al. describe developing 3-D renderings from conceptual designs based on deformation gradients [19]. Shape grammars have been used to create a variety of automotive shapes and brand identities [20-22]. These researchers used existing vehicles as the basis for development of methods that in turn could create new vehicles.

In this study, we were motivated to base our survey stimuli on new designs that were not based on existing vehicles. The stimuli created were vehicle silhouettes that included visual information about the wheels and the front windshield to help orient the direction of the vehicles. DOE was used to create sixteen different two-dimensional vehicle silhouettes. The DOE study varied each factor by two possible values (one high and one low) and the combination of factors was used in a MATLAB algorithm to generate each of the designs. Figure 2 shows a parameterized vehicle silhouette where the numbered points are varied along the *x* and *y* directions creating 14 factors. A 15th factor operates on the entire silhouette by controlling the smoothness of the splines. A Taguchi design was used to keep the number of vehicles small and avoid taxing the research subjects by presenting too many stimuli. This design with 15 factors produced 16 silhouettes (Table 1), which allowed us to explore a broad range of variations with a low number of stimuli. A 17th vehicle, not part of the DOE, with the shape of a 2007 Toyota Prius was included in the set presented to participants as a 'plant' (see Figure 3 for a complete set). We wanted to test whether people would choose and rate highly a silhouette that resembles the most commonly purchased "green" vehicle.

<u>Design of Survey Instrument</u>

Inspired by previous work [23], two hypotheses were tested through a survey instrument:

1. Subjects will assign higher perceived environmental friendliness (PEF) ratings to vehicle designs that have less abrupt line changes than those that have more discontinuities or have a boxy shape.
2. Subjects will assign higher PEF ratings to vehicle designs that are also rated as being inspired by nature compared to vehicles that are rated low on Inspired By Nature (IBN).

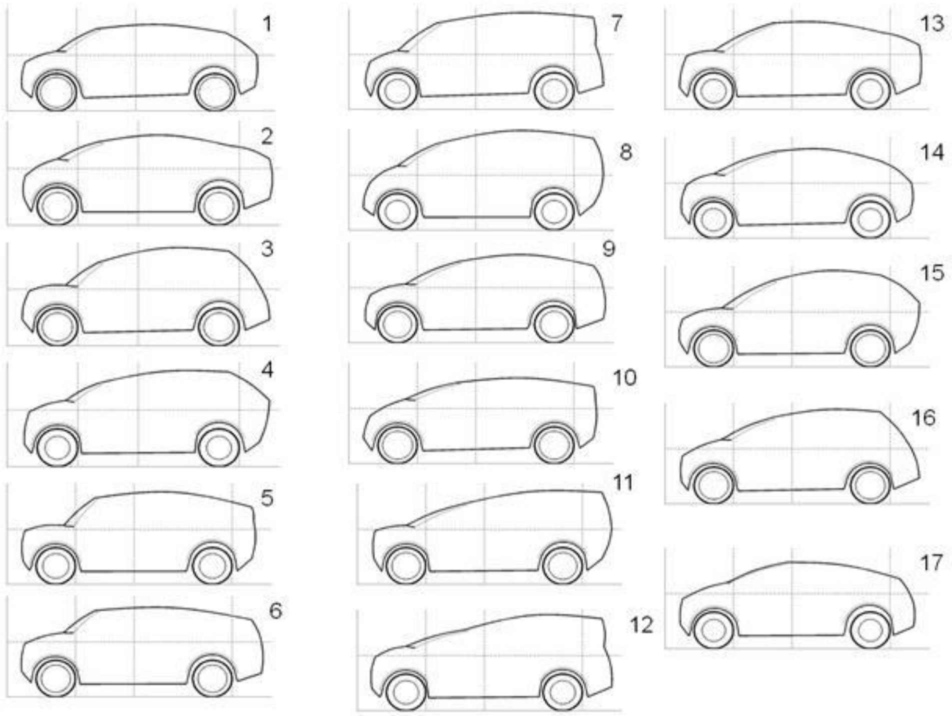


Figure 3: The set of 16 vehicles generated using the Taguchi DOE in Table 1; the 17^{th} vehicle is the 2007 Toyota Prius plant that was created without the DOE.

Vehicles that have less abrupt line changes include vehicles 1, 2, 9, 10, 13, 14, and 15. Those that have more discontinuities or a boxy shape include vehicles 3, 4, 5, 6, 7, 8, 11 12 and 16. The independent variables were the 15 factors that vary the shapes of the silhouettes. Dependent variables were self-report measures on PEF, the likelihood that the silhouettes were IBN, familiarity (FAMT), personal preference (PREF) and the degree of eco-consciousness of participants (based on [24]). All dependent variables above were ratings based on a 7-point Likert scale except for the preference measure, which was based on selecting the top two favorites. The IBN variable was additionally measured using a sorting task where the online subjects selected the vehicles they thought were likely inspired by nature and the in-person subjects were given a stack of 17 cards to sort into two categories. Each card displayed one of the vehicles. Table 2 gives examples of how each of the questions was worded. Subjects were also provided a list of assumptions that applied to all vehicle designs in the study:

For all the vehicles shown, assume that all:

- *have excellent fuel economy*
- *have clean emissions*
- *have an equal number of doors*
- *carry the same number of passengers*
- *are equally priced*
- *belong to the same vehicle class (i.e., are cross-over vehicles)*

For the PEF portion of the survey, a working definition for environmental friendliness was also provided:

Environmental friendliness is a term used to describe products, ideas, or concepts that have minimal to no impact on the environment (i.e. air, water, land and natural resources). Examples of negative impacts on the environment include water pollution, the removal of resources from nature that once removed cannot be replaced, and the release of air pollutants that reduces the ozone layer which protects us from the harmful rays emitted from the sun.

<u>Data Collection and Analysis</u>

A total of 195 participants (102 online and 93 in person) of varying ages, geographic locations, occupations, and almost equal split on gender participated in the study (Table 3). The data from the online and in-person administrations were combined because there was little difference between the two administrations. The study was conducted using the Sawtooth computer-based survey program [25]. Subjects were shown each vehicle one at a time and were asked to make several judgments on the vehicles as discussed above. The data were analyzed using descriptive and inferential statistics.

For the rating tasks, each of the 17 vehicles was shown one at a time in randomized order. For the preference task, a total of six trials of six vehicles were presented to subjects also in randomized order. Each vehicle was shown twice and two vehicles were shown three times to balance the choice sets.

4. RESULTS

Descriptive statistics assessed which vehicles received the highest ratings on the PEF and how much they thought the shapes were IBN. Vehicle 14 (M = 5.12, SD =1.38), vehicle 2 (M = 4.56, SD =1.45) and vehicle 17 (M = 4.61, SD =1.42) were perceived as the most environmentally friendly. The same vehicles were also perceived as inspired by nature with similar ratings. Mean ratings (or mean values from the sorting tasks) are presented in the text and figures.

Table 4: ANOVA summary of main effects and two-way interaction effect for measures of PEF, IBN (rating), and IBN (sorting). Items in **bold** indicate significance.

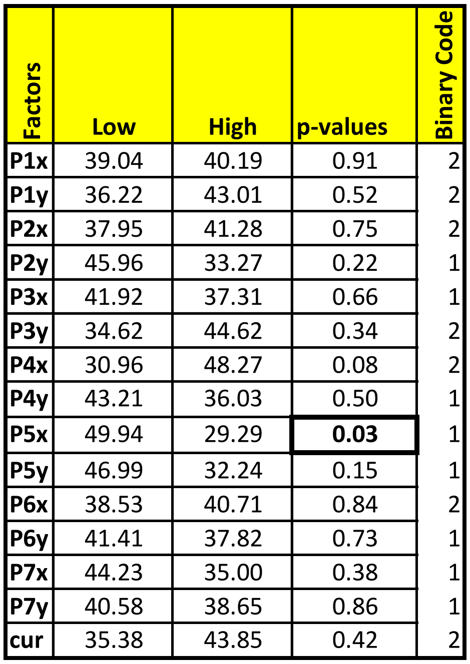
Factor # On Table 1	Point On Fig.2	PEF	IBN (rating)	IBN (sorting)
P1x P1y P1x:P1y	1	F(1,1)=0.14, p > .05 F(1,1)=0.12, p > .05 F(1,1)=0.24, p > .05	F(1,1)=0.08, p > .05 F(1,1)=0.20, p > .05 F(1,1)=0.02, p > .05	F(1,1)=0.01, p > .05 F(1,1)=0.37, p > .05 F(1,1)=0.17, p > .05
P2x P2y P2x:P2y	2	F(1,1)=0.02, p > .05 F(1,1)=0.90, p > .05 F(1,1)=4.21, p > .05	F(1,1)=0.16, p > .05 F(1,1)=2.06, p > .05 **F(1,1)=6.95, p < .05**	F(1,1)=0.00, p > .05 F(1,1)=1.86, p > .05 **F(1,1)=4.92, p < .05**
P3x P3y P3x:P3y	3	F(1,1)=0.04, p > .05 F(1,1)=2.18, p > .05 F(1,1)=0.08, p > .05	F(1,1)=0.00, p > .05 F(1,1)=0.92, p > .05 F(1,1)=0.27, p > .05	F(1,1)=0.01, p > .05 F(1,1)=1.49, p > .05 F(1,1)=0.26, p > .05
P4x P4y P4x:P4y	4	**F(1,1)=8.38, p < .05** F(1,1)=0.41, p > .05 **F(1,1)=8.17, p < .05**	F(1,1)=4.19, p > .05 F(1,1)=0.01, p > .05 **F(1,1)=8.95, p < .05**	**F(1,1)=6.82, p < .05** F(1,1)=0.38, p > .05 **F(1,1)=8.57, p < .05**
P5x P5y P5x:P5y	5	**F(1,1)=5.83, p < .05** **F(1,1)=5.86, p < .05** F(1,1)=0.44, p > .05	**F(1,1)=8.94, p < .05** **F(1,1)=6.52, p < .05** F(1,1)=0.05, p > .05	**F(1,1)=5.81, p < .05** F(1,1)=4.25, p > .05 F(1,1)=0.29, p > .05
P6x P6y P6x:P6y	6	F(1,1)=0.01, p > .05 F(1,1)=0.53, p > .05 F(1,1)=4.09, p > .05	F(1,1)=0.45, p > .05 F(1,1)=1.22, p > .05 **F(1,1)=6.70, p < .05**	F(1,1)=0.05, p > .05 F(1,1)=0.49, p > .05 F(1,1)=4.48, p > .05
P7x P7y P7x:P7y	7	F(1,1)=0.40, p > .05 F(1,1)=0.08, p > .05 F(1,1)=4.07, p > .05	F(1,1)=0.69, p > .05 F(1,1)=0.43, p > .05 **F(1,1)=6.45, p < .05**	F(1,1)=0.94, p > .05 F(1,1)=0.30, p > .05 **F(1,1)=4.72, p < .05**

The benefit of using silhouettes that varied only 15 factors is that one can identify the factors that influenced these judgments. Individual factors were tested using two-sample t-tests to identify the specific level (high or low) of the factors that significantly influenced these judgments. The binary value of each factor, called the "high" and "low" conditions, was used as the grouping for the t-test. For example, vehicles 1 – 8 have a low value for the x-coordinate of Point 4 (P4x) and vehicles 9 – 16 have a high P4x value (see Table 1).

The results indicate that P4x and P5x had a significant effect on PEF and IBN judgments. Moving point 4 in the *x*-direction affects the angle of the front windshield and moving point 5 in the *x*-direction affects the angle of the backend. The t-test identified that when P4x and P5x are high and low respectively, the vehicles are seen as being more inspired by nature and environmentally friendly. A high P4x and a low P5x make the vehicle appear more curved and smooth and less boxy.

Factor 15 controls the smoothness of the entire vehicle but did not lead to significant differences in ratings. We believe the values selected for factor 15 do not provide sufficient variation that can be detected visually. This can be seen by comparing the 8 silhouettes with low values on F15 (i.e. vehicles 1, 4, 6, 7, 10, 11, 13, 16) to the 8 with high values on F15 (vehicles 2, 3, 5, 8, 9 , 12, 14, 15) as seen in Figure 3. In addition, the combination of the other 14 factors influences the

Table 5: Results of two-sample t-test for the IBN measure (sorting). Low = mean rating when factors are low and High = mean rating when factors are high.



Factors	**Low**	**High**	**p-values**	**Binary Code**
P1x	39.04	40.19	0.91	2
P1y	36.22	43.01	0.52	2
P2x	37.95	41.28	0.75	2
P2y	45.96	33.27	0.22	1
P3x	41.92	37.31	0.66	1
P3y	34.62	44.62	0.34	2
P4x	30.96	48.27	0.08	2
P4y	43.21	36.03	0.50	1
P5x	49.94	29.29	**0.03**	1
P5y	46.99	32.24	0.15	1
P6x	38.53	40.71	0.84	2
P6y	41.41	37.82	0.73	1
P7x	44.23	35.00	0.38	1
P7y	40.58	38.65	0.86	1
cur	35.38	43.85	0.42	2

curved and boxy perception of the silhouette as seen in the combination of P4x and P5x in the perceptions of PEF and IBN.

Factors associated as pairs in *x-y* coordinates were analyzed together in a two-way ANOVA, which assesses both main effects and interactions between factors. Factor 15 was excluded from the ANOVA because it was not a member of an *x-y* pair. When examining the factors that influenced judgments on PEF, the two-way ANOVA yielded a significant main effect on P4x and the interaction effect between P4x and P4y. There was also a main effect on P5x and P5y. None of the other ANOVA results on PEF reached statistical significance.

Similarly, several factors influenced the IBN rating and sorting judgments. Points 2, 4, 5, 6, and 7 had significant effects, either on an individual factor or the interaction between factors. Table 4 shows a complete summary of the ANOVA results for PEF and IBN. The results indicate that changes in the appearance of the windshield (variations of point 4), the height and shape of the back end (variations of

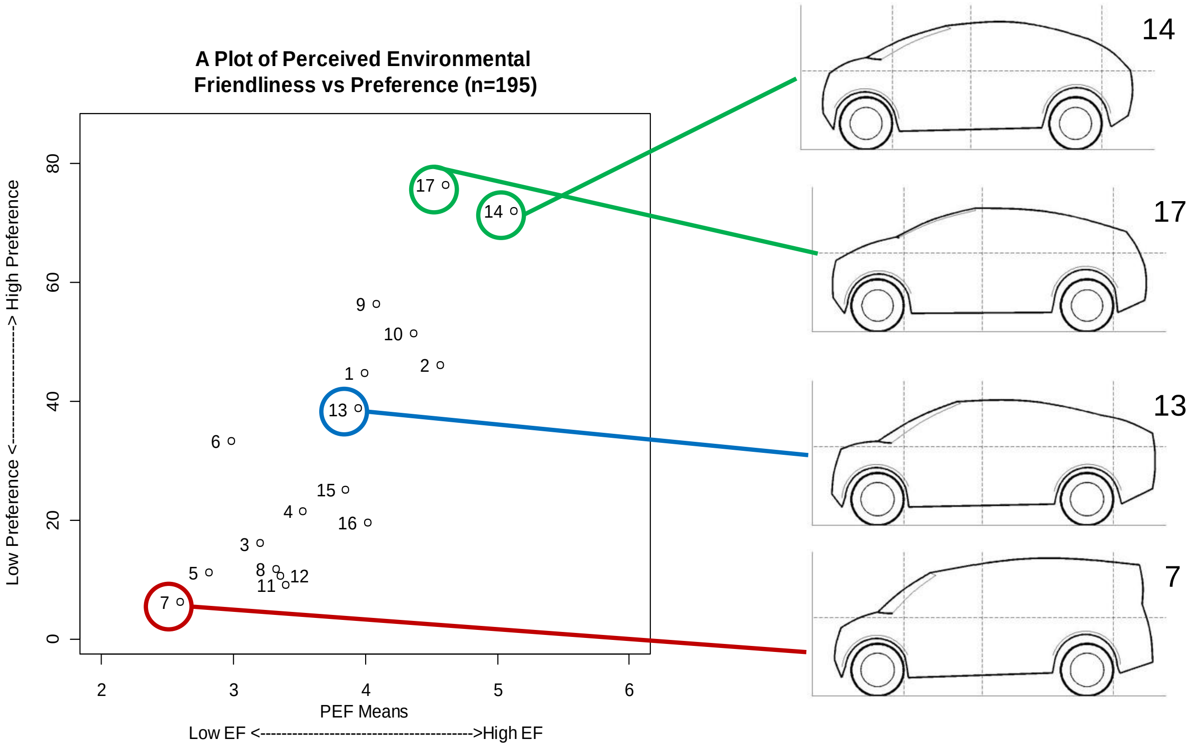


Figure 4– Scatter plot showing the correlation between judgments on perceived environmental friendliness and preference (mean ratings on both variables)

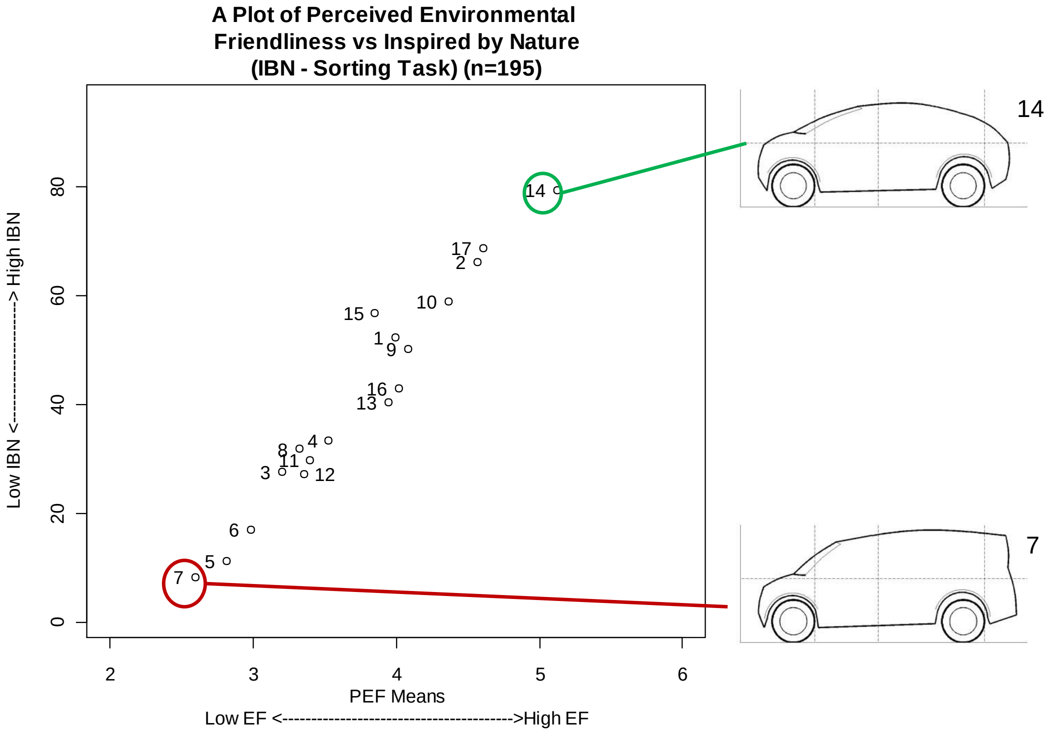


Figure 5 – Scatter plot showing the correlation between judgments on perceived environmental friendliness and the degree to which shapes are the inspired by nature sorting task (mean ratings on both variables).

Table 6: Sample binary code of potential new IBN designs based on results of the t-test (IBN2-IBN4) and the ANOVA (IBN5a – IBN8c)

	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	cur
IBN1	2	2	2	1	1	2	2	1	1	1	2	1	1	1	2
IBN2	2	2	2	1	1	2	2	1	2	1	2	1	1	1	2
IBN3	2	2	2	1	1	2	2	1	1	2	2	1	1	1	2
IBN4	2	2	2	1	1	2	2	1	2	2	2	1	1	1	2
IBN5a	2	2	2	1	1	2	1	1	1	1	2	1	1	1	2
IBN5b	2	2	2	1	1	2	2	2	1	1	2	1	1	1	2
IBN5c	2	2	2	1	1	2	1	2	1	1	2	1	1	1	2
IBN6a	2	2	1	1	1	2	2	1	1	1	2	1	1	1	2
IBN6b	2	2	2	2	1	2	2	1	1	1	2	1	1	1	2
IBN6c	2	2	1	2	1	2	2	1	1	1	2	1	1	1	2
IBN7a	2	2	2	1	1	2	2	1	1	1	1	1	1	1	2
IBN7b	2	2	2	1	1	2	2	1	1	1	2	2	1	1	2
IBN7c	2	2	2	1	1	2	2	1	1	1	1	2	1	1	2
IBN8a	2	2	2	1	1	2	2	1	1	1	2	1	2	1	2
IBN8b	2	2	2	1	1	2	2	1	1	1	2	1	1	2	2
IBN8c	2	2	2	1	1	2	2	1	1	1	2	1	2	2	2

Table 7: Sample binary code of potential new PEF designs based on results of the t-test (PEF1-PEF3) and the ANOVA (PEF4a – PEFc9)

	P1x	P1y	P2x	P2y	P3x	P3y	P4x	P4y	P5x	P5y	P6x	P6y	P7x	P7y	cur
V14	2	2	2	2	1	2	2	2	1	1	1	1	1	1	2
PEF1	2	2	2	2	1	2	1	2	1	1	1	1	1	1	2
PEF2	2	2	2	2	1	2	2	2	2	1	1	1	1	1	2
PEF3	2	2	2	2	1	2	1	2	2	1	1	1	1	1	2
PEF4a	2	2	2	2	1	2	1	1	1	1	1	1	1	1	2
PEF4b	2	2	2	2	1	2	2	1	1	1	1	1	1	1	2
PEF4c	2	2	2	2	1	2	1	2	1	1	1	1	1	1	2
PEF5a	2	2	2	2	1	2	2	2	2	1	1	1	1	1	2
PEF5b	2	2	2	2	1	2	2	2	1	2	1	1	1	1	2
PEF5c	2	2	2	2	1	2	2	2	2	2	1	1	1	1	2
PEFc1	2	2	2	2	1	2	1	1	2	1	1	1	1	1	2
PEFc2	2	2	2	2	1	2	2	1	2	1	1	1	1	1	2
PEFc3	2	2	2	2	1	2	1	2	2	1	1	1	1	1	2
PEFc4	2	2	2	2	1	2	1	1	1	2	1	1	1	1	2
PEFc5	2	2	2	2	1	2	2	1	1	2	1	1	1	1	2
PEFc6	2	2	2	2	1	2	1	2	1	2	1	1	1	1	2
PEFc7	2	2	2	2	1	2	2	1	2	2	1	1	1	1	2
PEFc8	2	2	2	2	1	2	2	1	2	1	1	1	1	1	2
PEFc9	2	2	2	2	1	2	1	2	2	2	1	1	1	1	2

Table 8: Summary of significant ($p < .05$) factors on the two-sample t-test for the validation study (n=46)

	PEF	IBN-sort	IBN-rating
P1y	-	high	-
P3x		low	
P3y	-	high	high
P4x	-	high	-
P5x	low	low	low
P5y	low	low	low
P7x	-	low	-
cur	-	-	high

point 5, 6 and 7) and the height and shape of the front end (point 2) influence the IBN judgments. When these points combine to produce silhouettes that have less abrupt changes in the lines, the silhouettes are rated as being more inspired by nature.

The PEF and preference measures are highly correlated, *r(15)* = 0.85, $p < 0.01$ (Figure 4). Because the points that influence PEF are a subset of those that influence IBN, it is expected that there will be an overlap in vehicles judged as being more environmentally friendly as well as inspired by nature, which is consistent with our second hypothesis. There is a very high correlation between PEF and IBN (sorting), *r(15)* = 0.98, $p < 0.01$ (Figure 5) and between PEF and IBN (rating), *r(15)* = 0.95, $p < 0.01$.

Data on measures of familiarity are not presented because they were not significant and did not correlate with measures of PEF. In addition, measures of eco-consciousness scales will not be presented here.

Data-driven design generation

The results provide insight on how the manipulation of specific control points influence judgments. This information can be used to create new silhouettes designed to have higher PEF or IBN ratings than those in the original set. A set of new designs was generated based on the user-driven data for both IBN and PEF vehicles.

To create higher IBN vehicles, the factor levels with the highest means based on the two-sample t-test and ANOVA were used to describe each of the factors. Table 5 provides results from the two-sample t-test and shows the corresponding binary code that was generated based on the survey data. In the binary code column, a value of 1 is recorded when the mean

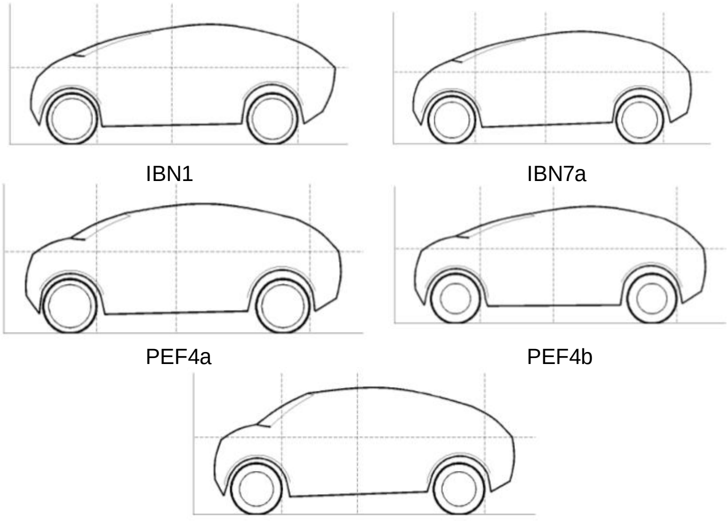


Figure 6: Examples of vehicle silhouettes developed from the survey data. See Tables 6 and 7 for binary code used to create these vehicles.

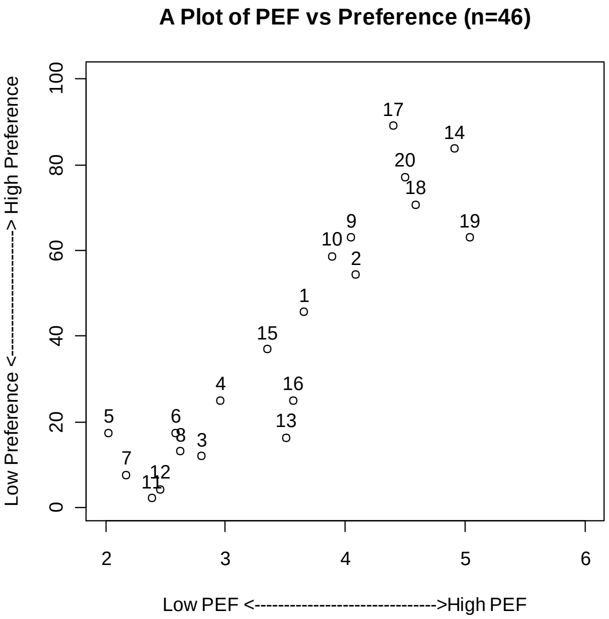


Figure 7: Scatter plot showing correlations between PEF and preference (mean ratings on both variables). Vehicle 19 is relatively higher on PEF than some of the original designs

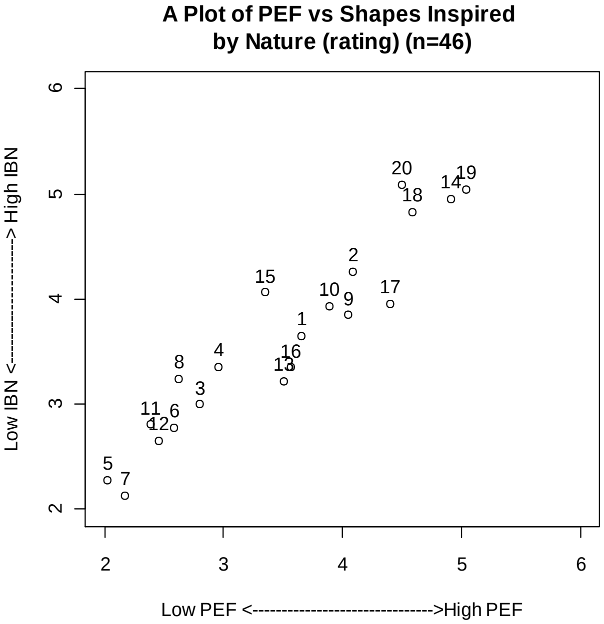


Figure 8: Scatter plot showing correlations between PEF and IBN (mean ratings on both variables). Vehicles 19 and vehicle 20, which are new designs, are rated as more IBN and are relatively higher on PEF than the original designs and even the Toyota Prius (vehicle 17)

rating in the “Low” column was higher than that of the “High” column and a value of 2 is recorded when the mean rating in the “High” column was higher than that of the “Low” column.

This binary code is converted into specific values that correspond to each control point. For example, the two possible values for P1x are -1.75 and -1.65, which corresponds to low and high, respectively. These values are passed to the MATLAB algorithm that generates new designs. The algorithm uses piece-wise polynomials.

The factors represent *x* and *y* coordinates of a point, and so both factors are varied even if one factor in the pair is not statistically significant. Table 6 provides a sample of the possible ways to manipulate the most significant factors. The binary code on the last column of Table 5 provides the baseline from which new designs are generated. In Table 6, these values are stored in the first row labeled IBN1, which generates “IBN1” in Figure 6.

The cells that are darkened in Table 6 represent the factors that were varied to create new designs. These factors were selected because they had at least one measure that was significant at the 0.05 confidence level based on the two-sample t-tests and ANOVA results. As shown, there are many possible combinations of factor levels that could lead to new designs, but only 15 are shown.

Each of the binary code strings was used in the algorithm to generate the corresponding silhouette thus creating a variety of designs. The designs that had a back end that looked too boxy or had any abrupt changes in lines were excluded because the data showed that vehicles that were boxy in the back often were rated as less inspired by nature and not perceived as environmentally friendly, as discussed earlier. In general, the code produces many designs, but some can be eliminated because they lead to patterns known not to fit the criteria derived from the survey data. To create the designs with higher PEF, the binary code of vehicle 14 was used as a reference and Factors P4x, P5x and P5y were varied based on the results of the inferential statistics. Table 8 shows the 18 possible variations that can be achieved from the data. Similar to the ideal IBN vehicles, those that deviated from the survey results (i.e., boxy back end) were not considered.

In Tables 6 and 7, the first few rows represent factors selected using the two-sample t-tests (i.e., IBN1 – IBN4 and PEF1 – PEF3). The other rows are based on results from the ANOVA that identify other factors that were statistically significant. For example, IBN5a – IBN5c represent a 5th category of vehicle that is varied based on P4x and P4y only.

Validation

A validation study was conducted using 3 of the 5 samples shown in Figure 6 to verify that these vehicles were rated by research participants as higher in PEF and IBN than the silhouettes in the original set. We used PEF4a as vehicle 18, IBN7a as vehicle 19, and PEF4b as vehicle 20. We selected the 3 vehicles that had the least apparent sharp corners or boxy appearance, since the data already indicated such features would be seen as less PEF. We predicted that each of these vehicles would show the highest ratings in their respective scales (e.g., vehicles PEF4a and PEF4b would be rated highest on PEF, IBN7a would be rated as highly inspired by nature).

A total of 46 new survey respondents participated in this validation study using the same survey design as before, except with the inclusion of the three new vehicle designs. Figure 7 indicates that the new vehicle 19 is rated relatively high in PEF as well as in preference. Vehicle 19 has approximately the same PEF rating and lower PREF score than vehicle 14, one of the original designs.

We predicted that vehicle 19 would be rated the highest in IBN measures. Figure 8 shows that vehicle 19 is rated second highest to another new vehicle, vehicle 20. Again, this can be expected because the factors that influence judgments about IBN also include factors that influence PEF.

As before, inferential statistics were used to assess the factors that influenced the judgments. For PEF, the two-sample t-tests identified that low values for P5x and P5y have a significant effect on the judgments; the ANOVA showed significance on interactions between P4x and P4y, main effects on P5x and P5y, interactions between P2x and P2y, and interactions between P1x and P1y.

For IBN (rating), the two-sample t-test identified significance when there were low values for P5x and P5y and high values for P3y and the curvature factor. Similarly, the IBN (sorting) indicated significance when P1y, P3y, and P4x were high and when P3x, P5x, P5y, and P7x were low. Table 8 summarizes the results of the two-sample t-tests for PEF and IBN. For the IBN (rating), the ANOVA indicated a main effect on P5x. For the IBN (sorting), there were main effects on P3x, P5x and P7x, and interactions between P1x and P1y.

The PEF and preference measures are highly correlated, $r(18) = 0.91$, $p < 0.01$ (Figure 7). Correlations also exist between PEF and IBN (sorting) $r(18) = 0.73$, $p < 0.01$ (Figure 8) and also between PEF and IBN (rating) significant, $r(18) = 0.88$, $p < 0.01$.

5. CONCLUSIONS

A methodology for studying perceived environmental friendliness was demonstrated using a design science approach, namely, integrating analytical capabilities from both engineering and behavioral science. We showed that perception-based attributes can be systematically quantified and used to develop new designs, some of which outperform existing 'green' vehicles, in terms of ratings of inspired-by-nature and perception of environmental friendliness. This ability to capture preference and evaluation beyond the confines of a typical marketing approach such as conjoint analysis is important for design studies.

The proposed approach explored a set of designs that were not derived from existing vehicle models as done previously [19, 20]. We examined both main effects and interactions that provide more insight about how the factors may be influencing people's judgments. Previous work considered main effects only and acknowledged the need to examine interactions in studies of this kind [13, 14,]. Extensions of the current work on a binary code system can define distance metrics (e.g., the Hamming distance) that can be incorporated into an engineering optimization framework, and used to generate and choose new designs. In addition, we surveyed a very diverse population of subjects largely external to university and engineering settings.

A general limitation in this work is that perceptions can change with time and this can certainly be true about 'green' perceptions. One extension is to embed the survey in a longitudinal design to allow modeling of changing perception over time. A further limitation is that automobile silhouettes are useful during the early conceptual stage, and later stages of development require more visual information, such as 3D body shapes. The method can be further extended by allowing for more complicated DOE that permit testing of higher order interactions of the design factors. The combination of 3D body shapes with the ability to examine higher order interactions between factors will provide a rich framework in which to implement perception-based attributes in engineering design.

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