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# BALANCING DESIGN FREEDOM AND BRAND RECOGNITION IN THE EVOLUTION OF AUTOMOTIVE BRAND STYLING

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## ABSTRACT

Designers faced with the task of developing the next model of a brand must balance several considerations. The design must be novel and express attributes important to the customers, while also recognizable as a representative of the brand. This balancing is left to the intuition of the designers, who must anticipate how all customers will perceive the new design. Oftentimes, the design freedom used to meet a styling attribute such as aggressiveness can compromise the recognition of the product as a member of the brand. In this paper, an experiment is conducted measuring change in ten styling attributes common to both design freedom and brand recognition for automotive designs, using customer responses to vehicle designs created interactively. Results show that, while brand recognition is highly dependent on the particular manufacturer, tradeoffs between design freedom and brand recognition may be measured using predictive models to inform strategic design decisions.

## 1 INTRODUCTION

In developing the next generation of an existing vehicle model, an automotive designer must make strategic tradeoffs between competing considerations. One consideration is the human desire for novelty, as the appeal of the current model fades with time [1], [2]. Another consideration is the desire for consistency with past designs, often referred to as brand character. Much as there is “family resemblance” among members of a family, the designer seeks to maintain a recognizable brand character among all the brand’s members. Any deviation from the past may reduce the new design’s association with the brand, as how well as how it conveys attributes known to be important to the target customers (e.g., luxuriousness) [3].

Particularly for the automotive industry, brand loyalty is a significant driver of customer purchase decisions. Brands such as BMW and Cadillac have taken more than 100 years to build a brand reputation; oftentimes, in stated customer responses, brand is near or at the top in influencing purchase decisions [4]. By maintaining brand recognition, the equity of the brand may be leveraged for new products, thus influencing customer preference [5]–[8].

At the same time, design freedom, sometimes called design “reach,” is the extent to which designers are able to deviate from past designs. This extent significantly contributes to a corporation’s innovation capacity and market competitiveness [9]–[11]. Previous studies have shown that vehicle manufacturers that focus on maximizing designer freedom for vehicle styling are more likely to capture market share, particularly during early stages of the product life cycle [12].

Consequently, both design freedom and brand recognition are competing considerations during the design process that must be traded off with each other. Strategic design decisions involving tradeoffs between styling design freedom and brand recognition are paramount to realizing market success in the future [13]—akin to musicians aiming to produce their next great hit while still sounding true to themselves.

Within academia, balancing between design freedom and brand recognition has been studied extensively in the product innovation and styling strategy literatures, with a consensus that there is an optimal amount of deviation from previous designs [14], [15]. Within industry, it is known that given too little design reach relative to the market's desire for change and the brand's history of change, the product appears weak and stale: given too much reach, the customer reaction may be anxiety and discomfort [16]. If the reach is in the wrong direction, because it either violates the brand's identity or strays from the benefits desired by the target market, the product may fail to meet its objectives [17].

In this study, we measure how brand recognition and design freedom interact and trade off with each other for four automotive vehicle brands—Audi, BMW, Cadillac, and Lexus. To make such measurements, we decompose both brand recognition and design freedom to a common set of styling design attributes—an approach supported by psychology and design research suggesting styling design attributes such as 'aggressiveness' may be more representative of visceral human perceptions of design than geometric design variables such as '120 cm vehicle grill' [18]–[20]. By manipulating the values of these styling design attributes rather than geometric design variables, we are able to trace relative changes in both design freedom and brand recognition better.

Manipulation of these design attributes, however, still requires a mapping from the geometric design variables that the designer controls: We cannot simply dial up the 'aggressiveness' of the vehicle, but we can decide the width of the wheelbase. Accordingly, we build on a general methodology common in the design community—determining the values of design attributes as functions of the underlying geometric design variables using customer responses [21]–[23]. A key difference in our approach, however, is that we do not explicitly model the functional form of the nonlinear mapping between styling attributes and geometric variables. Instead, we crowdsource this mapping as a black-box function that exists in the minds of the customers.

An experiment is conducted involving three steps: (1) determination of styling attribute values for existing vehicles using a Markov chain derived for partial rankings over customer responses to 2D design representations, (2) generation of new conceptual designs using morphable 3D design representations, and (3) determination of design freedom and brand recognition via deviations of both styling design attributes and geometric design variables using a proposed design freedom distance metric and conditional multinomial logit model. Customer responses and new concept designs are gathered using an online interactive survey comprised of sequential design evaluation and design generation stages using both two-dimensional (2D) images and three-dimensional (3D) morphable vehicle models rendered in real time.

Results show that there is indeed a tradeoff between brand recognition and design freedom according to the proposed design freedom metric. This tradeoff is predicted to affect BMW and Cadillac the most, suggesting that these brands face greater challenges to maintain brand recognition while evolving the styling of future vehicles. The tradeoff is less conclusive for Audi and Lexus, as these brands are found to have low absolute brand recognition across a number of customers surveyed throughout the world.

The main contribution of this work is an extension of previous *descriptive* investigations [24]–[26] of brand recognition and design freedom to a *predictive* investigation involving modeling of brand recognition and design freedom. While it is often *qualitatively* recognized that brand recognition and design freedom must trade off with each other, we make a preliminary inroad to *quantitative* measurement. This work does not attempt to optimize the tradeoff between design freedom and brand recognition, as that decision is comprised of a multitude of stakeholders—particularly designers, marketers, and strategic design managers. Instead, we posit that the present work can augment stakeholder intuition during the strategic design decision-making process.

Additional contributions include: (1) the combined use of multiple design representations for predictive modeling including styling attributes and more conventional geometric variables as have been recently studied [21], [27]–[29]; (2) a hybrid combination of parametric models and non-parametric representations; (3) the use of realistic, morphable 3D modeling techniques in an interactive web-based environment; (4) filtering crowdsourced data on "brand-conscious" customers to clamp data relevant for this study; and (5) using the crowd as a "black box" for modeling an implicit nonlinear function distributed over a number of people.

The rest of the paper is structured as follows: Section 2 describes related work from the design and management fields. Section 3 sets up the problem formulation and formalizes the notion of design freedom and brand recognition. Section 4 discusses the experimental setup. Section 5 gives the results of the experiment, including discussion of its implications. Section 6 concludes with a summary of this study.

## 2 BACKGROUND AND RELATED WORK

We build on two major bodies of related literature for this study. From the strategic management and customer product innovation communities, we establish foundation using qualitative justifications for upholding design freedom and brand recognition. From the design community, we consider previous efforts towards measuring tradeoffs between design styling and other considerations, as well as methodologies towards eliciting customer preferences via various design representations.

### 2.1 Design Freedom and Brand Recognition

A number of studies have considered the importance of design freedom from the perspective of organizational innovation capability. Customers expect novelty in new product offerings [1], yet such novelty must be bounded [16].

Figure 3: Example images shown to customers during the 2D representation portion of the experiment. These images were used to assess styling attribute values, as well as brand recognition. Note that these images remained static (were not morphed by customers) during the experiment, and did not contain brand logos.

Figure 4: Example baseline 3D model and customer-morphed 3D model used during the 3D representation and design portion of the experiment. These models are morphable so that customers are able create conceptual designs to achieve a given design attribute using the crowdsourced web application. Similar to the 2D representation, these 3D models did not contain brand logos

Companies that follow a "design-driven" approach towards balancing this tradeoff via strategic design decisions have been shown empirically to capture larger market shares [15].

The effect of brand recognition on customer preferences has been studied in depth for new product offerings [3]. General conclusions from these studies are that brands are comprised of highly complex associations between within-brand products and features [30], as well as related people, places, and out-of-brand products [31]. Particularly because vehicles fall under the category of "durables," namely, products where lifecycle use is important to the customer, brand recognition plays a very important role [32]. These conclusions are aligned with observations in the automotive sector, where brand has been shown to be one of the foremost contributors to customer preference [4].

The current study builds on recent results that have shown that the "face" of the vehicle—the view looking directly at the front of the vehicle—is most closely associated with vehicle brand [25]. Moreover, anecdotal evidence from experienced sources within the industry support this notion [33]. Accordingly, all experiments conducted in this study consider the face view of vehicle designs.

## 2.2 Brand-Conscious Customers

Brand-conscious customers, able to correctly identify brand from unbranded vehicles, are used for filtering the data collected in the study. These brand-conscious customers are filtered as data from customers unable to identify brand add noise to the construction of predictive models for brand recognition. Moreover, appealing to brand-conscious customers has been found to be important for premium brands such as those considered in this study [34].

To identify brand-conscious customers, we filter out customers not able to correctly identify brands above a given threshold for designs that already exist in the market. Recent literature in crowdsourcing research has shown that data from "experts" within a crowd, in this case "brand-conscious customers" within a crowd, may be aggregated to obtain an accurate 'crowd consensus vote' using simple algorithms such as majority vote [35], [36].

On the other hand, if such filtering on the "experts" in the crowd is not done, simple algorithms to aggregate customer input may result in heavily biased crowd-level evaluations [37]. In our case, this may skew estimates of design freedom when trading off brand recognition. Such filtering of customer data to guide the design process has been similarly explored by using customers to interactively help guide the creative aspect of early-stage design [38], [39].

## 2.3 Design Representation

Design representation refers to the method that a design artifact is captured to either a computer or a customer during one of many steps during the design process [40]. We make the distinction between the two as it has been shown that computer representations and human representations may be entirely different, resulting in the need to construct models and conduct experiments in the appropriate space [41], [42]. Moreover, we consider three different factors of design representation, 2D and 3D; parametric and non-parametric; and styling attributes and geometric variables.

***2D and 3D Representations*** Recent studies have shown that brand recognition is dependent on the fidelity of the design representation [25]. Informally, there is a certain level of realism to the design that must be achieved for customers to correctly identify vehicle brand. We build on this notion by representing vehicle designs using the highest fidelity representation possible whether a 2D image or a 3D high polygon mesh, as shown in Figure 3 and Figure 4, respectively.

Studies have also shown that there exist differences between 2D and 3D design representations regardless of fidelity. In particular, customer preferences assessed via conjoint analysis have been found to be inconsistent when contrasting the type of design representation [43]–[45].

***Parametric and Non-Parametric*** Design representations may additionally be categorized as parametric or non-parametric. Parametric design representations have numerous applications via 2D silhouettes [20], [28], [29], [46] or 3D interpolated Bezier curves [47], [48]; however, perhaps the most realistic 3D interpolated Bezier curves come from design research done within the automotive industry [49].

In the shape grammar literature, non-parametric design representations are used as basic constituent shape elements to generate larger and more complex forms. These include automotive applications [50], some with focus on vehicle face details [24], [51] and vehicle side profiles [52], [53].

The present study is qualitatively similar to the shape grammar approach in that it employs a design generation process where an agent creates new designs, but it is limited in scope when contrasting the corresponding design spaces. In particular, shape grammars are able to generate a much larger set of possible designs as defined by the Cartesian product of grammar enumeration, whereas the design generation considered in this study is limited to the convex hull defined by the morphing bounds on the 3D design representations.

In this study, we cast the 3D design representation as a set of geometric features that morph not strictly related via a mathematical function, but instead requiring pre-defined input from professional vehicle designers [33]. This results in a hybrid of both parametric and non-parametric design representations, where a number of geometric features morph the 3D design via Laplacian deformation of its constituent polygonal mesh [54]. Note that we only consider static images for the 2D design representations in this study.

***Visceral Attributes and Geometric Variables*** While geometric variables via 2D and 3D representations, parametric or non-parametric, capture the physical form of the design as a computer may interpret it, human perceptions are better suited to a different representation [2], [19]. In particular, design attributes such as 'Friendly' versus 'Aggressive' have been shown to be more 'chunkable' in human perceptual understanding than variables such as '130 cm long airdam' [19].

Expanding on the information processing flow in Crilly et al. [39], we assume that the perceptual transmission from transmitter (designer) to receiver (customer) is conveyed through a vector of attribute values representing the design artifact. To develop analytical decision-making models [55], we further assume that the attributes themselves are functions of geometric design variables. Styling attributes are likely nonlinear functions of geometric variables, e.g., slight geometric changes in the edges between a smile and a frown may make large differences in an attribute such as 'happiness' [4]. By gathering customer responses within the space of design attributes versus design variables, we are more likely to be capturing data representative of human perception [42].

### 2.4 Quantitative Models of Product Styling

Some early work for quantitatively modeling styling and aesthetics comes from the marketing community, where conjoint analysis has proved valuable [56]. This modeling technique takes a number of variables representing the design's form as input, and uses customer preferences across a set of discrete points within the design space.

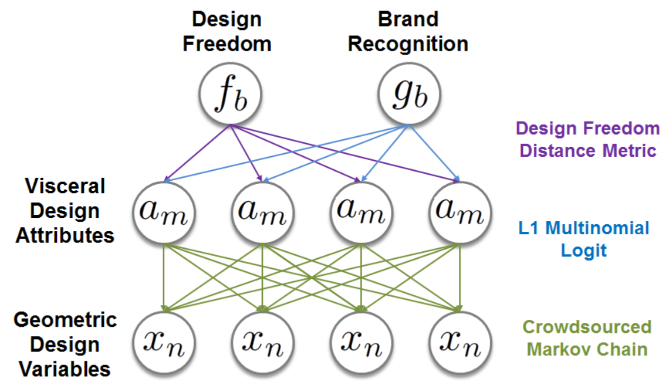


Figure 1: Dependencies between design freedom and brand recognition, design attributes, and design variables. Note that while design freedom and brand recognition are explicit linear functions of design attributes, design attributes are nonlinear functions of geometric design variables implicit in the customer perceptions of vehicles. On the right hand side, we denote the functional form of the associated dependencies

The design community has similarly used conjoint analysis to model styling form in efforts to optimize customer preferences through decision-based design [57]–[59]. Relevant examples of such applications include 2D vehicle side view silhouettes [20], [28] and 2D vehicle faces [46], [60]. Recently, 3D vehicles studies such as perceived safety [47] and virtual reality studies have been implemented [48]. Some applications have used nonlinear conjoint models such as explicit feature mappings [61] and implicit feature mappings [47].

## 3 PROBLEM FORMULATION

We formally define brand recognition and design freedom, and the manner in which the two are measured. We additionally define how customer responses to conceptual designs are aggregated to assess the overall crowd consensus to various changes in conceptual designs.

Let $f: A \rightarrow \mathbb{R}$ and $g: A \rightarrow [0,1]$ denote design freedom and brand recognition, respectively, in which $A = \{\mathbf{a} = [a_1, \ldots, a_M]: a_m \in [0,1]\}$ is the space of styling attribute vectors. Note that as discussed in Section 2, this definition assumes the styling design attributes are a common set of inputs to both design freedom $f(\mathbf{a})$ and brand recognition $g(\mathbf{a})$, and that both are defined over the set of existing and conceptual designs $\mathbf{x} \in \{\mathbf{x} = [x_1, \ldots, x_N]: x_n \in \mathbb{R}\}$ for an associated brand $b = 1 \ldots B$.

These design attributes $\{a_m\}_1^M$ are defined as the building blocks of customer perceptual representations of design styling [42], as they are representative of how human perception is chunked [19]. Informally, humans conceptualize a vehicle using terms such as 'sportiness' rather than the huge number of geometric design variables that constitute sportiness such as 'length of upper airdam.'

The design attributes must be able to be empirically manipulated to measure relative changes across brand recognition and design freedom. Accordingly, we parameterize the design attributes as a nonlinear function of a set of predefined geometric design variables denoted $\{x_n\}_1^N$. We make this parameterization to capture the notion that changing a given design variable may affect multiple attributes at the same time in a complex manner.

The dependencies of design freedom and brand recognition, design attributes, and design variables are shown in Figure 1. We next define the functional form of each dependency. In particular, we detail the mathematical relationship between (1) design freedom and design attributes, (2) brand recognition and design attributes, and (3) design attributes and design variables.

### 3.1 L1 Multinomial Logit for Brand Recognition

We define brand recognition as a linear combination of design attributes, in which the attributes maximally discriminate between the brands considered in this study.

To determine the linear coefficients to predict brand, we assume a multinomial logistic regression functional form, conditioned only on brand-conscious customers and regularized using the L1-norm, as given in Equation (1).

$$g_b(\boldsymbol{a}) = \frac{e^{\boldsymbol{\omega_b}^T \boldsymbol{a}}}{\sum_{b=1}^{B} e^{\boldsymbol{\omega_b}^T \boldsymbol{a}}} + |\boldsymbol{\omega_b}|_1 \qquad (1)$$

To train the coefficients $\boldsymbol{\omega}_b$ of this model, we use l-BFGS optimization to maximize the penalized multinomial likelihood [55]. Note that we use the notation for coefficients from the machine learning community; these coefficients are also often denoted β in marketing and θ in statistics. The data is conditioned using a hard threshold, where a brand-conscious customer must achieve greater than *T* percentage correct recognition of brands across a set of existing designs.

### 3.2 Design Freedom Distance Metric

Design freedom is the leeway designers have to generate conceptual designs while accounting for many implicit and explicit constraints [33]. In this work, we define design freedom as a distance from existing designs to a new conceptual design. While design distance metrics have been used for engineering specifications and various representations [40], [62], these metrics do not accommodate various stakeholder input as needed in this study.

We propose a distance metric between two designs $\alpha$ and $\beta$ for brand $b$ as given in Eq. (2). This metric is used to assign a scalar value that captures both geometric and perceptual styling differences between designs.

This distance metric captures stakeholder considerations to the overall design freedom in two ways: First, design freedom

$$\left|\left|f_b^{\alpha} - f_b^{\beta}\right|\right| = \sum_{m=1}^{M} \mathrm{I}_{\omega_{b,m} \neq 0} \left[\lambda_1 \left(a_m^{(\alpha)} - a_m^{(\beta)}\right)^2 + \lambda_2 \sum_{n=1}^{N} \left(r_{b,nm}[x_n^{(\alpha)} - x_n^{(\beta)}]\right)^2\right] \qquad (2)$$

$a_m$= design attributes measured using 2D representation
$x_n$= geometric design variables common to both 2D and 3D representation
$\lambda_1$ = importance parameter of design attributes
$\lambda_2$ = importance parameter of geometric design variables
$\mathrm{I}_{\omega_{b,m} \neq 0}$ = indicator function if attribute *m* is important for brand *b*
$r_{b,nm}$ = sensitivity of attribute *m* to variable *n* for brand *b*

*implicit* in the mind of the customer is captured using $r_{b,nm}$ and $\mathrm{I}_{\omega_{b,m} \neq 0}$, both of which are assessed using the customers crowd. Informally, these values capture the notion that differences between two designs exists using both geometric and perceptual representations in the mind of the customer.

Second, design freedom *explicit* from stakeholders within the producing organization are captured using $\lambda_1$ and $\lambda_2$, which may represent, say, relative influences of the marketing and engineering departments, respectively. Informally, we use these parameters to tune how important it is to maintain an attribute like "aggressiveness" for a marketing campaign, or a certain geometric shape for vehicle aerodynamics. Accordingly, the value of this parameter is specific to the corporation being considered.

Using this distance metric, overall design freedom is assed as the distance from the current design in MY2014 to a proposed design $(\boldsymbol{x}', \boldsymbol{a}')$. Denoting the existing design $(\boldsymbol{x}^*, \boldsymbol{a}^*)$, design freedom for the proposed design is given by Eq. (3) using vector notation for brevity.

$$\begin{aligned} f_b'(\boldsymbol{x}', \boldsymbol{a}') &= \left|\left|f_b(\boldsymbol{x}', \boldsymbol{a}') - f_b(\boldsymbol{x}^*, \boldsymbol{a}^*)\right|\right| \\ &= \lambda_1 (\boldsymbol{a}' - \boldsymbol{a}^*)^{\boldsymbol{T}} \operatorname{diag}\left[\mathbf{I}_{\boldsymbol{\omega}_b \neq 0}\right](\boldsymbol{a}' - \boldsymbol{a}^*) \\ &+ \lambda_2 (\boldsymbol{x}' - \boldsymbol{x}^*)^{\boldsymbol{T}} \operatorname{diag}[\mathbf{R}\mathbf{I}_{\boldsymbol{\omega} \neq 0}](\boldsymbol{x}' - \boldsymbol{x}^*) \end{aligned} \qquad (3)$$

$\mathbf{I}_{\boldsymbol{\omega}_b \neq 0}$ = *M* x 1 vector of indicator functions for brand *b*
$\mathbf{R}$ = *N* x *M* matrix of attribute-variable sensitivities
diag[·] = operator to transform vectors to diagonal matrices

To calculate the sensitivities of design attributes to design variables $r_{b,nm}$, we conduct a one-sided *t*-test between the baseline design variable $x_n^*$ and the morphed design variable $x_n'$ from customer responses for a given attribute *m* and brand *b*. This hypothesis test sets the $r_{b,nm}$= 1 if the p-value for the *t*-test is less than 0.05, and $r_{b,nm} = 0$ otherwise.

The values of the indicator function $\mathrm{I}_{\omega_{b,m} \neq 0}$ are calculated by assigning the value 1 to all non-zero elements of the corresponding weight vector described in Section 3.1. Note that this weight vector is already sparse due to L1 regularization.

 

### 3.3 Crowdsourced Markov Chain for Design Attributes

While the representation of the styling design attributes and geometric design variables are *explicitly* defined, both the attribute values and the nonlinear function relating design attributes to design variable are not. Conventionally, this function is approximated by explicitly assuming a functional form, such as the linear logit model often used in design utility theory treatments, followed by estimating part-worth coefficients of the assumed model.

We take a different approach by assuming the nonlinear function relating design attributes to design variables is *implicitly* captured within the minds of the customers. By crowdsourcing the attribute values of the designs—asking a crowd of customers to evaluate designs over attributes—we avoid needing to determine this complex nonlinear function form explicitly. This has advantages as we are now capturing a function that may exist in a much more expressive function space, allowing more realistic modeling of nonlinear interactions. Moreover, we avoid the need of explicitly mathematically representing geometric variables, as realistic 3D vehicle polygon meshes may be upwards of 100,000 vertices.

To obtain this implicit and distributed function, we instead need a method of aggregating customer responses to capture changes in design attribute values as a function of changes in design variable values. Accordingly, we aggregate the responses $\{r_c\}_1^C$ made by customers $c = 1 \dots C$, in which each response is in the form of a partial ranking for a single design attribute. Partial rankings without ties are chosen as they are more intuitive for human evaluation [63], and importantly do not require the notion of a non-relative scale, i.e., "what would it mean to give the first seen design a 4 /10 'aggressive' score without seeing the entire set of designs?"

To aggregate these partial rankings, we derive a Markov chain solved using a modified version of PageRank [64]. The states of this Markov chain correspond to the cars to be ranked as shown in Figure 2. The transition probabilities depend on those partial rankings. The stationary probability distribution of this Markov chain will be used as the value of the attribute.

The transition probability $P_{ij},\ i,j = 1, \dots, N$ from the state representing car $i$ to the state representing car $j$ is defined as the frequency that car $j$ is ranked higher than car $i$ in all partial ranks that contain car $i$. If the transition probability $P_{ij}$ is large, then it means that car j is more likely to have higher value of the attribute than car $i$. We define the transition probability matrix $\mathbf{P} = (P_{ij})$ as the raw transition probability matrix.

Note that the stationary distribution $\boldsymbol{\pi}$ of a Markov chain is a distribution vector, which is unchanged after the operation of transition matrix $\mathbf{P}$ as given in Eq. (4).

$$\boldsymbol{\pi} = \boldsymbol{\pi}\mathbf{P} \quad (4)$$

$$\boldsymbol{\pi} = (\pi_1, \pi_2, \dots, \pi_N)$$

$$\pi_i \geq 0 \text{ and } \textstyle\sum_{i=1}^{N} \pi_i = 1$$

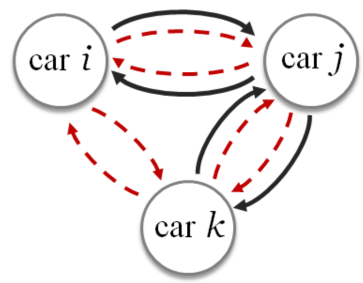


Figure 2: Diagram of Markov chain used to aggregate customer responses in the form of partial rankings of cars to obtain design attribute values for each brand. Black arrows show non-zero transition probabilities from the raw transition matrix, while red dashed arrows show perturbation probabilities added to ensure a unique stationary distribution.

According to Markov chain theory, there is no guarantee that the raw transition probability matrix $\mathbf{P}$ will have unique stationary distribution [65]. To achieve this uniqueness, we make two extensions to convert the raw transition matrix $\mathbf{P}$ to a stochastic, irreducible, and aperiodic matrix [64].

*Extension 1* The first extension is that the rows in P that only contain 0's are replaced with $\frac{1}{N}\boldsymbol{e}^T$, where $\boldsymbol{e}^T$ is a column vector consisting of 1's. This adjustment results in a stochastic matrix denoted S as given in Eq. (5).

$$\mathbf{S} = \mathbf{P} + \boldsymbol{\theta}(\frac{1}{N}\boldsymbol{e}^T) \quad (5)$$

$$\theta_i = \begin{cases} 1 \text{ } if \text{ i} - \text{th row in } \mathbf{P} \text{ consists of 0s} \\ \text{0 otherwise} \end{cases}$$

*Extension 2* The second extension is made to convert $\mathbf{S}$ into an irreducible and aperiodic matrix. We define this new matrix $\mathbf{G}$ as given in Eq. (6).

$$\mathbf{G} = \gamma\mathbf{S} + (1-\gamma)\frac{1}{N}\boldsymbol{ee^T} \quad (6)$$

where $\gamma$ is a scalar between 0 and 1 controlling the intensity of the perturbation that ensures uniqueness.

With these extensions, a unique stationary distribution exists for $\mathbf{G}$. From Eq. (6), the stationary distribution vector $\boldsymbol{\pi}$ can be obtained by calculating the eigenvectors of $\mathbf{G}$, or by iteratively calculating $\pi^{(k+1)} = \pi^{(k)}\mathbf{G}, k = 1,2, \dots$ until convergence. To calculate the values of attributes $\boldsymbol{a}_b$ for brand $b$ based on the set of all partial rankings from customer responses $\{r_c\}_1^C$, we simply define the attribute value for car $i$ as $\pi_d, d = 1,2, \dots, D$.

## 4 EXPERIMENT

We conduct an experiment involving three steps. First, we develop a predictive model for brand recognition as a function of ten styling design attributes. This model acts as an objective "baseline" to measure changes for both design freedom and brand recognition. To develop the model, we ask customers to evaluate attributes for 2D images data past vehicle designs of each manufacturer.

Next, customers create morphed designs from the baseline models. These designs are used to quantify how much a change from the baseline designs affects a change in brand recognition. Customers are asked to morph 3D models of previous designs to be more or less like one of the ten design attributes.

The third step essentially runs the first step again, but using 2D images of the morphed 3D designs. By assessing brand recognition of the morphed designs, this step allows us to measure how changes in design freedom affect changes in brand recognition.

### 4.1 Participants

Customers were gathered through the crowdsourcing platform Amazon Mechanical Turk. These participants were composed of 315 people. Note that while we crowdsource these data through an open call, we filter out all participants who did not achieve a 30% or greater percentage at correct brand recognition of current vehicle designs. This enabled us to use customer response data only from brand-conscious customers as justified in Section 2.

### 4.2 Vehicle Brands and Models

The brands chosen were Audi, BMW, Cadillac, and Lexus, due to their relative similarities over targeted market segment, as well as similarity of product offerings across vehicle classes. For each brand, five models were chosen from model year 2014 (MY2014) corresponding to five vehicle classes as given in Table 1.

Table 1: Description of the four vehicle manufacturer brands and five associated vehicle classes used in this study.

| Brand | Compact | Midsize | Fullsize | Crossover | SUV |
|---|---|---|---|---|---|
| Audi | A4 | A6 | A8 | Q5 | Q7 |
| BMW | 3 series | 5 series | 7 series | X3 | X5 |
| Cadillac | ATS | CTS | XTS | SRX | Escalade |
| Lexus | IS | GS | LS | RX | GX |

### 4.3 2D Images and 3D Morphable Vehicle Models

Images of the vehicle face, the front view of the vehicle, were sourced from an online vendor [66]. The face image has been shown to have more correlation with brand recognition than either the side view or rear view [25]. Each image was comprised of a white vehicle on a white background to minimize confounding interactions from color as shown in Figure 3. Moreover, the brand logo was removed for each vehicle image using Adobe Photoshop in order to focus customer responses just on styling.

Four morphable 3D models, one for each brand, were developed for use in this study as shown in Figure 4. Morphing was pre-computed offline using Laplacian deformation and volumetric-based mesh defomation techniques [54]. These models were imported into the web-based survey using the browser-based WebGL renderer, allowing real-time and realistic deformation via client side GPU interpolation.

### 4.4 Design Attributes

As described in Section 3, design attributes are used as a common set of values that are used to link brand recognition with design freedom. We sourced ten design attributes from real design teams, specifically those used within the automotive industry [4].

Table 2: Styling design attributes used in this experiment. Each of the ten attributes was captured by a semantic differential with a corresponding "low" and "high" value.

| Low Attribute | High Attribute |
|---|---|
| Awkward | Well Proportioned |
| Weak | Powerful |
| Conservative | Sporty |
| Basic | Luxurious |
| Conventional | Distinctive |

| Low Attribute | High Attribute |
|---|---|
| Passive | Active |
| Traditional | Innovative |
| Understated | Expressive |
| Friendly | Aggressive |
| Mature | Youthful |

### 4.5 Procedure

A web-based interactive survey was developed to capture customer responses in the form of partial rankings for the 2D portion of the site, and customer responses in the form of dragging sliders to morph designs for the 3D portion of the site.

The overall flow was as follows: Participants were first directed to an introduction page, where they were given instructions on ranking vehicles according to a semantic differential. This semantic differential consisted of only one of the ten attributes from either low to high value or vis-versa, to act as a counter balance for ordering biases. Note that over the entire interactive survey, a participant was always given the same semantic differential to reduce participant burden.
Next, participants were directed to the 2D design ranking page, with the 4 vehicles in a top row and 4 outlined placeholders in a bottom row. Instructions on the page were given to drag and drop the 4 vehicles from the top row to the bottom row using the mouse, including possibility of reordering the partial ranking.

Upon clicking the "Submit" button for the partial ranking, participants were then asked to choose the brand of each vehicle using a drop-down menu with 34 possible options (e.g., Audi, Volvo, Toyota). Only after participants chose a recognized brand for each of the vehicles, were they allowed to continue to the next partial ranking.

After each participant completed five partial rankings on the 2D portion of the site, they were directed to the 3D portion of the site for generating new designs. In this portion, each participant was given a randomly chosen 3D model in the midsize vehicle segment from the four brands as described in Section 4.2. Participants were then asked to maximize the 3D design using four sliders that controlled vehicle morphing along the same design attribute as their semantic differential from the 2D portion of the site. Customers were able to rotate the 3D vehicle model to assess the overall gestalt of the face.

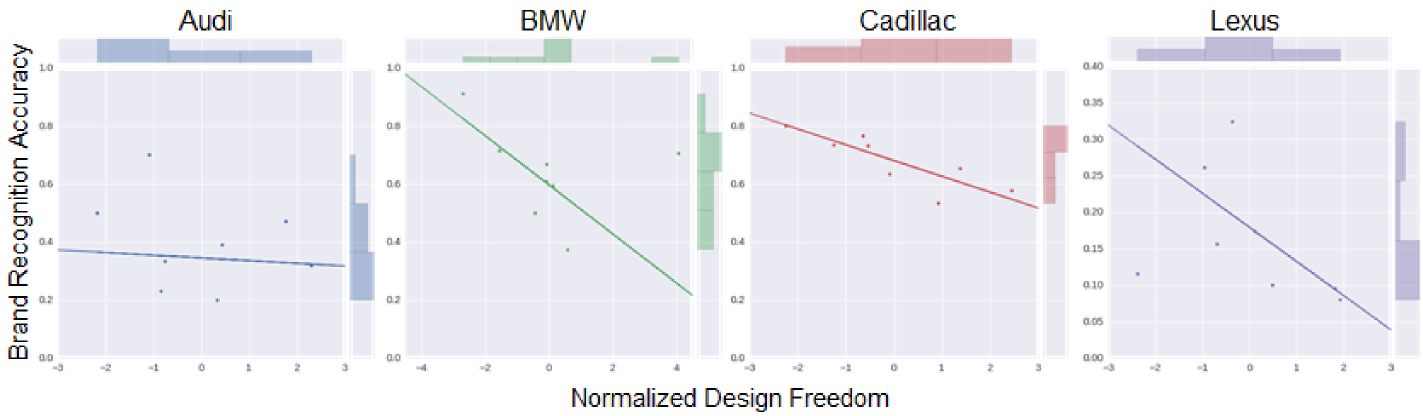


Figure 5: Brand recognition versus design freedom for the four vehicle brands in this study over 2D images taken of the conceptual designs generated during the 3D portion of the experiment. Note that brand recognition accuracy is defined as the percentage of time a brand-conscious customer—a customer who correctly identified more than 30% of the MY2014 baseline vehicle brands—was able to correctly recognize a new morphed design.

Upon submitting their chosen 3D design, participants were then directed to a short survey in which they were asked basic demographic information as well as task relevant information. The task relevant information included questions regarding commute time, as this has been shown to be correlated with brand recognition [25].

In the third step of the experiment, 3D designs from brand-conscious customers were used to create 2D images by taking snapshots from the face of the vehicle model. These new 2D images of the morphed 3D vehicles were then used according to the same partial ranking procedure described in this subsection, except now with a new crowd of customers. This step was used to measure geometric variable and attribute changes for the design freedom metric described in Section 3.2, and to validate the brand recognition model described in Section 3.1 from the non-morphed 2D designs. Note that these new 2D images came from 32 randomly selected 3D designs from brand-conscious customers.

### Data Analysis

Online crowdsourcing has often been empirically shown to be a noisy process partially due to various motivations of participants [35], [67]–[69]. Accordingly, while the vast majority of data was kept, we filtered out data from participants using several data processing steps to ensure data fidelity. First, participants that simply "clicked through" the survey were filtered out by requiring they average time on the 2D portion of the site was greater than 6 seconds per ranking.

Second, data from non-brand-conscious customers were filtered as described in Section 2.2. A brand recognition accuracy threshold of 30% was chosen after viewing the brand recognition accuracy for the entire crowd. Note that brand recognition accuracy was treated as a constant variable across the entire survey, and all data were filtered out for a given participant if he or she did not fall above the threshold.

Third, using the data filtered from these two processes, we then aggregated the partial rankings from each brand-conscious customer using the method described in Section 3 to obtain the design attribute values for each new conceptual design. These design attributes were used to build a model of brand recognition according to the method described in Section 3.1. Note that this filtered data included participants from both 2D images of non-morphed designs and 2D images of the morphed designs due to the relative values obtained using the partial ranking aggregation method described in Section 3.3.

Brand recognition was assessed by calculating the number of correct responses to the set of 32 morphed conceptual designs over the total number of times that that particular conceptual design showed up in the partial rankings.

Normalized design freedom was calculated using the metric described in Section 3.2. The values of $\lambda_1$ and $\lambda_2$ were chosen for each brand to scale the design freedom by subtracting the mean and dividing the standard deviation. This operation was chosen on a brand-by-brand basis as this did not change the brand recognition versus design freedom distributions.

## 5 RESULTS AND DISCUSSION

Four plots capturing the empirical relationships between brand recognition and design freedom for each manufacturer are given in Figure 5. Each plot includes a trend line obtained using Thiel-Sen robust linear regression to capture (to first order) how fast brand recognition decreases as design freedom is increased, with the slopes of each of these trend lines given in Table 3. Histograms showing the marginal distributions are also plotted to convey the relative coverage of the data for each brand.

Table 3: Slope coefficients of L1 regularized linear model fit to brand recognition vs design freedom for four brands.

| Brand | Slope of Brand Recognition vs Design Freedom |
|---|---|
| Audi | - 0.009 |
| BMW | - 0.085 |
| Cadillac | - 0.054 |
| Lexus | - 0.047 |

The brand recognition versus design freedom slope for each of the four manufacturers is negative, confirming intuition that increasing design freedom results in decreased brand recognition, a result obtained entirely from the data.

From these slopes, we can see that BMW and Cadillac have the quickest loss of brand recognition with increased design freedom. Lexus and Audi are shown to be third and fourth in this ranking, however, our results for Lexus and Audi may not be as warranted largely because both of these manufacturers have low absolute brand recognition.

In particular, Figure 6 shows the absolute brand recognition across the four brands for brand-conscious customers and non-brand conscious customers. We observe that BMW and Cadillac have the most recognizable brand, justified as the data consists of over 5000 brand identifications from a pool of 315 customers distributed throughout the world. Lexus was found to have the lowest brand recognition, both amongst brand-conscious customers as well as non-filtered customers.

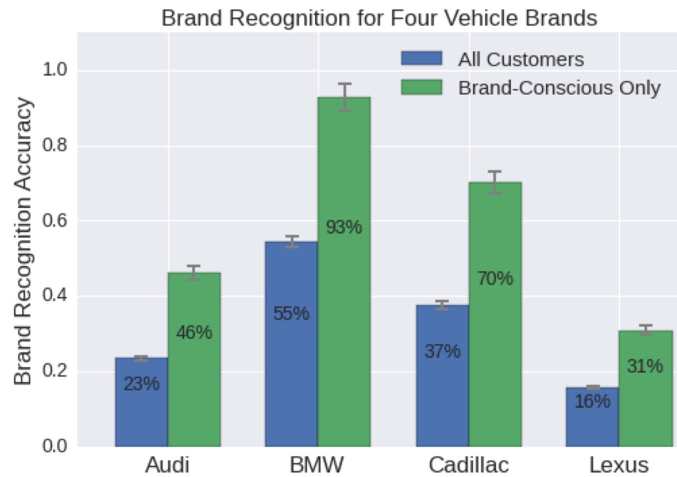


Figure 6: Brand Recognition for the four vehicle brands in this study. Brand-conscious customers refer to those customers who could correctly identify at least on average 30% the brands of baseline (MY2014) designs.

## Applications to Industry

The study was conducted largely following ideas and needs of real industrial design teams and immediate practical applications are likely. For example, the procedure used in this study may be used as a decision support tool for product researchers and strategic design managers to explicitly show which visceral design attributes and geometric design variables have the most leeway when creating a future design.

Advantages of such a tool would be in putting design decisions in the hands of the experience and intuition of designers and strategic design managers, while giving near real-time feedback from a targeted crowd of customers. Such tools may be complemented by recent advances in virtual and augmented reality technologies for designs and customers alike.

## Limitations

The design space spanned by the parameterization of geometric variables for the 3D models does not capture the entire set of possible vehicle face design concepts. While this is in part why we assumed brand recognition as a linear function of attributes, and attributes as an (implicit) nonlinear function of geometric variables, it must be noted that future studies may greatly differ in their parameterizations.

Filtering the data for brand-conscious customers has some limitations. We assumed that brand recognition accuracy is a static quantity throughout the survey. This does not account for familiarity with the brands after consistently seeing the same four throughout the survey. A larger number of data points must be collected in future studies to reduce the uncertainty in Figure 5. We also note that increased data would allow filtering on customers with higher average brand recognition accuracy over current MY2014 vehicle.

Moreover, this study only considered designs from MY2014, limiting these static findings from time-series trends. Future work considering design data over a number of years would provide additional insight as brands and design languages often undergo dramatic shifts in design language. Along these lines, this study only considered luxury brands. Insights into whether these same findings and methodology are appropriate for non-luxury brands would provide additional support along this line of study.

Limitations to the crowdsourced function estimation approach detailed in Section 3.3 are now noted: First, attribute values will change depending on which cars are involved in the ranking, a point that we will revisit in Section 4. Second, the formulation assumes that customers are homogeneous in their perceptions of the design attributes. While this assumption is certainly not always true, we mitigate the effect of heterogeneity by normalizing for the relative contribution of a design attribute to either design freedom or brand recognition as given in Eq. (6).

Finally, we note that including heterogeneity in customer responses to design attributes may significantly increase fidelity of the brand recognition prediction model described in Section 3.1. Such heterogeneity may be captured using models that incorporate clustering formulations or formulations that impose deviations from a common crowd prior distribution [70].

# 6 CONCLUSION

Design freedom and brand recognition are considerations that were measured for four vehicle manufacturers—Audi, BMW, Cadillac, and Lexus—as balancing between these two considerations has been shown to significantly influence consumer purchase decision. An experiment was conducted measuring change in ten styling attributes common to both design freedom and brand recognition for automotive designs, using customer responses to vehicle designs created interactively using 2D and 3D design representations. Results show that, while brand recognition is highly dependent on the particular manufacturer, measuring tradeoffs between design freedom and brand recognition using predictive models can augment intuition in making strategic design decisions.

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## REFERENCES

[1] C. Martindale, *The Clockwork Muse: The Predictability of Artistic Change*. New York, NY: Basic Books, 1990.

[2] D. Coates, *Watches Tell More Than Time: Product Design, Information, and the Quest for Elegance*. McGraw-Hill London, 2003.

[3] D. A. Aaker and K. L. Keller, "Consumer Evaluations of Brand Extensions," *The Journal of Marketing*, vol. 54, no. 1, pp. 27–41, 1990.

[4] "General Motors Brand Equity Research," General Motors, Warren, MI, Internal, 2014.

[5] O. Person and D. Snelders, "Brand styles in commercial design," *Design Issues*, vol. 26, no. 1, pp. 82–94, 2010.

[6] B. Schmitt, "The consumer psychology of brands," *Journal of Consumer Psychology*, vol. 22, no. 1, pp. 7–17, Jan. 2012.

[7] J. Barney, "Firm Resources and Sustained Competitive Advantage," *Journal of Management*, vol. 17, no. 1, pp. 99–120, Mar. 1991.

[8] R. Srinivasan, G. L. Lilien, and A. Rangaswamy, "The Emergence of Dominant Designs," *Journal of Marketing*, vol. 70, no. 2, pp. 1–17, Apr. 2006.

[9] O. Person, D. Snelders, T.-M. Karjalainen, and J. Schoormans, "Complementing Intuition: Insights on Styling as a Strategic Tool," *Journal of Marketing Management*, vol. 23, no. 9–10, pp. 901–916, Nov. 2007.

[10] P. H. Bloch, "Seeking the Ideal Form: Product Design and Consumer Response," *Journal of Marketing*, vol. 59, no. 3, p. 16, Jul. 1995.

[11] H. Yin Wong and B. Merrilees, "The performance benefits of being brand-orientated," *Journal of Product & Brand Management*, vol. 17, no. 6, pp. 372–383, Sep. 2008.

[12] K. Talke, S. Salomo, J. E. Wieringa, and A. Lutz, "What about design newness? Investigating the relevance of a neglected dimension of product innovativeness," *Journal of Product Innovation Management*, vol. 26, no. 6, pp. 601–615, 2009.

[13] T. Moulson and G. Sproles, "Styling Strategy," *Business Horizons*, vol. 43, no. 5, pp. 45–52, 2000.

[14] P. Hekkert, D. Snelders, and P. C. Wieringen, "'Most advanced, yet acceptable': typicality and novelty as joint predictors of aesthetic preference in industrial design," *British Journal of Psychology*, vol. 94, no. 1, pp. 111–124, 2003.

[15] O. Person, J. Schoormans, D. Snelders, and T.-M. Karjalainen, "Should new products look similar or different? The influence of the market environment on strategic product styling," *Design Studies*, vol. 29, no. 1, pp. 30–48, Jan. 2008.

[16] D. E. Berlyne, *Aesthetics and Psychobiology*. East Norwalk, CT, US: Appleton-Century-Crofts, 1971.

[17] J. Hartley, "Brands Through the Lens of Style," presented at the Annual Meeting, Quest and Associates, San Diego, California, 1996.

[18] D. A. Norman, A. Ortony, and D. M. Russell, "Affect and machine design: Lessons for the development of autonomous machines," *IBM Systems Journal*, vol. 42, no. 1, pp. 38–44, 2003.

[19] D. A. Norman, *Emotional Design: Why We Love (or Hate) Everyday Things*. New York, NY: Basic books, 2004.

[20] T. N. Reid, R. D. Gonzalez, and P. Y. Papalambros, "Quantification of Perceived Environmental Friendliness for Vehicle Silhouette Design," *Journal of Mechanical Design*, vol. 132, no. 10, p. 101010, 2010.

[21] G. McWilliam and A. Dumas, "Using metaphors in new brand design," *Journal of Marketing Management*, vol. 13, no. 4, pp. 265–284, May 1997.

[22] M. Mulder-Nijkamp and W. Eggink, "Brand Value by Design: The Use of Three Levels of Recognition in Design," in *Proceedings of the 5th International Congress of International Association of Societies of Design Research*, Tokyo, JP, 2013.

[23] P. Louridas, "Design as bricolage: anthropology meets design thinking," *Design Studies*, vol. 20, no. 6, pp. 517–535, 1999.

[24] J. P. McCormack, J. Cagan, and C. M. Vogel, "Speaking the Buick language: capturing, understanding, and exploring brand identity with shape grammars," *Design Studies*, vol. 25, no. 1, pp. 1–29, Jan. 2004.

[25] C. Ranscombe, B. Hicks, G. Mullineux, and B. Singh, "Visually decomposing vehicle images: Exploring the influence of different aesthetic features on consumer perception of brand," *Design Studies*, vol. 33, no. 4, pp. 319–341, Jul. 2012.

[26] R. Kreuzbauer and A. J. Malter, "Embodied Cognition and New Product Design: Changing Product Form to Influence Brand Categorization," *Journal of Product Innovation Management*, vol. 22, no. 2, pp. 165–176, 2005.

[27] I. Ersal, P. Papalambros, R. Gonzalez, and T. J. Aitken, "Modelling perceptions of craftsmanship in vehicle interior design," *Journal of Engineering Design*, vol. 22, no. 2, pp. 129–144, Feb. 2011.

[28] S. Orsborn, J. Cagan, and P. Boatwright, "Quantifying Aesthetic Form Preference in a Utility Function," *Journal of Mechanical Design*, vol. 131, no. 6, p. 061001, 2009.

[29] B. Sylcott, J. Cagan, and G. Tabibnia, "Understanding consumer tradeoffs between form and function through

 

metaconjoint and cognitive neuroscience analyses," *Journal of Mechanical Design*, vol. 135, no. 10, p. 101002, 2013.
[30] A. Ranawat, S. Tuteja, and K. Höltta–Otto, "Contribution of Visual Design Elements to the Perceived Product Family Look," *Journal of Design Research*, vol. 10, no. 3, pp. 189–205, 2012.
[31] K. L. Keller, "Brand Synthesis: The Multidimensionality of Brand Knowledge," *Journal of Consumer Research*, vol. 29, no. 4, pp. 595–600, Mar. 2003.
[32] V. A. Zeithaml, "Consumer Perceptions of Price, Quality, and Value: A Means-End Model and Synthesis of Evidence," *Journal of Marketing*, vol. 52, no. 3, pp. 2–22, Jul. 1988.
[33] J. Manoogian II, "Vehicle Design Process used at General Motors," 12-Jun-2013.
[34] D. A. Aaker, *Managing Brand Equity*. New York, NY: Simon and Schuster, 2009.
[35] A. Sheshadri and M. Lease, "SQUARE: A Benchmark for Research on Computing Crowd Consensus," in *Proceedings of the First AAAI Conference on Human Computation and Crowdsourcing*, Palm Springs, CA, USA, 2013.
[36] V. S. Sheng, F. Provost, and P. G. Ipeirotis, "Get another label? improving data quality and data mining using multiple, noisy labelers," in *Proceedings of the 14th ACM SIGKDD international conference on Knowledge discovery and data mining*, 2008, pp. 614–622.
[37] A. Burnap, Y. Ren, R. Gerth, G. Papazoglou, R. Gonzalez, and P. Y. Papalambros, "When Crowdsourcing Fails: A Study of Expertise on Crowdsourced Design Evaluation," *Journal of Mechanical Design*, vol. 137, no. 3, p. 031101, 2015.
[38] N. Ind and C. Watt, "Brands and breakthroughs: How brands help focus creative decision making," *The Journal of Brand Management*, vol. 13, no. 4–5, pp. 330–338, 2006.
[39] N. Crilly, J. Moultrie, and P. J. Clarkson, "Seeing things: consumer response to the visual domain in product design," *Design Studies*, vol. 25, no. 6, pp. 547–577, Nov. 2004.
[40] S. K. Chandrasegaran, K. Ramani, R. D. Sriram, I. Horváth, A. Bernard, R. F. Harik, and W. Gao, "The evolution, challenges, and future of knowledge representation in product design systems," *Computer-Aided Design*, vol. 45, no. 2, pp. 204–228, Feb. 2013.
[41] A. Tversky and I. Gati, "Studies of similarity," *Cognition and categorization*, vol. 1, no. 1978, pp. 79–98, 1978.
[42] A. Tversky and J. Hutchinson, "Nearest neighbor analysis of psychological spaces.," *Psychological Review*, vol. 93, no. 1, p. 3, 1986.
[43] Q. Bao, S. El Ferik, M. M. Shaukat, and M. C. Yang, "An Investigation on the Inconsistency of Consumer Preferences: A Case Study of Residential Solar Panels," in *Proceedings of the 2014 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Buffalo, NY, 2014.
[44] T. N. Reid, E. F. MacDonald, and P. Du, "Impact of product design representation on customer judgment," *Journal of Mechanical Design*, vol. 135, no. 9, p. 091008, 2013.
[45] C. A. Toh and S. R. Miller, "The Impact of Example Modality and Physical Interactions on Design Creativity," *Journal of Mechanical Design*, 2014.
[46] J.-F. Petiot and A. Dagher, "Preference-Oriented Form Design: Application to Cars' Headlights," *International Journal on Interactive Design and Manufacturing*, vol. 5, no. 1, pp. 17–27, Oct. 2010.
[47] Y. Ren, A. Burnap, and P. Papalambros, "Quantification of Perceptual Design Attributes Using a Crowd," in *Proceedings of the 19th International Conference on Engineering Design*, Seoul, Korea, 2013.
[48] N. Tovares, P. Boatwright, and J. Cagan, "Experiential Conjoint Analysis: An Experience-Based Method for Eliciting, Capturing, and Modeling Consumer Preference," *Journal of Mechanical Design*, vol. 136, no. 10, p. 101404, 2014.
[49] I. Kókai, J. Finger, R. C. Smith, R. Pawlicki, and T. Vetter, "Example-Based Conceptual Styling Framework for Automotive Shapes," in *Proceedings of the 4th Eurographics Workshop on Sketch-Based Interfaces and Modeling*, Riverside, CA, 2007, pp. 37–44.
[50] S. Orsborn and J. Cagan, "Multiagent Shape Grammar Implementation: Automatically Generating Form Concepts According to a Preference Function," *Journal of Mechanical Design*, vol. 131, no. 12, p. 121007, 2009.
[51] S. Orsborn, J. Cagan, R. Pawlicki, and R. C. Smith, "Creating cross-over vehicles: Defining and combining vehicle classes using shape grammars," *AIE EDAM: Artificial Intelligence for Engineering Design, Analysis, and Manufacturing*, vol. 20, no. 03, pp. 217–246, 2006.
[52] B. Yannou, M. Dihlmann, and R. Awedikian, "Evolutive Design of Car Silhouettes," in *ASME 2008 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, New York, NY, 2008, pp. 15–24.
[53] M. J. Pugliese and J. Cagan, "Capturing a rebel: modeling the Harley-Davidson brand through a motorcycle shape grammar," *Research in Engineering Design*, vol. 13, no. 3, pp. 139–156, 2002.
[54] M. Botsch and O. Sorkine, "On Linear Variational Surface Deformation Methods," *IEEE Transactions on Visualization and Computer Graphics*, vol. 14, no. 1, pp. 213–230, Jan. 2008.
[55] P. Y. Papalambros and D. J. Wilde, *Principles of Optimal Design: Modeling and Computation*. Cambridge University Press, 2000.
[56] P. E. Green, J. D. Carroll, and S. M. Goldberg, "A General Approach to Product Design Optimization Via Conjoint Analysis," *Journal of Marketing*, vol. 45, no. 3, p. 17, 1981.

 

[57] W. Chen, C. Hoyle, and H. J. Wassenaar, *Decision-Based Design*. London: Springer London, 2013.

[58] G. A. Hazelrigg, "A framework for decision-based engineering design," *Journal of mechanical design*, vol. 120, no. 4, pp. 653–658, 1998.

[59] P. Y. Papalambros, "An Enterprize Context for Design Optimization," in *Proceedings of the ESDA 2002 6th Biennial Conference on Engineering Systems Design and Analysis*, Istanbul, Turkey, 2002.

[60] Chen, Kang, and Hung, "Effects of Design Features on Automobile Styling Perceptions," presented at the IASDR07, Hong Kong, 2007.

[61] M. Fuge, J. Stroud, and A. Agogino, "Automatically Inferring Metrics for Design Creativity," in *ASME 2013 International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, 2013, pp. V005T06A010–V005T06A010.

[62] T. W. Simpson, D. Rosen, J. K. Allen, and F. Mistree, "Metrics for assessing design freedom and information certainty in the early stages of design," *Journal of Mechanical Design*, vol. 120, no. 4, pp. 628–635, 1998.

[63] R. Gonzalez and T. O. Nelson, "Measuring ordinal association in situations that contain tied scores.," *Psychological bulletin*, vol. 119, no. 1, p. 159, 1996.

[64] S. Brin and L. Page, "The anatomy of a large-scale hypertextual Web search engine," *Computer networks and ISDN systems*, vol. 30, no. 1, pp. 107–117, 1998.

[65] S. M. Ross, *Stochastic processes*, vol. 2. John Wiley & Sons New York, 1996.

[66] "EVOXSTOCK.COM | Car Stock Photos On-Demand™." [Online]. Available: http://www.evoxstock.com/index.asp. [Accessed: 05-Dec-2014].

[67] D. Pilz and H. Gewald, "Does money matter? Motivational factors for participation in paid-and non-profit-crowdsourcing communities," *Wirtschaftsinformatik Proceedings 2013*, no. 23, 2013.

[68] N. Kaufmann, T. Schulze, and D. Veit, "More than fun and money. worker motivation in crowdsourcing–a study on mechanical turk," *AMCIS 2011 Proceedings - All Submissions. Paper 340*, 2011.

[69] A. Kittur, E. Chi, and B. Suh, "Crowdsourcing User Studies with Mechanical Turk," in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems*, Florence, Italy, 2008, pp. pp. 453–456.

[70] T. Evgeniou, M. Pontil, and O. Toubia, "A Convex Optimization Approach to Modeling Consumer Heterogeneity in Conjoint Estimation," *Marketing Science*, vol. 26, no. 6, pp. 805–818, Nov. 2007.