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MODELS FROM PSYCHOLOGY AND MARKETING APPLIED TO KANSEI ENGINEERING

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ABSTRACT

This paper considers new models from Psychology and Marketing that extend the general Kansei approach. We sketch a framework that views design as understanding (1) the consumer's representation of the product space, (2) the consumer's choice function, (3) the designer's representation of the design space, (4) the designer's choice function, and a connection between those four properties. This framework helps organize some existing methods and points to areas ripe for development of new models.

Keywords: Psychology, Choice, Multivariate Analysis

1. INTRODUCTION

Kansei methodology provides a scientific basis for relating user-defined characteristics to engineering variables. The ability to convert user-defined concepts to concrete engineering attributes is an important aspect of any analytic design process that uses inputs from the end-user in a quantitative way. Kansei engineering uses several techniques from the social sciences and statistics, including multidimensional scaling (MDS), the semantic differential procedure and advanced regression techniques. In this paper, we bring modern methods from the social sciences, such as discrete choice models and mixture models, and methods from engineering, such as functional dependence table analysis, to relate user-defined characteristics to engineering attributes. We show how Kansei and related methods can model consumer choice and heterogeneity across consumers.

Traditional Kansei methodology has focused on the semantic differential procedure, which is an important tool from psychology for understanding meaning and concepts as defined by users. The typical analysis of semantic differential data uses techniques such as linear regression and

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factor analysis. Heterogeneity, allowing for variability across consumer or consumer segments, can be incorporated into the analysis by assigning consumers different values (e.g., this could be accomplished through random effect terms in a regression, random effect terms in the weights of an individual difference multidimensional scaling, or random effects terms for ideal points in multidimensional unfolding models). However, those techniques assume that meaning and concepts comprise a dimensional space. Modern psychological research has challenged this dimensional assumption and has suggested that semantic domains are represented better by tree structures, which impose a different structure on the data set. We briefly review tree structures, including tree models that allow for heterogeneity, and discuss their applicability in a Kansei approach.

It is important to relate both user concepts and engineering attributes to consumer choice. A consumer may be satisfied that the product design meets their concept, but the key business question is whether that individual will choose the product over other available products. Other attributes such as price, budget constraints, and variability of choice will factor into an individual's choice, which should be considered in the firm's decision to pursue the project (e.g., if manufacturing costs make the product too expensive for consumer's budget constraints, then even a product that meets Kansei criteria may not be profitable to bring to market). This suggests the need for richer models that incorporate additional information into product design and a firm's decision making. We show how to use a discrete choice model to relate user concepts about perceived environmental friendliness of vehicles to engineering in a manner that uses consumer choice information.

The link between product characteristics and engineering attributes can be improved through techniques such as functional dependence table analysis. This technique helps to reduce the dimensionality of the characteristics $\times$ attributes matrix to identify the underlying structure of the design problem. The merger of subjective data with functional dependence table analysis provides an opportunity to develop new methods for model-based interdisciplinary design, an approach that connects user concepts, product characteristics, engineering attributes, and consumer choice. In this paper we review this general approach and discuss an example modeling user perception of vehicle craftsmanship that connects user perception to engineering attributes.

2. DEVELOPING A FORMAL REPRESENTATION: THE CHOICE FUNCTION FRAMEWORK

There are at least two choice models to consider in design: the consumer's choice of product and the designer's choice of design. The designer decides which designs to bring forward; the consumer decides which product to purchase. The key design research problem is to understand how the designer creates and chooses designs that will produce market share for the firm. Thus, the fundamental problem in design is to find the relation between two choice models: the designer chooses a design that she believes the consumer will likely choose. The design space is typically represented differently than the product space. A feature in design space (e.g., torque ratio) may not directly correspond to a feature in product space (e.g., vehicle sportiness), and vice versa. The designer considers design features and attributes, the consumer considers product features and attributes. Further, the dimensionality of the design space may not correspond to the dimensionality of the product space. The consumer may consider additional properties not present in the design space and not computable from the design features; the designer may consider features and attributes that are not considered by the consumer.

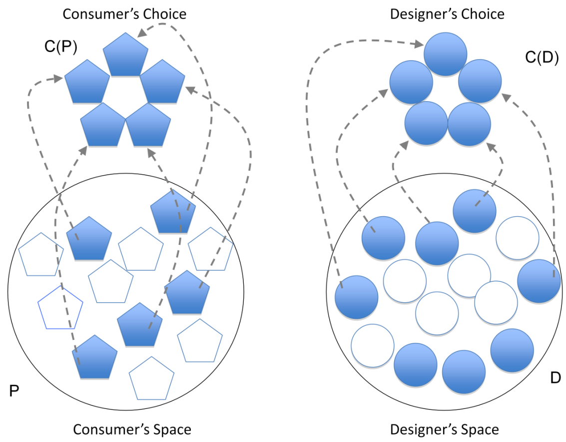

Figure 1: Fundamental Design Problem. How to link the designer's choices and their representation of the design space D with the consumer's choices and their representation of the product space P?

Choice models for the consumer are based on representing binary relations. For example, the choice of product a over b is represented with a binary relation $a \succ b$ endowed with particular properties such as transitivity. Behavioral decision theory models the binary relation $\succ$ using various formalisms, such as discrete choice models, multiattribute utility theory, preference maps, and unfolding models. Each of these models use continuous functions to represent the choice relation, thus are easier to work with when making predictions, or embedding into other frameworks such as the optimization models used in engineering design.

Formalism will provide clarity to the problem. We make use of theoretical results by Wakker [1] showing the connection between a choice function and a binary relation. A designer explores a design space D, which we consider as the set of feasible designs given the constraints of the problem. Likewise, the consumer considers a product space P, the set of possible products from which the consumer will choose given the consumer's constraints. The choice function $C()$ selects points in the set that is supplied as an argument. The designer's choice $C_d(D)$ is a subset of D. The designer is indifferent between the elements of the subset $C_d(D)$. Likewise, the consumer's choice is a subset $C_c(P)$ of the product set P, and the consumer is indifferent between the elements of $C(P)$. The choice function $C()$ may return a point, that is, only one item is chosen. We subscript the choice function C with either d or c to indicate that the choice function used by the designer or the consumer, respectively, may differ; that is, the designer may follow a different preference relation than the consumer. A different preference relation means the designer and the consumer have different indifference curves in their respective design or product spaces or that their binary relation may have different properties such as one may be transitive and the other not.

More structure can be added to this basic choice function framework. For example, rather than choosing from the design space D or product space P directly, the choice function C could operate on the set of "choice situations", i.e., choice objects are chosen in a context such as choosing one option from the subset {a, b, c} from D or choosing from the subset {a, b, e, f, "no choice"} in D. Thus, a choice situation S is an element of 2^D ($S \in 2^D$) and the choice function C is a mapping from S to 2^D. The superscript denotes the dimensionality of the respective space. One can impose constraints on the possible choice situations, which will be useful when an optimization framework is considered. Under standard regularity conditions, such as a nonempty set, Wakker [1] proved that the usual binary relation $\succeq$ one sees in the choice literature (a is preferred or indifferent to b) represents the choice function C.

One benefit of this formalism is that it provides some structure and understanding for the role of different data analytic techniques that have been proposed in Kansei engineering and other related methods that use social science techniques. For example, the following techniques provide information about the product space P: factor analysis of the semantic differential scale, multidimensional scaling of products and clustering of products. To make this point more concrete, we can impose more structure on the product set P and define it as the Cartesian product of k attributes. That is, the product set P can be formalized as a Cartesian product of k attributes $A_1 \times A_2 \times \ldots \times A_k$, so an element of product set P can be described in terms of the values on each of the attributes A_1 to A_k. Techniques such as factor analysis, principal components analysis (PCA), clustering and MDS are helpful at providing empirically-derived attributes, especially in subjective domains where there may not be *a priori* theory or knowledge to guide the researcher in well-defined attributes. This choice function framework shows that multivariate techniques such as factor analysis, MDS, PCA and clustering can inform us about the structure of product set P. Further, the choice function framework shows that MDS, PCA and clustering do not tell us a key piece of information–what will people choose? These techniques tell us about the structure of the product space P but do not inform us about the choice function $C_c(P)$, which is a key limitation of those "off the shelf" statistical techniques. Our reading of the literature is that Kansei is concerned with understanding the structure of the product space P as well as the choice function $C(P)$, but it is this later concern about the consumer's choice function that we believe still requires additional research since it is missing from techniques such as the semantic differential. Some multivariate techniques such as unfolding models attempt to model both the space of objects as well as the choice function on the objects. For a recent attempt at modeling choice and preference from a Kansei approach using rough set theory see [2].

The choice function framework illuminates the role of various discrete choice models (used in marketing, decision making and some areas of engineering) that are currently used in design research. Using the product set $A_1 \times A_2 \times \ldots \times A_k$ and making additional assumptions about the structure of the choice function C, one can derive, say, the logit choice model. Here the utility of an element of the product set P, called p, is modeled as an additive combination of the attribute utilities

$$u(p) \quad = \quad u_1(a_1) + u_2(a_2) + \ldots + u_k(a_k)$$

where the utility of the product p is defined as an additive combination of attribute-wise utilities. The utility $u(p)$, defined on the real line for a single product, can be construed as the value assigned to the product p. This additive utility function imposes requirements on the binary choice relation

$\succeq$ such as monotonicity in each attribute. This additive utility is then transformed to a "choice probability" (i.e., utility is transformed to the closed 0,1 interval) using the following formula over the subset of products under consideration

$$\text{Prob}(p) = \frac{\exp(u(p))}{\sum(u(p_i))}$$

In the context of the present choice function framework, the logit model provides one definition of the choice function C.

An important observation is that the attribute structure of the product space must already be known in order to apply the logit model. We need to know the attributes in advance to estimate the utilities, or part-worths. This is implicit, for instance, when one performs a conjoint analysis to estimate the parameters of the logit model–it is necessary to have the attributes defined in advance to manipulate their values in the context of a conjoint survey and its associated experimental design. Thus, there is an opportunity to develop new choice models that simultaneously estimate the dimensions of the product space P, and estimate the choice function $C_p(P)$, for designs that don't currently exist. A good potential technique is a variant of PREFMAP [3] but many other approaches are possible.

The discrete choice literature has recently been concerned with heterogeneity. This allows for consumers to have different utility functions. In the present formalism, heterogeneity in the choice model amounts to having unique choice functions for each consumer, or $C_p^c(P)$. The superscript c on the function C denotes that one consumer c may follow a different choice function than another consumer. Of course, there are subtleties about whether the variability across consumers is defined in terms of the structural model of the consumer (such as different utility functions on a particular attribute, which is considered an individual difference on the systematic part of choice) or defined in terms of random effects (such as a stochastic term that produces individual differences). For our purposes, the distinction between structural and stochastic is immaterial because both lead to the same modeling outcome of superscripting the choice function C by the consumer c. Different versions of discrete choice models can allow for complete heterogeneity (each consumer has his or her own unique choice function) or can define subsets of consumers (or what are called latent classes or segments or mixture models where individuals within the segment are modeled as having identical estimates but heterogeneity is permitted across a finite number of classes). Intuitively, one can view a random effects discrete choice model as the limiting case of a latent class model where each class contains a single consumer. The general choice function framework presented here is not limited to the heterogeneous logit choice model–the framework can invoke any model that represents the consumer's product choice $C(P)$.

There has been an attempt in the psychology and marketing literature to develop techniques that simultaneously assess the structure of the product set P and the choice function $C(P)$. One such model is PREFMAP, which merges a multidimensional scaling approach with a choice model. Another is the general class of unfolding models that model simultaneously both the dimensional structure of the product set P and the choice function $C(P)$, e.g., [4]. Extensions of unfolding models that permit heterogeneity have been proposed and are currently in development. Overall, these models that attempt a simultaneous estimation of P and $C(P)$ are difficult problems and much work is needed to develop better algorithms. Thus, a major area of research is understanding the connection between the product space P and the choice function $C(P)$. Kansei ideas can continue to play a role in facilitating answers to these important questions.

2.1. Kansei Engineering: Linking Consumer and Designer Choice

Kansei uses techniques to understand the attributes and dimensionality of how products are represented, with the hope of connecting that information to the design process. In traditional Kansei there is an attempt to assess both the subjective attributes of a product and its objective properties. An example is from Tanouet, Ishazaka and Nagamachi [5], who performed a Kansei engineering analysis on the interior of a vehicle. Participants were shown the interiors of 20 vehicles (sedans and coupes) and asked to respond to a semantic differential scale. This type of scaling uses a factor analytic technique to reduce the dimensionality of the data. The resulting dimensions then need to be interpreted. Correlations with objective measures provide one way to define the factors that emerge from the statistical analysis. For example, if the data reduction suggests a dimension of "roominess" from the semantic differential data collection, then objective measurements of the interior can be correlated with the subjective factor that emerges from the factor analysis. It is necessary to test with objective data the interpretation of the factors or dimensions, otherwise the dimensions remain subjective, vague and poorly defined.

Kansei is a systematic method to relate (a) the subjective attributes that emerge from a dimensional reduction of rating scale data and (b) the more objective design variables that can be measured. For example, in a vehicle interior one can measure distances, or quantify the shape of the instrument panel and the size of the instrument cluster. This method is good at identifying the dimensions that a consumer may use to classify and comprehend the differences across existing products. But connected to the choice function framework introduced in the previous section these advances reside mostly in our understanding of the product space P. The traditional Kansei view addresses primarily (but not exclusively) the question: How does a consumer represent the products and what are the design features of those products? Kansei, in the published literature at least, focuses less on the question: Which product does the customer choose?

While Kansei engineering has made many contributions to the engineering design literature, there remain two main areas that still require more attention in order to realize Kansei's full potential. One issue is to expand the approach to identify underlying dimensions that guide a consumer's perception and that links to choice $C(P)$. A consumer may use "perceived roominess" of a vehicle interior as one dimension to categorize the vehicles that are presented in a Kansei study, but the question that matters at the end of the day is which vehicle the consumer chooses to purchase. Due to budget constraints, vehicle storage constraints, transportation and hauling requirements, or any number of other concerns, the consumer may choose a vehicle using a choice procedure that is not necessarily guided by their perceptions of roominess. Techniques such as PREFMAP and unfolding analysis will be helpful in addressing this choice problem and the representation of the consumer product space. Thus, they will be useful tools to add to the Kansei toolbox.

The second issue is that the semantic differential as it is typically used in an engineering design context is limited if one seeks information about new designs. One typically performs a semantic differential on products that currently exist, or perhaps new products can be shown as sketches or described verbally as a set of features. Is the consumer's thinking, or "sensing," limited by presentation of existing products in a semantic differential? Is the consumer's conceptualization in terms of possible functions and uses of the product limited by the semantic differential procedure?

An analogous limitation occurs at the level of the designer as well. The designer seeks to find new attributes that have yet to be considered, search new regions of the design space D, push the envelope on possible new functions of the design, etc. Is the designer constrained by examining the perceived dimensions of existing products? Is the designer's search constrained when using data from a traditional semantic differential procedure?

There is a need for the creation of tools that allow the measurement of the product space P and the choice $C(P)$ in a manner that can be linked to the search of the design space D so the designer can select optimal designs $C(D)$. Ideally, the method would work in real time so that the consumer's product space P and the designer's design space D, as well as their respective choice functions $C()$, can be simultaneously explored. For instance, a set of designs could be generated and presented to the consumer for evaluation. Then, subjective data from the consumer could be collected and analyzed, with that information used to search the design space D to produce new designs. The process iterates until the designer understands the design and product spaces and also understands the consumer's choice function. Of course, the choice of the designer $C(D)$ could be formulated as an optimization problem under a set of constraints. An analogous method was described by Nagamachi [6].

3. ILLUSTRATIONS OF CONSIDERING BOTH DESIGN AND PRODUCT SPACE

In our own design science research we have used two additional procedures for simultaneously exploring the product and design spaces. One method uses a genetic algorithm to present stimuli to consumers. In one toy demonstration using bottle shape, a doctoral student Jarod Kelley [7], developed an algorithm defined in terms of physical dimensions along with some constraints related to feasible designs (such as the bottle has to have a sufficiently wide base to remain upright); that is, it is defined with respect to design space D. The algorithm displays these designs to the consumer in the form of visible bottle shapes (product space P). Through a series of repeated presentations the genetic algorithm identifies the properties of the consumer's choice function $C(P)$. Given that the algorithm has also defined these shapes in terms of the design space D, the end result of the consumer's choices $C(P)$ is understood immediately in terms of the characteristics of the design space D.

In a second attempt at making the link between P, $C(P)$, D and $C(D)$, we developed a web-based survey methodology that can be used to present products to consumers to assess their choice $C(P)$ in a form that relates back to the engineer's design variables [8]. The demonstration of this technique involved 2-dimensional vehicle silhouettes. A design of experiments using engineering control points created a set of candidate designs that was represented as two dimensional vehicle silhouettes to potential consumers in the context of a web-based survey. The data were used to generate new candidate designs predicted to be more preferred than those designs in the original web-based survey. Those new designs were then presented to consumers to validate that they were indeed more preferred designs, or rated higher on particular dimensions such as "perceived environmental friendliness", than the designs in the original set. This research showed that it is possible to take a new attribute such as "perceived environmental friendliness," which is not currently well-defined in terms of objective criteria, collect specialized data from consumers, relate the consumer's subjective data to engineering variables to create new designs, and link that to the stated preferences of the consumer.

In all data analytic techniques one needs to ensure that the assumptions of the model one uses are consistent with the phenomenon one is modeling. So far in this paper we have characterized the prototypic case of using the semantic differential and factor analysis. There are other analytic techniques depending on whether the data are qualitative and there are different categorization frameworks such as the Kohonen self-organizing map (see [5] for examples). Our point is that matching the analytic technique to one's type of data is one step in the right direction, but there is an even more important step—matching the assumptions of the technique with the phenomenon being modeled. Most factor analytic and classification techniques rely on some notion of distance. The assumption is that there is a psychological metric space in which products are represented as points. Techniques such as PCA, factor analysis, and multidimensional scaling each assume a particular metric, usually Euclidean distance, though other metrics are possible. The use of a distance metric makes assumptions such as symmetry (the perceived distance between product A and B is the same as the perceived distance between product B and A) and the triangle inequality (the distance between A and B is constrained by the distance of A and C and the distance between B and C).

There is much evidence in the psychological literature that such assumptions do not hold, especially with semantic dimensions [9]. Similarity judgments are frequently asymmetric: the similarity of the father to the son is not the same as the similarity of the son to the father. It appears that some domains such as color are consistent with the metric assumptions, but domains that are categorical or semantic tend to violate the metric assumptions. New techniques that do not make the standard metric assumptions have been proposed. In one of the more well-known versions, similarity is defined with respect to a weighted combination of feature sets. Each product has a set of features. The similarity of product A to B is represented as a weighted combination of features unique to A, features unique to B, and features common to both A and B. The weights on each of those subsets of features allows for additional psychological effects such as emphasis on common features versus distinctive features (such as when one asks a "how different are these products from each other" versus a "how similar are these products to each other" question). This method can be represented using an additive tree clustering structure as opposed to the more common hierarchical clustering method [10].

It is important to check the assumptions of one's models. Standard models used with behavioral data make many assumptions that are important not only for making statistical inferences (including estimating parameters, confidence intervals and statistical tests), but also because the assumptions frequently have substantive implications. If data suggest that consumers' violate symmetry, then it is not possible to use modeling methods that invoke a distance representation (such as factor analytic techniques) and more importantly it opens the door to explore to new models of how consumers represent the product space.

4. CONNECTING THE SUBJECTIVE WITH THE OBJECTIVE

The issue of the underlying assumptions of the analytic model and its relation to the phenomenon under investigation is an important aspect of any model of consumer choice and engineering design. Some Kansei researchers have used clustering techniques in their analysis. For example, [11] and [12], who describe a clustering method used to design a roadster for Mazda. They claimed that "[t]his Kansei engineering method is very effective and efficient to find out the relationship between customer's Kansei and product design specification" (p. 764). But how does one move from the language of the customer to the language of the designer (space P to space D)? How does one convert the language of the consumer into actual design variables with a clear direction of what needs to be done in the design to meet the consumer's needs and preferences [6]? An example used in the Kansei literature [6] is one of hair care products where Kansei techniques suggest a particular desire among female consumers to have the hair product make them "feel like a queen." This may be useful information by itself but what is the designer supposed to do with this information from the consumer? What design attributes should be examined or added in order to produce such a feature in the product? Is this too vague to be useful in design? Will different designers interpret this information in different ways? Is there an analytic procedure that can facilitate the connection to design variables? How should the subjective statement "feel like a queen" be operationalized in the context of an analytic engineering design problem?

A recent paper examined the subjective and vague category of "craftsmanship" [13]. The research showed that, using an industry-based tool to assess craftsmanship, there was little agreement across raters of vehicle interiors and there were no interpretable dimensions or clusters that emerged using MDS and clustering analyses on these perception variables. We developed a more concrete set of attributes to rate the craftsmanship of vehicle interiors. This set followed from a functional dependence table analysis linking objective design characteristics (such as gap size, drop angle of glovebox lid, compressibility of components) to perceived attributes such as stitching quality, material sound response, and usability of glovebox. A functional dependence table contains binary entries in each cell, with rows indicating perceived attributes and columns indicating design characteristics. An entry of 1 in cell i,j indicates that the characteristic j is relevant to attribute i. This binary matrix can be partitioned. We were able to achieve acceptable cross-rater agreement in the evaluation of craftsmanship using the newer list of clearly defined attributes. Further, the attributes (described in product space P) were linked directly to design attributes (which were described in design space D), providing a link between what the consumer wants and a list of attributes the designer can use.

5. DISCUSSION

The Kansei approach has already contributed much to our understanding of engineering design, the user experience and how to link the two. But we believe that major contributions from this approach are still to come. We provided some possible new directions for analytic tools and some suggestions for directions one can take for adding more tools to the Kansei toolbox. These tools rely on new developments in the social sciences that provide more realistic models of customer preference and customer perception.

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