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MODELING CUSTOMER PERCEPTIONS OF CRAFTSMANSHIP IN VEHICLE INTERIOR DESIGN

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ABSTRACT

The craftsmanship concept in vehicle interior design is explored in a quantitative manner. A proprietary process by Johnson Controls, Inc. was used as a basis to investigate customer perceptions through surveys. A list of vehicle interior characteristics and perceived craftsmanship attributes was developed and analyzed using multidimensional scaling, cluster analysis, and decomposition. Designers can use this list to guide their work and anticipate customer satisfaction due to high quality craftsmanship.

KEYWORDS

Craftsmanship, customer perceptions, agreement measures, multidimensional scaling, cluster analysis, vehicle interior design

1. INTRODUCTION

Craftsmanship is defined as the technique, style, and quality of working (Roget's 1995). Craftsmanship is a property that gives the product the appeal of being well made and well functioning at its very early interactions with the customer. In the automotive business, craftsmanship is often associated with high scores on the JD Power ratings. However, it is not obvious how design engineers can make everyday decisions based on such ratings or decisions that may increase subsequent ratings. Craftsmanship should be linked to discernible design attributes, as much as possible, and attribute interactions should be included in the models. Clearly, complex human feelings play a major role in forming impressions, and thus much will remain outside our ability to formalize and quantify craftsmanship. Nevertheless, analyzing and organizing user preferences employing methods from cognitive mathematical psychology in a manner that design engineers can use is worthwhile and is the main focus of this article.

The concept of craftsmanship includes attention to detail, material selection, careful workmanship and innovative product design (Wang and Holden, 2000). Several studies show that craftsmanship plays an important role in consumer perception of quality (Sherman, 1989; Winter, 1997, Ganguli et al., 2003). The literature on customer preferences and perceptions includes studies that employ quality function deployment (Vairaktarakis, 1999; Askin and Dawson, 2000; Yang et al., 2003), kansei engineering (Jindo and Hirasago, 1997; Tanoue et al., 1997; Nagamachi, 1999; Tsuchiya et al., 1999; Hsu et al., 2000), multidimensional scaling (Hooley, 1984; Kamoshita and Yano, 1984; Rao and Lohse, 1993; Lin et al., 1996; Zhang et al., 1996; Hsiao and Wang, 1998; Kleiss and Enke, 1999; Mojsilovic et al., 2000; Chuang and Ma, 2001; Yannou and Petiot, 2002), cluster analysis (Toms et al., 2001), and conjoint analysis of consumer data (for a review, see Green and Srinivasan, 1978, 1990).

Liu (2000) points out the need of adding aesthetics to the field of human factors, and recognizes the lack of systematic, scientific and engineering methods to help designers study aesthetic concepts and incorporate them in design decisions. MacDonald (2001) discusses the concept of "aesthetic intelligence": people's innate, often subconscious, ability to perceive a wide range of qualities in products that shape our responses to them. He links sensorial qualities to cultural values and proposes a process of designing for the senses to create products with which customers can feel a greater degree of empathy.

Other than the basic ideas for methods such as multidimensional scaling and cluster analysis, the above referenced work is not directly related to the present investigation. In some recent work, Wang and Holden (2000) studied the craftsmanship issue in automotive products and proposed a methodology for craftsmanship assessment. They examined the influence of consumers' demographic backgrounds on their craftsmanship assessment and found that gender, age and education were not significant factors impacting the craftsmanship assessment. Their approach is similar to the starting point of the present study, which was proprietary material developed at Johnson Controls Inc. (JCI) involving a vehicle assessment process. Various vehicle attributes are given scores through human inspection, like a showroom experience, rather than derived from physical measurement instruments. Unlike a typical vehicle buyer, however, a team with calibrated observational skills systematically combs the complete interior for assessment of attributes.

In what follows we describe the evolution of a craftsmanship attributes checklist tuned to engineering designers' expectations. A pilot study is described, followed by analyses (correlation, multidimensional scaling, cluster, decomposition) and a second study that confirms the efficacy of the proposed approach. This is an exploratory study to investigate the link between craftsmanship perceptions and engineering decisions, and does not test a specific theoretical framework. A theoretical formulation is expected to emerge as this investigation matures.

2. EARLY ANALYSIS

Previous work has shown that perception differences exist between designers, engineers and customers (Hsu et al., 2000). Therefore, investigation of customer perceptions must be studied first in order to provide the appropriate attributes to the designers. A good attributes checklist should have acceptable consistency of attribute values throughout the population of subjects.

2.1. Pilot survey

An initial list of attributes was created and a pilot survey was conducted with the following questions: (1) Are the interpretations of the attributes consistent among people? (2) If yes, what are the underlying dimensions of the craftsmanship concept?

Five male, graduate student mechanical engineers participated at the survey. The main reason for this selection is to reduce noise in the data resulting from gender, background and age differences. This limits the generality of the results but it is sufficient for the initial study. Participants were asked to complete two types of tasks. In the first task the subjects were presented six vehicle interiors. They were asked to evaluate these interiors along the attributes of the checklist on a 7-point Likert scale. A sheet with short attribute explanations was provided as well. The goal was to test the consistencies among people's perceptions, i.e., whether or not people who were presented with the same vehicles rated them in the same order. In the second task the subjects were asked to sort the attributes written on cards into piles according to any criterion that makes sense to them. For example, one subject could group "gaps" into the same pile as "color harmony", because he thinks that both relate to visual impressions. Another subject, however, might group them into different piles, because he thinks that "gaps" is an assembly problem, whereas "color harmony" is a purely subjective matter of aesthetics. Each subject was allowed to create as many piles as they wanted (but more than one and less than the total number of the attributes). The collected survey data were used for three different analyses: correlation, multi-dimensional scaling and cluster analysis.

2.2. Gamma measure of agreement

A somewhat liberal measure of agreement, usually called gamma (Goodman and Kruskal, 1963), is an index of monotonic agreement between a pair of ratings in the following sense. Suppose Rater A gave a vehicle a lower rating on color harmony than on gaps (e.g., 5 on color harmony, and 6 on gaps), and Rater B also gave the vehicle a lower rating on color harmony than on gaps (e.g., 3 on color harmony, and 5 on gaps). These two pairs of ratings are called concordant because the two raters assigned consistent order ratings on these two attributes. Ratings are discordant when they do not have this property. The gamma measure is a normalized difference of the total number of concordant pairs and the total number of discordant pairs over all possible pairwise comparisons of attributes between two raters. The gamma index ranges from -1 (perfect ordinal inconsistency) to 1 (perfect ordinal consistency).

Table 1 Average gamma values for each vehicle

Vehicle	Average Gamma
Toyota	-0.09
Saab	0.01
VW	-0.05
Nissan	-0.09
Chevy	-0.09
Honda	0.11

There exist other measures of agreement, such as absolute agreement, which counts the proportion of times two raters each assign exactly the same rating on an attribute, but we believe that the other measures are too conservative a criterion given the ordinal nature of the seven point response scale (ranging from failure to excellent). A reliable rating index should yield near perfect ordinal consistency. Many domains in social sciences do yield near perfect consistency measures between pairs of raters, so we know that it is possible for people to agree about relatively "fuzzy" or vague concepts.

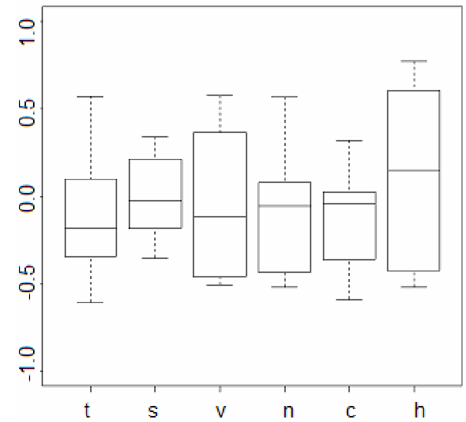
Survey results are shown in Table 1 and Figure 1. For each vehicle we computed gamma between all possible pairs of raters. Table 1 presents the average gamma (over the 10 observed gammas for each pair of raters) for each vehicle. All gammas are close to zero, which suggests no concordance between two raters. No pair of raters consistently agreed over the 40 ratings over the six vehicles in the study. For example, a pair of raters that showed moderate agreement on the VW (gamma = 0.57) showed moderate disagreement on the Honda (-0.52) and virtually no agreement on the Saab (gamma -0.02).

In Figure 1 gammas are summarized in a standard boxplot developed by John Tukey (Wu and Hamada, 2000). A boxplot displays the 1st and 3rd quartile (ends of the rectangle), the median (horizontal line inside the rectangle), and outliers ("whiskers" that emerge from the rectangle). All medians are around zero with relatively wide ranges, suggesting a relatively high degree of variability around the lack of agreement.

2.3. Multidimensional scaling (MDS) and cluster analysis

The possible design "dimensions" of craftsmanship were explored next. A multidimensional scaling analysis (MDS) was applied to the survey data. MDS represents measurements of perceived dissimilarity among pairs of stimuli as distances between points of

Figure 1 Boxplot of the gamma distribution for Toyota, Saab, VW, Nissan, Chevy and Honda



a low-dimensional space. It uses proximity values, i.e. how similar or dissimilar two objects are perceived to be among any kind of objects, as input, and produces a spatial representation, consisting of a geometric configuration of points, as output. Each point in the output configuration corresponds to one of the given objects. The larger the dissimilarity between two objects, the further apart they would be in the spatial configuration (Chen et al., 2001). Useful insights generally result from simply looking at the arrangement of points to discover the dimensions that underlie judgments of dissimilarity. In the present context, the emerging dimensions can be interpreted as perceptual dimensions that characterize craftsmanship.

Binary dissimilarity information was used to analyze the survey data, i.e., attributes grouped into the same pile were defined as similar (0), and attributes grouped into separate piles as dissimilar (1). The data collected from five subjects provided five binary dissimilarity matrices. The matrices of each subject were then added to create the total dissimilarity matrix. The MDS analysis was conducted from two to six dimensions with no meaningful results, suggesting high attribute ambiguity.

Cluster analysis was also applied to the dissimilarity data. Cluster analysis joins stimuli together into successively larger clusters, using some measure of dissimilarity or distance. Cluster members share certain properties and the resultant classification may provide insights by reducing the dimensionality of the data set. The agglomerative technique was used here (Kaufman and Rousseeuw, 1990). The method starts when all objects are apart, i.e., at Step 0 we have n clusters, where n is the number of stimuli. At Step 1, the two objects with smallest dissimilarity are joined, leaving n-1 clusters, one with two objects and the rest with one. In subsequent steps, two clusters are merged again, until only one is left.

Cluster analysis of the survey data set did not result in meaningful clusters, i.e., attributes clustered together did not seem to share implicit or explicit properties, again signaling high ambiguity in the attribute interpretations.

3. CRAFTSMANSHIP CHECKLIST

Lack of agreement among relatively knowledgeable subjects, who were engineers but responded as customers led to a deeper study of the requisite design attributes. Admittedly, the original scale was not intended for use by consumers. The lack of agreement found in the pilot survey suggests that a new instrument will likely be needed in order to assess customers' perception of craftsmanship.

3.1. Craftsmanship attributes and product characteristics

The first step was to refine craftsmanship attribute definitions by expressing them in terms of measurable quantities as much as possible. Both JCI and JD Power attributes were used. An example is given in Table 2.

The next step was to introduce a distinction between "product characteristics" and "perceived attributes." Quantities directly measurable and manipulated (e.g., "number of buttons on the dashboard") are called product characteristics, whereas a perceived attribute is a more general concept resulting from assigning values to two or more product characteristics (e.g., "stitching quality"). This distinction serves to express craftsmanship in terms of product characteristics, which in turn can be expressed in terms of the product characteristics. If such a mapping could be established it would enable designers and engineers to "control" craftsmanship by directly changing product characteristics. Following this idea craftsmanship can be represented as a function of perceived attributes f_i, which are functions of the product characteristics **x.** Each attribute provides a weighted contribution as follows.

Table 2 Example: proposed quantities to replace the attribute "gaps"

Gaps:
-Number of gaps
-Gap size
-Variation between gaps within grouping
-Variation within each gap
-Number of gaps not covered in swing positions
-Number of interference fits for soft-trim surfaces
-Number of self-centering stops to align 'at-rest' position

$$C = \sum_{i=1}^{k} \omega_i f_i$$
$$f_i = f_i(\mathbf{x}) \qquad (1)$$
$$\mathbf{x} = (x_1\ x_2 \ldots x_n)^T$$

where

C: craftsmanship index (level of craftsmanship value)

f_i: perceived attributes, which contribute to craftsmanship

ω_i: weights that define how much each attribute contributes to craftsmanship

x: vector of product characteristics

k: number of perceived attributes

n: number of product characteristics

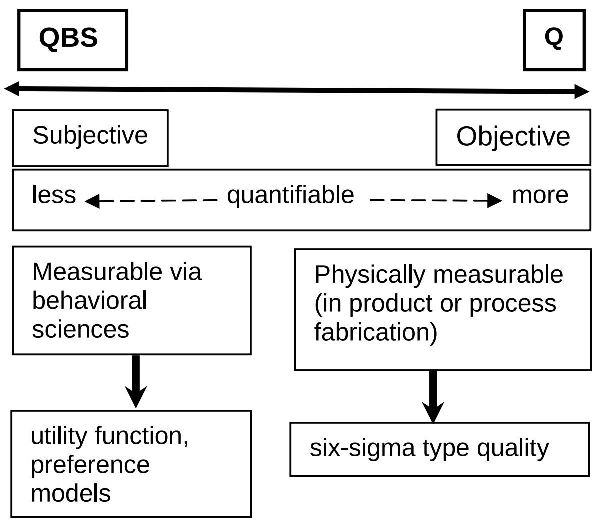
Note that this model assumes linear superposition of the perceived attributes, and is only one simple way to combine them. Also note that, though omitted from the above formalism, the perceived attributes are functions of customer characteristics as well as of product characteristics. This makes the problem further subjective; for example, the difficulty of reaching controls or the perception of the stitching quality will depend on the individual user.

3.2. Quantification scale

Product characteristics can be placed on a "quantification scale," according to how well they can be quantified, Figure 2. Characteristics physically measurable (e.g., "volume of the glovebox") are called "quantifiable" and denoted with a Q; characteristics measured to a certain degree using behavioral sciences methods (e.g., "similarity of tactile feel") are called "quantifiable in behavioral sciences" and denoted with QBS.

"Statistical" characteristics denoted with an S, are statistically quantifiable, meaning that their mean values and standard deviations are taken as measures (e.g., "deviation within multi-seam alignments"). The

Figure 2 Quantification scale

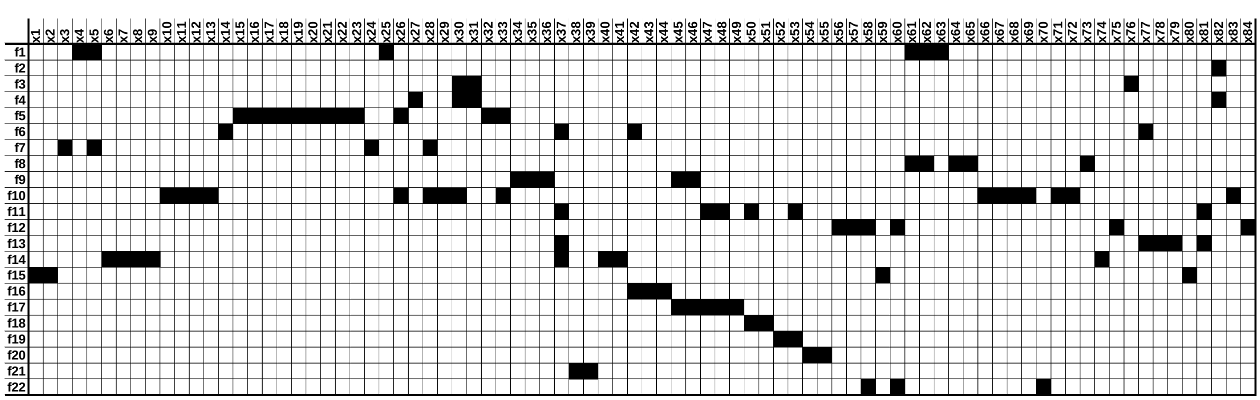


objective here is to classify as many characteristics as possible into the "quantifiable" category, because they are easier to address in a repeatable manner. Also, because the eventual goal is to quantify customer preferences and relate them to engineering decisions, the units used to measure each product characteristic and the direction of desired improvement (to maximize, minimize or optimize) for each attribute and product characteristic have been added to the list. For the QBS product characteristics the column for the measurement unit is left blank. The complete list of perceived attributes is given in Table 3 and a partial list of product characteristics in Table 4. There are a total of 22 perceived attributes and 84 product characteristics considered in this study.

Table 3 Complete list of perceived attributes

#	Name	Direction
f_1	Ability to easily discern where all controls are located	max
f_2	Material sound response	min
f_3	Component feel/sound of activation/ engagement (Seatbelts, doors, buttons)	max
f_4	Buzz, squeak, and rattle (BSR)	min
f_5	Stitching quality	max
f_6	Adjustability of components	opt
f_7	Shape harmony	max
f_8	Color harmony	max
f_9	Storage space in front console	opt
f_{10}	Visibility of mechanical elements & manufacturing distortions	min
f_{11}	Component/passenger interference	min
f_{12}	Material quality	max
f_{13}	Seated comfort	max
f_{14}	Difficulty reaching controls, lights, seatbelts	min
f_{15}	Consistency of tactile feel	max
f_{16}	Usability of vents	max
f_{17}	Usability of glovebox	max
f_{18}	Usability of door pockets	max
f_{19}	Usability of sun visors	max
f_{20}	Usability of cup holders	max
f_{21}	Usability of trunk	max
f_{22}	Quality of finishing	max

Figure 3 Functional dependence table



3.3. Functional dependence table

To examine the interactions between product characteristics and perceived attributes a functional dependence table (FDT) is created (Wagner, 1993). The FDT for the craftsmanship checklist is given in Figure 3. It provides a visual representation of the functional dependences: dark cell indicates dependence of f_i on x_j and empty cell indicates independence. When the FDT has large dimensions and sparsity (empty space), an abridged FDT is visually helpful, as in Table 5. In this table each line f_i (representing the *i*th attribute in the checklist) is a function of the following x_j's (representing the jth characteristic in the checklist). For example, f_{20} is a function of x_{54} and x_{55}.

3.4. Partitioning of the FDT

A large complex problem is often easier to analyze if it can be decomposed into smaller subproblems. In the case of craftsmanship it is interesting to see if attributes and characteristics can be grouped together based on their interrelations. Such decomposition may be obtained via partitioning of the FDT (Wagner, 1993). The partitioning process groups the functions (the perceived attributes) together based on their shared variables (the product characteristics). Each block defines a subproblem. Variables belonging to more than one subproblem are the linking variables. The partitioning process aims to minimize the number of linking variables, i.e. to separate the subproblems as much as possible. When a large problem is divided into smaller subproblems and decisions are made about the linking variables, the subproblems become independent and can be handled separately, Figure 4.

To gain more insight of the overall structure of the craftsmanship problem, an initial partitioning was performed on the FDT specifying the number of subproblems from two to ten. Using higher numbers of subproblems resulted in at least three linking variables. Therefore, it was determined that the best

Figure 4 Partitioning of a master problem into subproblems

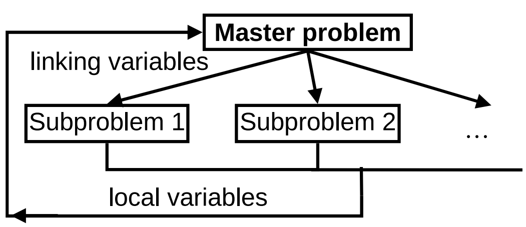


Table 4 Partial list of product characteristics

#	Type	Name	Direction	Unit
x_1	QBS	Consistency of button / knob activation feel within grouping	max	
x_3	Q	Number of different geometries for buttons and knobs	opt	#
x_4	Q	Number of buttons and knobs	opt	#
x_{10}	Q	Number of gaps	min	#
x_{11}	Q	Gap size	min	mm
x_{12}	S	Variation between gaps within grouping	min	mm
x_{13}	S	Variation within each gap	min	mm
x_{17}	S	Deviation within multi-seam alignments	min	mm
x_{18}	Q	Number of radius sews on A-surfaces causing cover tension and wrinkles	min	#
x_{31}	Q	Number of unsecure component fastenings	min	#
x_{32}	Q	Number of places where tautness in materials shows stitch holes	min	#
x_{47}	Q	Drop angle of glovebox lid	opt	rad
x_{48}	Q	Drop speed of glovebox lid	opt	rad/s
x_{49}	QBS	Accessibility of glovebox from driver's side	max	
x_{57}	Q	Number of places where different materials have to mimic the same grains	min	#
x_{59}	QBS	Similarity of tactile feel between similar components	max	
x_{64}	Q	Number of similar components (having the same texture and form) that do not match in color	min	#
x_{66}	Q	Number of visible internal components that could have been masked with matt black coloring	min	#
x_{67}	Q	Number of visible mechanical elements and exposed fasteners	min	#
x_{69}	Q	Number of places where carpets and other finished surfaces do not extend far enough into visible areas	min	#
x_{72}	Q	Number of visible parting lines	min	#
x_{75}	Q	Number of places for potential wear paths from interactions between components	min	#
x_{80}	Q	Compression uniformity among similar components	max	N/m
x_{81}	Q	Compressibility of components where body contacts regularly and for prolonged time	opt	N/m

Table 5 Abridged functional dependence table

f_1	x_4 x_5 x_{25} x_{61} x_{62} x_{63}
f_2	x_{82}
f_3	x_{30} x_{31} x_{76}
f_4	x_{27} x_{30} x_{31} x_{82}
f_5	x_{15} x_{16} x_{17} x_{18} x_{19} x_{20} x_{21} x_{22} x_{23} x_{26} x_{32} x_{33}
f_6	x_{14} x_{37} x_{42} x_{77}
f_7	x_3 x_5 x_{24} x_{28}
f_8	x_{61} x_{62} x_{64} x_{65} x_{73}
f_9	x_{34} x_{35} x_{36} x_{45} x_{46}
f_{10}	x_{10} x_{11} x_{12} x_{13} x_{26} x_{28} x_{29} x_{30} x_{33} x_{66} x_{67} x_{68} x_{69} x_{71} x_{72} x_{83}
f_{11}	x_{37} x_{47} x_{48} x_{50} x_{53} x_{81}
f_{12}	x_{56} x_{57} x_{58} x_{60} x_{75} x_{84}
f_{13}	x_{37} x_{77} x_{78} x_{79} x_{81}
f_{14}	x_6 x_7 x_8 x_9 x_{37} x_{40} x_{41} x_{74}
f_{15}	x_1 x_2 x_{59} x_{80}
f_{16}	x_{42} x_{43} x_{44}
f_{17}	x_{45} x_{46} x_{47} x_{48} x_{49}
f_{18}	x_{50} x_{51}
f_{19}	x_{52} x_{53}
f_{20}	x_{54} x_{55}
f_{21}	x_{38} x_{39}
f_{22}	x_{58} x_{60} x_{70}

approach would be to use the result for two subproblems and apply a re-partitioning to each of them separately. The subproblems were then partitioned into two new subproblems each. Figure 5 shows the partitioned FDT, a rearranged version of Figure 3.

Figure 6 represents the final structure of the craftsmanship problems with four subproblems: SP1-1 contains visual, auditory and tactile perceptions; SP1-2 contains visual elements as well, but they are mostly "pure quality" issues; SP2-1 includes everything about overall comfort, whereas all the usability items are in SP2-2.

4. FURTHER ANALYSIS

Product characteristics were not used consistent with our earlier definition of attributes, and consumer decision theory stating that consumers compare products on the basis of attributes and not characteristics (Kaul and Rao, 1995).

4.1. Gamma results

A second survey that is identically structured as the first one was conducted using only the list of perceived attributes, with 9 subjects (male graduate engineering students) and 8 vehicles. The subjects were not provided with attribute explanations. The same set of analyses (Gamma, MDS and Cluster) was carried out. With nine raters there were 36 estimates of gamma for each vehicle and Table 6 presents the average vehicle gammas. Although the average gamma values do not seem high, they are much higher than the first survey results. All gamma values are positive pointing towards concordance, whereas in the first survey most of the gamma values were negative pointing towards discordance. The boxplot in Figure 7 shows that all the medians are above zero with relatively smaller ranges around them, compared to the first survey results.

Figure 5 Partitioned FDT

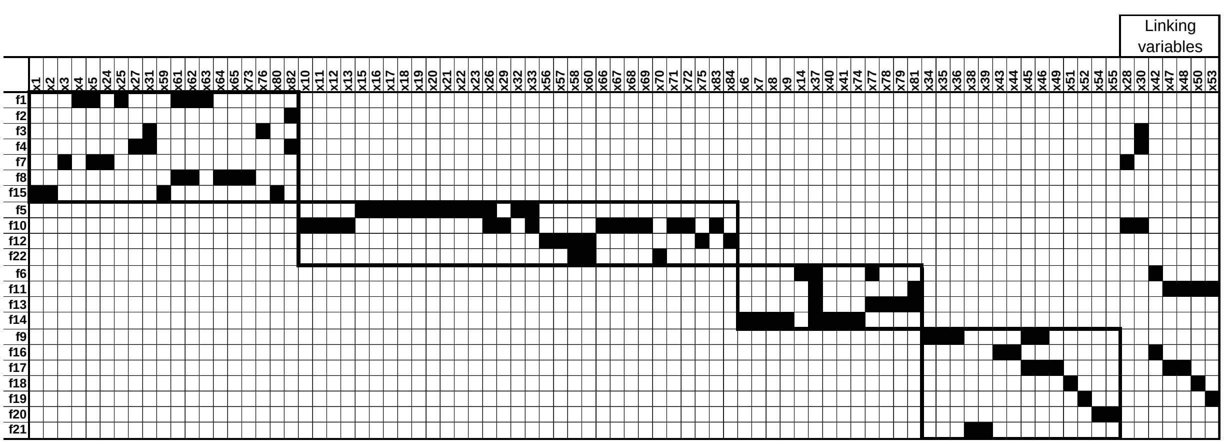
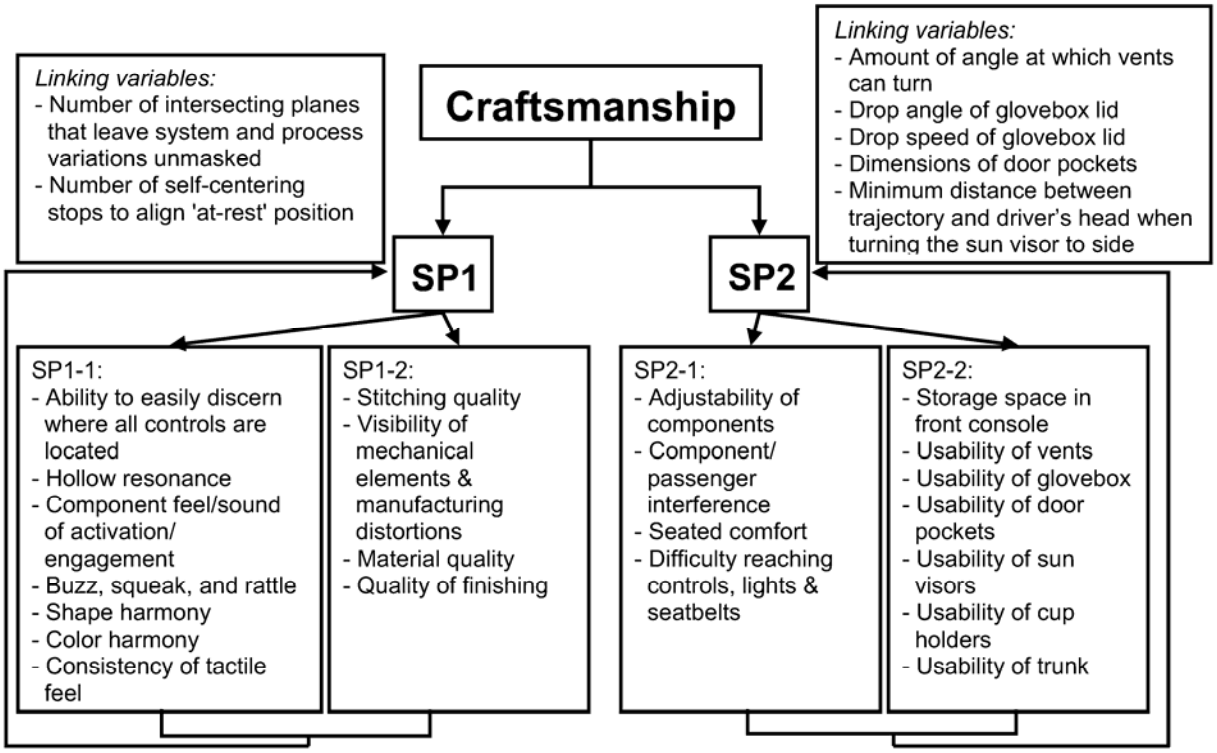


Figure 6 Structure of the craftsmanship problem (SP: subproblem)



4.2. Cluster analysis and MDS

Dissimilarity data for the cluster analysis were collected and analyzed similarly to the first survey described.

Four clusters were identifiable with a meaningful context. The first cluster contains all the auditory attributes; the second cluster relates to quality issues; the third cluster is about driving comfort and finally all the usability items belong to cluster four. Table 7 lists all the attributes in each cluster. Note that these clusters are close to the subproblems in the partitioned FDT. Cluster 4 completely overlaps with SP2-2. Cluster 3 includes all attributes of SP2-1 plus one additional attribute, and Cluster 2 includes all attributes of SP1-2 plus three additional attributes. Those additional attributes together with the

Table 6 Average gamma values for each vehicle

#	Vehicle	Average Gamma
1	Hyundai	0.34
2	Mercury	0.08
3	Ford Focus	0.28
4	Ford Taurus	0.03
5	Mazda	0.20
6	Nissan	0.26
7	Buick	0.11
8	Chevrolet	0.04

Figure 7 Boxplot of the gamma distribution for the eight vehicles

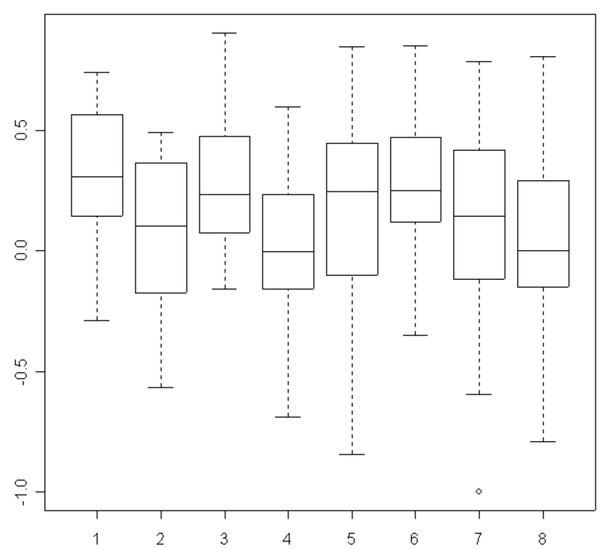


Table 7 Clusters of craftsmanship attributes

Cluster 1: Auditory attributes	**Cluster 2:** Quality issues	**Cluster 3:** Driving comfort	**Cluster 4:** Usability
- Material sound response - Component feel/sound of activation/engagement - Buzz, squeak and rattle	- Stitching quality - Shape harmony - Color harmony - Visibility of mechanical elements/manufacturing distortions - Material quality - Consistency of tactile feel - Quality of finishing	- Ability to easily discern where all controls are located - Adjustability of components - Component/passenger interference - Seated comfort - Difficulty of reaching controls/lights/seatbelts	- Storage space in front console - Usability of vents - Usability of glovebox - Usability of door pockets - Usability of sun visors - Usability of cup holders - Usability of trunk

attributes of Cluster 1 correspond to the SP1-1. This fact is interesting, because the partitioning of an FDT is purely mathematical, whereas cluster analysis employs perceptual data. The practical implication of this finding for engineers and designers is the following: in order to improve a particular aspect of craftsmanship perception (a cluster), an engineer can refer to the FDT to determine the product characteristics that relate to the perceived attributes of that cluster. Modifying these characteristics along the specified directions will improve the corresponding aspect of craftsmanship without interfering with the rest of the craftsmanship perception, as long as the linking variables remain unchanged.

MDS analysis was conducted from two to six dimensions. To interpret the dimensions of the perceptual spaces, i.e., name the axes, the clusters resulted from the cluster analysis were used. The goal was to see whether the attributes in each cluster conform to the spatial configurations and span a meaningful space. After analyzing the multidimensional spaces, the 2-D space showed the most meaningful characteristics in terms of ability to identify the dimensions.

Figure 8 Figure 8 shows the position of the clusters in the 2-D perceptual space. The layout of the clusters is meaningful in terms of the relative positions of the clusters. The first axis spans one dimension from "sensory requirements" to "functional requirements", whereas the second axis spans another dimension from "overall comfort" (physical and psychological) to "overall quality" (design and manufacturing).

There are two attributes that are semantically misplaced in the 2-D space, namely, Attributes #4 and #20, circled in Figure 9. This misplacement may be due to the loss of dimensionality that occurs in MDS. On the other hand, Attribute #4 ("Buzz, squeak and rattle") could indeed appear in the cluster of driving comfort, since continuous BSR noise would affect driver's comfort. These MDS results, being much clearer than the first survey results, show that it is indeed possible to represent people's perception of craftsmanship in a space of reduced dimensionality.

This application is different than the previous uses of MDS and clustering analysis because it was informed by a functional dependence table that is explicit about the relation between product characteristics and perceived attributes.

5. CONCLUSIONS

An analytical approach to the craftsmanship problem in vehicle interior design is promising, in terms of developing design tools that appear less subjective but still capture the inevitable subjectivity of the customers. These results are preliminary and the surveys are limited. However, a foundation has been laid for a workable analytical-functional representation of the constitutive elements of craftsmanship and practical design decisions that the engineers can make. An important aspect of the problem still to be addressed is the selection of values for the attribute weights in Eq. (1), and/or the form of the aggregation equation itself.

Craftsmanship is about quality of design execution. This fact closely relates to the notion of six sigma design where the goal is to reduce the defects in a manufacturing process. Some aspects of craftsmanship identified above are directly related to manufacturing (or design for manufacturing), and so the link between the six sigma approach and craftsmanship would be a promising area for further research.

Relating design decisions to user perceptions is a very complex problem. A generalization of the findings here to craftsmanship perceptions for diverse products remains a challenge. A theoretical framework that encompasses engineering, product design and psychology is a desirable immediate research endeavor.

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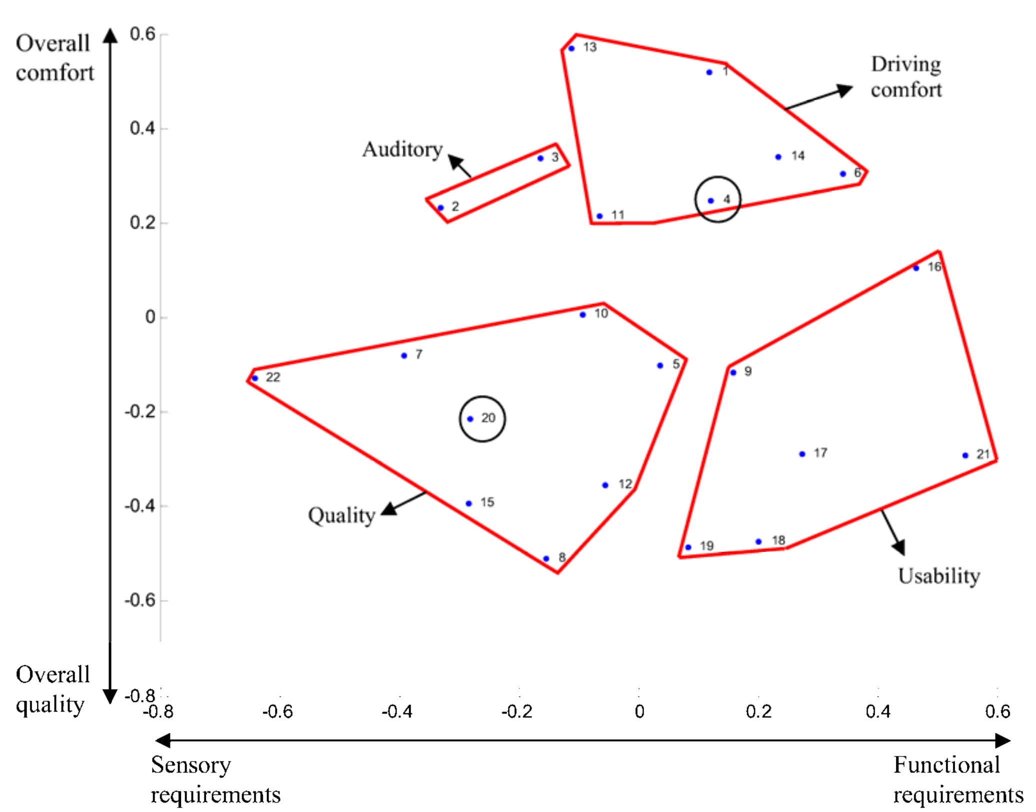
Figure 8 Position of the clusters in the 2D-perceptual space and interpretation of the axes



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