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A KANSEI ENGINEERING STUDY APPLIED TO HAMMERS
WITH SPECIAL ATTENTION TO THE SELECTION OF SEMANTICS

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ABSTRACT

Kansei Engineering is one of the forerunner methodologies which can help designers in designing products that provide a positive emotional response, and thus satisfying all the expectations required by the user. These techniques are being successfully applied in consumer product design (mobile phones, cars, printers, etc.), but they have been hardly applied to professional products.

In this work a Kansei engineering study applied to hammers (which may be considered as professional products) with special attention in the selection of semantics is presented. Firstly, a methodology based on hierarchical cluster analysis is used to select the adjectives of a semantic differential test. This method allows to structure the semantics with different level of detail and to select the semantics with an almost objective criteria (i.e. not very dependent of the opinion of the test designer). After this selection of semantics, a Kansei engineering process, based on multivariate statistical techniques (factorial analysis and multivariate regression analysis), is used to study the relationships between the most important features of the hammers (shapes, sizes, colours, etc.) and the perception of the semantics. The regression models obtained for three representative semantics (Strong, Pleasant and Stylish) are presented and discussed.

Keywords: *Kansei Engineering, semantic differential, hierarchical cluster analysis, multiple regression, hand tools*

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1. INTRODUCTION

Nowadays, when selecting a product, consumers do not just consider its functionality, usability, safety, and price, but also the emotions and feelings that it elicits. A good product should satisfy all the expectations required by the user, such as providing a positive emotional response. This goal may be achieved through a set of techniques known as emotional design [1-5]. Kansei Engineering (KE) [6] is one of the forerunner methodologies. These techniques are being successfully applied in consumer product design such as mobile phones, glasses, cars, etc. [7, 4, 8], but they have been hardly applied to professional products such as rocker switches, machining centers or construction machinery [9-11].

KE allows identifying the emotional user expectations and establishing mathematical models to predict the relationship between the features of a product and these expectations. In a first stage, the consumer's feelings that the product elicits are collected through field studies and/or laboratory experiments, normally using the Semantic Differential (SD) [12] and a set of images of different models of a product. In a second stage, the relationships between product design features and feelings are established. Finally, computer tools are used to build a KE frame that allows using these relationships to evaluate a product design or to plan further developments.

A critical point is the selection of the proper adjectives in a SD study in order to obtain the desired information about the product. Often, the test designer does it subjectively. A great number of adjectives make difficult the interpretation of the results and may fatigue the participants in the surveys; a small number of adjectives may disregard perceptions and meanings important for the global interpretation of the product. Furthermore, different number of adjectives may be needed depending on the level of detail required for the design phase considered [13]. It would be desirable to establish a methodology for selecting the adjectives enabling different levels of detail, and independent on the test designer's criteria.

Different methodologies for establishing relationships between product features and feelings have been described in KE literature. The simplest one is the Hayashi type I quantification theory [6, 14]. It is a kind of linear regression for categorical variables that uses some parameters (total and partial correlation coefficients and regression equation coefficients) of the complete regression model in order to calculate the power of the relationship. Its main drawback is the interdependency among variables [15, 16], which limits the number of features of the product that can be used to only a few general ones [17]. To solve this limitation, more complex methods (artificial intelligence based non linear methods) have been used, such as neural networks, fuzzy theory, genetic algorithms or rough sets theory [18-20].

In this work a KE study applied to hammers (which may be more considered a professional product than a consumer one) with special attention in the selection of semantics is presented. Firstly, a methodology based on hierarchical cluster analysis is used to select the adjectives of a SD test. This method allows to structure the semantics with different level of detail and to select the semantics with an almost objective criteria (i.e. not very dependent of the opinion of the researcher). After this selection of semantics, a KE process, based on multivariate statistical techniques (factorial analysis and multivariate regression analysis), is used to study the relationships between the most important features of the hammers (shapes, sizes, colours, etc.) and the perception of the semantics. The method presented is as simple as the Hayashi type I quantification theory, but allows considering numerical variables and gives recommendations to consider the problem of the interdependency among variables. Furthermore, it allows predicting the feelings from the product features, so that it may be considered as KE type IV.

2. MATERIAL AND METHODS

All the tests were conducted in Spanish. For brevity, only translation to English is shown in this communication.

2.1. Selection of semantics

Semantic Differential (SD) tests were used to measure the feelings and perceptions of the subjects about the hammers. In order to choose the semantic descriptors, a pilot study was conducted. Starting with 213 words obtained from ergonomics papers and web sites of hand tools manufacturers and suppliers, a total amount of 35 semantics were initially selected by discarding those related to hammer attributes not likely to be evaluated from an image and those obviously equivalent. As 35 pairs of semantics were considered excessive, 89 students (18-33 aged, 51 women and 38 men) were asked about the 35 pairs of semantics, but each one about one single hammer. The 89 hammers (Figure 1) were selected from 248 images obtained from commercial brochures and web sites, taking care to get different features and maintain a good quality of prints. Seven evaluation levels were considered for each semantic. The scale ranged from 3 to 3 without assigning signs to avoid connotative implications of negative signs (Figure 2 shows an example). In addition, the order of the semantics was randomized for each test.

Figure 1: Images of the 89 hammers used for the selection of semantics

	3	2	1	0	1	2	3	
Stylish								Conventional

Figure 2: Levels of the measurements for the opposite semantics

To reduce the semantics, a hierarchical cluster analysis (HCA) was performed. HCA is a multivariate analysis that allows the elements of a set (in this case, the semantics) to be classified into clusters by attending to its similarity according to a certain criterion. The classification is made in phases by clustering the two nearest elements in each phase, so that a tree structure (dendogram) is constructed. For the next phase the two clustered elements are considered as one group. In this case Pearson's correlation was used as the criterion for similarity in order to check for patterns in the answers and the centroid method to represent new clusters [16]. The dendogram has the advantage -in contrast with other methods with a fixed reduction- that different levels of reduction may be achieved depending on the aim of the study. The distances used to cluster may be used to detect the most suitable phases of reductions: bigger differences in consecutive distances means that the clustered groups in that phase are less similar, so that it is a better 'cut' for selection. Another advantage of HCA is that allows the positive semantic of the pair being identified (in some cases it is not straightforward for the product or user, e.g. young/mature). To obtain the positive (or negative) adjective in doubtful cases the HCA was performed using two variables for each pair of semantics, one for each of them but with opposite values. The HCA gives a duplicated dendogram, with the same structure for the positive and the negative adjectives. Figure 3 show only positive dendogram. Numerical results show that the two 'cuts' with continuous line are the most suitable (with a difference in distance > 0.1). Other possible cuts are shown with doted line (difference in distance > 0.05).

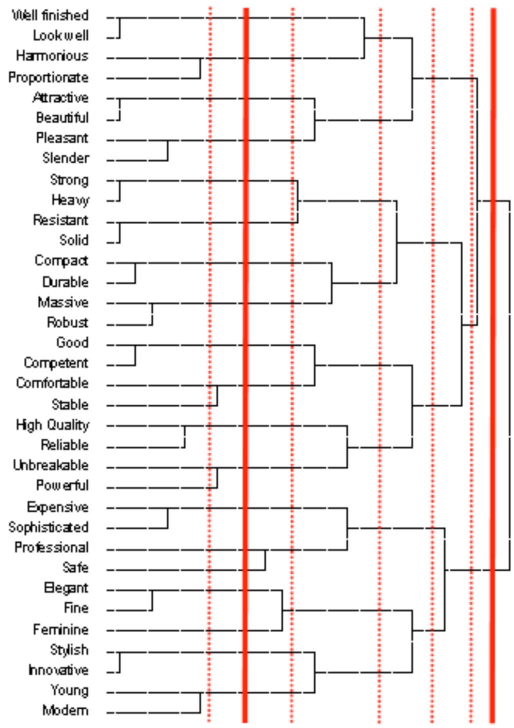

Figure 3: Dendogram of the HCA for the positive semantics with recommended 'cuts'

2.2. Kansei engineering study

For the KE study multiple linear regression models were used to relate the answers in a SD test with the features of the hammers.

2.2.1. Semantic Differential test

The reduced set of the 19 pairs of semantics shown in Table 1 was considered to be the best choice for the study.

Thirty six subjects participated in the study including do-it-yourself enthusiasts and professionals with differences degrees of experience with hammers (17-65 aged, 3 women and 33 men). Ten representative hammers were selected for the study (Figure 4). In this case photographs of real hammers were taken to know exactly the features of hammers and guarantee the same quality of images. To keep subjects from getting bored, each subject evaluated only 5 hammers, with random assignment, but ensuring the same number of tests per hammer. The order of the semantics and the column position of the two words of the pair were randomized for each test. A total number of 180 tests were performed, 18 per hammer. The pictures of the hammers were presented in the same scale on separate A4 sheets.

Table 1: Pair of semantics used in the kansei engineering study. The first word of each pair is the positive one identified in the previous HCA.

Well finished / Bad finished	Attractive / Ugly	Durable /Ephemeral
Proportionate / Disproportionate	Modern / Classic	Feminine / Masculine
Resistant / Non resistant	Strong / Weak	Stylish / Conventional
Professional / Do-it-yourself	Robust / Flimsy	Sophisticated / Simple
Comfortable / Uncomfortable	Good / Bad	Pleasant / Unpleasant
High quality / Low quality	Fine / Coarse	Safe / Dangerous
Unbreakable / Breakable		

Figure 4: Pictures of the 10 hammers used in the study

2.2.2. Features of hammers

Only general features of hammers that could be appreciated from a photograph were selected to be related to the semantic perceptions. Ten qualitative and five quantitative features were used. The former are listed in the first lines of table 2, the latest being general dimensions appreciated in the photograph: total length of hammer, thickness and length of handle, and thickness and length of head.

2.2.3. Regression models

Multiple linear regression (MLR) models were used to estimate the semantics (dependent variables) with the selected features of the hammers (independent variables). As stated before, in MLR models the correlation between independent variables is a problem [15, 16], what means that only a small number of product features can be introduced. A way to solve it is to make a full factorial design for all the features to be included. However, for the 15 features included this would imply the use of about 1500 different designs of hammers, which is unfeasible in practice. Using correlation coefficients between each semantic and the features separately could mask the results and wrong relations could be obtained; besides, they do not give a prediction model (only KE type III could be achieved, not KE type IV).

However, MLR analysis may be applied as well with somewhat correlated variables [16], although care has to be taken when interpreting the results and selecting the model. An initial study of independency of the features was performed in order to check for this issue. The five quantitative features were highly correlated so that they were substituted by four independent factors obtained in a Factor Analysis, representing each of them: F1. Length of handle and hammer, F2. Handle thickness, F3. Head thickness and F4 Head length.

With these 14 final features, the correlations were still high: 75% of the possible correlations between numerical and categorical features and 62% of the possible correlations between categorical features presented significant correlations ($p<0.05$ for Pearson and Kendall correlations respectively). In this case, tolerance of variables [16] has to be checked in order to prevent the negative effect of colinearity.

To select the best MLR model for each semantic, a two phase process was followed. Firstly, a complete MLR model with the features that had a significant Pearson correlation ($p<0.05$) with each semantic was performed. This was used to check the maximum fit with R square value (if this value is not high, no model is possible) and the most significant variables (for multivariate models the correlations may be different than for individual correlations when variables are not independent). Secondly, a stepwise process was performed, including the most significant variables detected in the first phase, and selecting variables for entry with a significant level of $p<0.05$ and for exclusion with $p>0.1$. For each semantic the selected model was the one that has the highest statistical validity, measured from [16]:

- R square value of the model (high value) and significance value of the model ($p<0.05$).
- For the variables: partial correlation coefficients (high values), significance levels ($p<0.05$), standardized Beta coefficients (high values) and tolerances (>0.1 to prevent effect of dependency of variables).
- Normal distribution of residuals (Kolmogorov-Smirnov tests)

2.3. Validation of MLR models

A SD study, similar to the previous one, was performed with: a new group of 12 subjects (18-59 aged, 1 woman and 11 men) and 8 hammers. The same protocol was used, but in this case each subject answered to 4 hammers, so that 48 tests were performed, 6 per hammer. The four factors of the numerical features were calculated and used in conjunction with the rest of the categorical variables for estimating the semantics for each hammer with the MLR models equations. Differences of these estimates and the observed values were used for validation.

3. RESULTS

3.1. Kansei engineering study

Although MLR models were built for all the semantics in the study, the detailed results are presented only for three of them, chosen to be representative in results: *Stylish*, *Pleasant* and *Strong* (all of them named by the positive adjective of the pair).

The significant correlations (Pearson coefficients with significance > 0.05) of these semantics with the features selected are shown in table 2. This table also shows the variables included in the selected MLR models for each semantic, marked with *.

Table 2: Significant Pearson correlations between the three semantics and the hammer features. Selected variables for the MLR models are marked with *.

	Stylish	Pleasant	Strong
Head shape: symmetrical	-0.43	-0.29	
Head cross-section shape: constant			
Head: solid (vs. lightened)	-0.63*	-0.23	
Head material: metal	0.25	0.26	
Head-handle joint: not integrated	-0.44	-0.20	-0.34*
Handle axis: straight	-0.61*	-0.41*	-0.27
Handle cross-section shape: constant	-0.16	-0.29	-0.31*
Grasping area: differentiated from rest of handle	0.52	0.33	
Small number of colours: (1-2)		-0.32*	
Main colour: wooden	-0.48*		
Main colour: black	0.26	0.36	
F1. Length of handle and hammer	0.32		-0.17
F2. Handle width	0.43	0.29	0.22
F3. Head width			
F4. Head length		0.16	0.28*

The three models were statistically significant ($p < 0.001$) although with a value of R squared not very high (0.579, 0.292 and 0.183 for *Stylish*, *Pleasant* and *Strong*, respectively). All the variables included in the model were statistically significant ($p < 0.03$ in all cases), with partial correlation coefficients relatively high (from 0.16 to 0.51, without signs), high values of the standardized Beta coefficients (from 0.16 to 0.44, without signs) and tolerances above 0.3. Distribution of residuals was checked to be normally distributed for *Stylish* and

Pleasant but there were significant differences with normal distribution (p = 0.029) for *Strong*. The model for *Strong* is statistically the least reliable, probably because this attribute is the most difficult to be perceived in a photograph.

From these results it may be argued that hammers perceived more *Stylish* have the head lightened, the axis of the handle curved and their main colour is not wooden. Also, but with less confidence, hammers perceived more *Pleasant* have the axis of the handle curved and have more than two colours. Finally, with much uncertainty, hammers perceived *Stronger* have the head-handle joint integrated, the handle cross-section shape variable and a long head.

3.2. Validation of MLR models

The estimated values for the three semantics were calculated with the next equations, which use unstandardised coefficients of the models. For qualitative variables the case expressed is valued with 1; any other case with 0.

$$\text{Stylish} = 2.389 - 1.944 \times \begin{pmatrix} \text{Straight} \\ \text{Handle Axis} \end{pmatrix} - 1.701 \times \begin{pmatrix} \text{Wooden} \\ \text{Main colour} \end{pmatrix} - 0.808 \times \begin{pmatrix} \text{Solid} \\ \text{Head} \end{pmatrix}$$

$$\text{Pleasant} = 2.398 - 1.531 \times \begin{pmatrix} \text{Straight} \\ \text{Handle Axis} \end{pmatrix} - 1.143 \times \begin{pmatrix} \text{Small (1 - 2)} \\ \text{Number of colours} \end{pmatrix}$$

$$\text{Strong} = 1.596 - 0.763 \times \begin{pmatrix} \text{Not integrated} \\ \text{Head - handle joint} \end{pmatrix} - 0.850 \times \begin{pmatrix} \text{Constant} \\ \text{Handle cross - section shape} \end{pmatrix} + 0.263 \times (\text{F4.Head\_Length})$$

Table 3 shows statistics for the errors (predicted - observed) of the 48 cases for the three semantics and figure 5 shows mean values of predicted and observed values per hammer.

Table 3: Errors in the predictions of semantics

Semantic	Mean	Standard deviation
Stylish	-0,705	0,918
Pleasant	-0,236	1,251
Strong	-0,348	0,743

4. DISCUSSION AND CONCLUSIONS

The methodology used to pre-select semantics for SD studies with Hierarchical Cluster Analysis has several advantages. First of all, the selected semantics are independent on the test-designer's criteria, as the selection considers the opinions of many other people which may be selected with the necessary profile. Another advantage is that different levels of detail achieved by the tree structure may be used depending on the objective of the study. For example, in an early phase of design a less detailed study could be needed, but in an advanced phase a more detailed selection may be used. Also the detailing may be addressed to some specific semantics (by expanding only some branches of the tree) making possible biased studies. The application to hammers has provided good results.

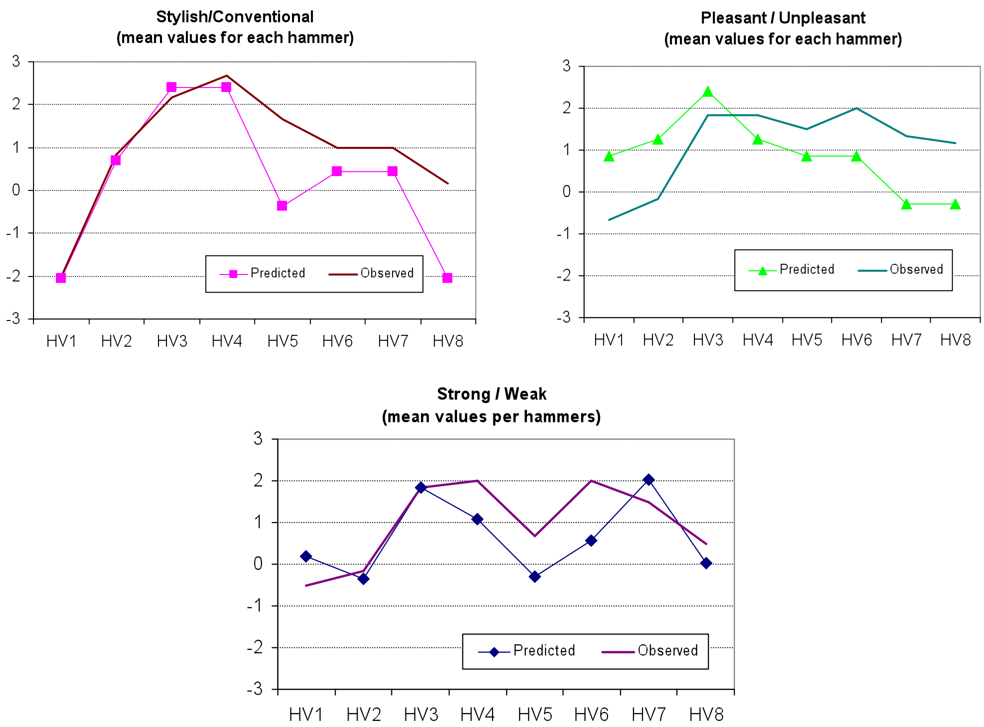

Figure 5: Mean values of predicted and observed values per hammer

MLR models have been used previously in KE studies, but their application to hammers is original. These models try to explain the measured scores in a SD test from hammer features, using only features that can be observed in photographs (the way the hammers have been shown in the test). The models have been obtained with a small number of hammers, although with different features. This may be considered as an advantage (little effort has been made) but is also a limitation (many more hammers should be included for a bigger reliability in the application of results). In effect, the small percentage of variance explained (R squared under 0.7 for all the models, i.e. less than 70% of variance) makes the models to be considered with care. However, the results in terms of predictions for other hammers make them hopefully reliable for direct application. The best models are obtained for the semantics that are more easily perceived in photographs and therefore are more related with the selected features of the hammers. For the three representative semantics presented in this communication the best model has been obtained for *Stylish* and the worst for *Strong*. However, the methodology proposed to obtain the model (pre-selection of features with correlation coefficients, making quantitative features as independent as possible using Factor Analysis and the way to select the final model) has enabled to include in the prediction many more features of hammers than other similar techniques previously described.

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