APPLYING KANSEI ENGINEERING ON THE INTERFACE DESIGN OF E-COMMERCE WEB FOR 3C PRODUCTS

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ABSTRACT

Due to the impact of the global economic downturn, developing new business opportunities by using e-commerce to save the cost of access and advertising becomes an important issue. In order to correctly catch the customer's demands and reduce the risk of developing new websites, this study aims to propose an interface design prediction methodology based on the integration of Kansei Engineering (KE), Rough Set Theory (RST), and Linear Regression (LR).

First of all, we collect and reduce websites of 3C product and Kansei words by the MDS and K-means clustering methods. Secondly, we get six interface elements of the web page: page width, font color, product image size , font size, area of blank space, layout of columns, and four pairs of Kansei words: complicated-simple, friendly-unfriendly, fashionable-unfashionable, amazing-plain. Thirdly, through the application of the RST, we find out the significance sequence of interface elements on Kansei words. Then a mapping relationship between Kansei words and interface elements via the LR Scheme is established. Finally, we combine the mapping result with database technology to develop a user-friendly interface design expert system to help web designers to work more quickly and efficiently, at the same time, meet the customer's preferences more accurately.

Keywords: *Kansei Engineering, User Interface Design, Rough Set Theory, Multiple Linear Regression Analysis*

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1. INTRODUCTION

Electronic Commerce is the buying and selling of goods and services or the transfer of money over the Internet. It has opened a whole new world for retailers, wholesalers, and other types of marketers [1]. According to some reports on E-commerce, Americans bought goods and services worth $81 billion from websites three years ago and the figure jumped to $95 billion in 2006 which may touch $144 billion in 2010. About 78 percent of Americans use the Internet to research a product or service before making a purchase [2].

E-commerce is not slowing down; however, it is rapidly growing around the world, making for a true global economy. Web page design and layout of user interface have become more important than before [3].

2. THEORETICAL BASIS

2.1. Kansei Engineering

Kansei is a Japanese word which means a consumer's psychological feeling and image regarding a new product. By *Kansei* words, the customers are guided to express their affective needs, their feelings, and their emotional states. These emotional and sensory wants are then translated into perceptual design elements of the product. *Kansei* Engineering is defined as "the translating technology of a consumer's feeling and image for a product into design elements." It has been successfully applied in the field of product design to explore the relationship between the feeling of the consumers and the design elements of the product. According to Nagamachi [4], there are six types of *Kansei* Engineering technique categorized as: (1)*Kansei* Engineering Type I: Category Classification, (2)*Kansei Engineering* Type II: *Kansei* Engineering System, (3)*Kansei* Engineering Type III: Kansei Engineering Modeling, (4)*Kansei* Engineering Type IV: Hybrid Kansei Engineering, (5)*Kansei* Engineering Type V: Virtual Kansei Engineering, (6)*Kansei* Engineering Type VI: Collaborative Kansei Engineering. A typical forward Kansei engineering system is shown in Figure 1. In this study, we intended to perform the Kansei modeling work (Type III) and build a backward Kansei engineering system (Type II).

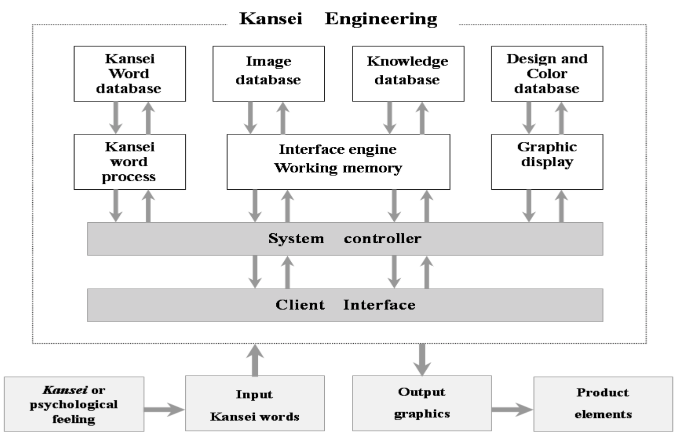

Figure 1: *Kansei* expert system

2.2. Rough Set Theory

The RS theory, first described by Pawlak [5], is a formal approximation of a crisp set (i.e., conventional set) in terms of a pair of sets which give the lower and upper approximation of the original set. In the standard version of rough set theory, the lower and upper approximation sets are crisp, but in other variations, the approximation sets may be fuzzy sets [6].

Rough Set methods can be applied as a component of hybrid solutions in machine learning and data mining. They have been found to be particularly useful for rule induction and feature selection (semantics-preserving dimensionality reduction). Rough Set-based data analysis methods have been successfully applied in bioinformatics, economics and finance, medicine, multimedia, web and text mining, signal and image processing, software engineering, robotics, and engineering (e.g. power systems and control engineering) [7]. The concept of Rough Set is shown as following:

2.2.1. Information System Framework

Let $I = (U, A)$ be an information system (attribute-value system), where U is a non-empty set of finite objects (the universe) and A is a non-empty, finite set of attributes such that $a : U \to V_a$ for every $a \in A$. V_a is the set of values that attribute a may take. With any $P \subseteq A$, there is an associated equivalence relation $IND(P)$:

$$IND(P) = \{(x, y) \in U^2 \mid \forall a \in P, a(x) = a(y)\} \tag{1}$$

The partition of U generated by $IND(P)$ is denoted $U / IND(P)$ and can be calculated as follows:

$$U / IND(P) = \otimes \{U / IND(\{a\}) \mid a \in P\} \tag{2}$$

If $(x, y) \in IND(P)$, then x and y are indiscernible by attributes from P. These indistinguishable sets of objects therefore define an equivalence or indiscernibility relation, referred to as the P-indiscernibility relation. The equivalence classes of the P-indiscernibility relation are denoted $[x]_P$.

Let $X \subseteq U$ be a target set that we wish to represent using attribute subset P; and we wish to express this class using the equivalence classes induced by attribute subset P. In general, X cannot be expressed exactly, because the set may include and exclude objects which are indistinguishable on the basis of attributes P. However, the target set X can be approximated using only the information contained within P by constructing the P-lower and P-upper approximations of X.

$$\underline{P}X = \{x \mid [x]_P \subseteq X\} \qquad \overline{P}X = \{x \mid [x]_P \cap X \neq 0\} \tag{3}$$

2.2.2. Lower Approximation and Positive Region

The P-lower approximation, or positive region, is the union of all equivalence classes in $[x]_P$ which are contained by the target set of X. The lower approximation is the complete set of objects in $U/IND(P)$ that can be positively (i.e., unambiguously) classified as belonging to target set X.

2.2.3. Upper Approximation and Negative Region

The P-upper approximation is the union of all equivalence classes in $[x]_P$ which have non-empty intersection with the target set. The upper approximation is the complete set of objects in $U/IND(P)$ that cannot be positively (i.e., unambiguously) classified as belonging to the complement of the target set $\overline{X}$. The set $U-\overline{P}X$ therefore represents the negative region, containing the set of objects that can be definitely ruled out as members of the target set.

2.2.4. Boundary Region

The boundary region, given by $\overline{P}X-\underline{P}X$, consists of those objects that can neither be ruled in nor ruled out as members of the target set X.

The tuple $(\underline{P}X,\overline{P}X)$ composed of the lower and upper approximation is called a rough set; thus, a rough set is composed of two crisp sets, one representing a lower boundary of the target set X, and the other representing an upper boundary of the target set X. The accuracy of the rough-set representation of the set X can be given by the following:

$$\alpha_P(X)=\left|\underline{P}X\right|/\left|\overline{P}X\right| \tag{4}$$

In general, the upper and lower approximations are not equal; in such cases, we say that target set X is indefinable or roughly definable on attribute set P. When the upper and lower approximations are equal, $\underline{P}X=\overline{P}X$, then the target set is definable on attribute P.

2.2.5. Reduct and Core

Often we wonder whether there is a subset of attributes which can, by itself, fully characterize the knowledge in the database; such an attribute set is called a reduct. Formally, a reduct is a subset of attributes $RED\subseteq P$ such that: (a) $[x]_{RED}=[x]_P$, that is, the equivalence classes induced by the reduced attributes set RED are the same as the equivalence class structure induced by the full attribute set P, (b) the attribute set RED is minimal, in the sense that $[x]_{(RED-\{a\})}\neq[x]_P$ for any attribute $a\in RED$.

The set of attributes which is common to all redacts is called the core: the core is the set of attributes which is possessed by every legitimate reduce, and therefore consists of attributes which cannot be removed from the information system without causing collapse of the equivalence-class structure. The core may be thought of as the set of necessary attributes.

2.2.6. The Dependency of Attribute

In a Rough Set information system, the attributes can be distinguished between useful and useless. We can evaluate how much decisions attributes depend on condition ones, then erase an attribute and evaluate again the dependency. From the difference of dependency, we can obtain a value for the utility of the attribute. This is done in two steps:

The first step is to evaluate dependency between attributes. It is defined in the following way:

$$\gamma(B,D) = \frac{\sum_{x \in IND_D(U)} |\underline{B}X|}{|U|} \tag{5}$$

If all sets X are crisp, $\gamma(B,D) = 1$. In fact, this means that using the attributes in B we can precisely define the partition $IND_D(U)$. If we can't precisely decide about the membership of any object, that is $\underline{B}X = \phi$, $\gamma(B,D) = 0$

Then, we calculate how much removing an attribute changes the original dependency:

$$\sigma_{B,D}(a) = \frac{\gamma\ (B,D) - \gamma(B - \{a\}, D)}{\gamma_c(B,D)} \tag{6}$$

If $B - \{a\}$ is a reduct, $\gamma\ (B,D) = \gamma(B - \{a\}, D)$ and $\sigma_{B,D}(a) = 0$ In fact, the attribute a is not significant at all. If B is a reduct, it may happen that some of its attributes are less useful then others, because they allow to distinguish between a few small classes.

3. PROCEDURES

The " E-commerce web page for 3C product " is used as our demonstration target in this study. The proposed design procedures and related techniques can be generalized to all kinds of web page. However, the influences of different cultures and genders would not be discussed here.

Followings are the manipulation processes.

3.1. Web Page Form Reduction

3.1.1. Collection of Samples

First, by using "E-commerce web" as a keyword we have collected totally 275 E-commerce web sites from the present market. The target group includes internet users, aged 18-35 years old, who have at least three years experience in online shopping. A result of 48 web sites for 3C (Computer, Communication, Consumer) products were chosen from 275 E-commerce web sites.

These web site samples were listed and linked in electronic questionnaire that had been done as similar and comparable as possible in the test. We then asked the 50 subjects of the first group to classify these 48 web page samples into 2~10 groups based on their similarity degree by KJ method. This method was introduced by Kawakida Jirou in 1953 for classifying ideas, concepts, or objects into several groups by their similarity degree.

3.1.2. Classification of Samples

Then, we built a similarity matrix from the previously obtained result. The similarity matrix was transformed into a dissimilarity matrix and analyzed by the multidimensional scaling (MDS) scheme. To determine the most appropriate dimensionality for the data, we examined 9 different dimensional spaces (ranging from 2 to 10 dimensions). A result of 6 dimensions with stress=0.03987 was suggested here, since a commonly used measure of fit in MDS is "stress", which is the square root of a normalized residual sum of squares. A smaller stress value indicates a better fit (an empirical suggested stress value is 0.05 [8]. Thus, the 6 dimensional spaces were the most appropriate. Finally, the cluster analysis was performed based on the MDS result.

3.1.3. Representative

The K-means method is then used to calculate the distance of individual sample to its group center of gravity. Eventually the sample which has the smallest distance can be visualized as the group representative. The obtained representatives of group 1~6 are shown in Figure 2.

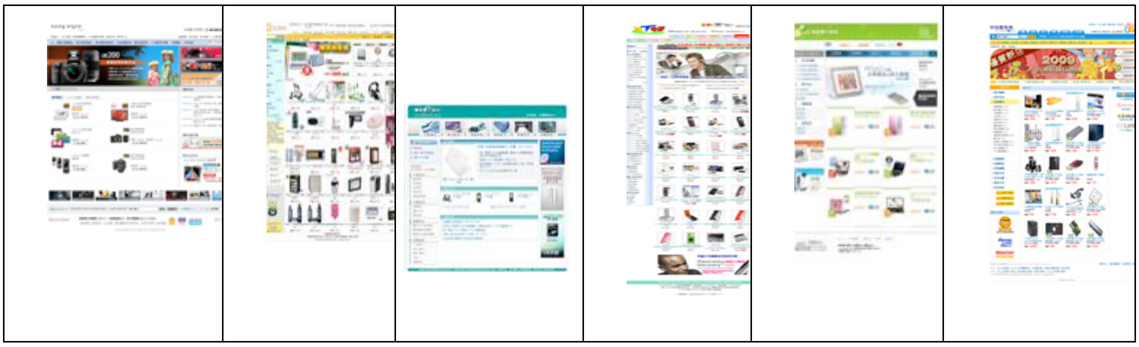

Figure 2: A selected result of K-means classification

3.2. Kansei Words Reduction

3.2.1. Collection of Kansei Words

A total of 120 low-level Kansei adjective words describing the out-looking of web page for 3C products are collected from internet, design magazines, literature, manuals, experts, experienced users, and 45 middle-level Kansei words are built up through discussions of the focus group.

3.2.2. Reduce The Collected Kansei Words Via Questionnaire Interview

To further reduce the collected low-level *Kansei* words, a questionnaire interview was done to 50 subjects of the second group and finally 15 middle-level *Kansei* word pairs were obtained. The obtained *Kansei* words are : attractive-unattractive, unique - public, advanced - elementary, fast - slow, figurative - abstract, systematic – chaotic, beautiful - ugly, actual - fantasy, exact - inexact, simple - difficult, popular - outdated, young-old, creative - imitative, peculiar-ordinary, technological – traditional.

3.3. Morphological Analysis

3.3.1. Further Reduction of Kansei Words

A questionnaire interview and then a factor analysis (FA) are applied to the obtained 15 middle-level *Kansei* word pairs and 6 representative samples. The semantic differential (SD) method is adopted in the FA, using seven-level scale as measurement standard. A total of 50 users of the third group help to perform the questionnaire interview. Eventually, four final high-level *Kansei* word pairs are obtained, which are amazing-plain (Eigen value: 1.624), fashionable-unfashionable (Eigen value: 2.089), friendly-unfriendly (Eigen value: 4.261), and complicated-simple (Eigen value: 8.326).

3.3.2. Web Page Form Decomposition

The form elements of E-commerce web page for 3C product, extracted and expanded by morphological analysis from previously obtained 6 groups of samples, are classified into 6 categories with 4 types for each category and expressed as X1~X6 . Each form element has different form types of its own, discretized as 1 to 4 as shown in Table 2.

Table 2: Form decomposition

	Form elements	**Types of form elements**			
X1	page width	800~959 px	960~1023 px	1024~1151 px	1152~1280 px
		1	2	3	4
X2	font size	9 pt	10 pt	11pt	12 pt
		1	2	3	4
X3	product image size	30~84 px	85~139 px	140~194 px	195~250 px
		1	2	3	4
X4	font color	2~4 colors	5~7 colors	8~10 colors	11~13 colors
		1	2	3	4
X5	area of blank space	10~19%	20~29%	30~39%	40~49%
		1	2	3	4
X6	layout of columns	2~3 columns	4~5 columns	6~7 columns	8~9 columns
		1	2	3	4

3.4. Kansei Evaluation Matrix

To establish the evaluation matrix for the four final selected high-level Kansei word pairs of web page user interface, a 7-point scale (1-7) of the SD method is used. As such, the 50 subjects are asked to assess the web page form elements on the scales of 1-7. The partly resultant Kansei evaluation matrix for 50 samples is shown in Table 3.

Table 3: Kansei evaluation matrix

	complicated-simple	friendly-unfriendly	fashionable-unfashionable	amazing-plain
Sample1	2.42	2.27	1.43	3.93
Sample2	3.25	2.33	1.67	2.20
Sample3	3.63	2.39	1.90	2.03
Sample4	3.74	2.17	2.86	1.20
Sample5	3.35	2.00	2.70	4.9
Sample6	3.78	1.64	2.20	4.17
Sample7	3.89	4.03	2.46	3.94
Sample8	1.63	1.19	1.46	1.29
Sample9	2.21	3.14	3.43	2.29
Sample10	2.84	3.03	3.24	2.33
Sample11	2.95	3.96	4.16	1.39
Sample12	2.43	3.70	2.83	2.47
Sample13	2.26	3.64	3.43	2.16
Sample14	1.37	3.77	3.06	1.36

3.5. Influence of Form Elements on Kansei Adjective words

In RS theory, one of the most important aspects of database analysis or data acquisition is the discovery of attribute dependencies; that is, we want to discover which variables are strongly related to which other variables. These strong relationships will warrant further investigation, and will ultimately be of use in predictive modeling.

By solving above Eq.(6), we can obtain the significance values ($\sigma_1 \sim \sigma_6$) of the form elements ($_1$ ~ $_6$) on Kansei words ($_1$ ~ $_4$) as following : (1) For $_1$ (complicated-simple), σ_1 =0, σ_2 =0.0833, σ_3 =0.3125, σ_4 =0.1875, σ_5 =029167, σ_6 =0.2083 (2) For $_2$ (friendly-unfriendly), σ_1 =0, σ_2 =0.04166, σ_3 =0.3125, σ_4 =0.1250, σ_5 =02291, σ_6 =0.1458. (3)For $_3$ (fashionable-unfashionable), σ_1 =0.625, σ_2 =0.010417, σ_3 =0.3125, σ_4 =0.1250, σ_5 =02291, σ_6 =0.2083. (4)For $_4$ (amazing-plain), σ_1 =0, σ_2 =0.1458, σ_3 =0.3125, σ_4 =0.1250, σ_5 =00625, σ_6 =0.2708.

According the above results, the ranking sequence of the significance values is $\sigma_3 > \sigma_5 > \sigma_6 > \sigma_4 > \sigma_2 > \sigma_1$.

3.6. Mapping Relationship

According to the previously mentioned RS theory, fast modeling is not only a need but also a must. We delete the relatively low-significance-value attributes in order to build the mapping relationship as quickly and accurately as possible.

Finally, the mapping relationship is built by LR model as following:

$$
\begin{aligned}
C_1 &= 0.0833 X_2 + 0.3125\ X_3 + 0.1875\ X_4 + 0.2916\ X_5 + 0.2083\ X_6 \\
C_2 &= 0.0416\ X_2 + 0.3125\ X_3 + 0.125\ X_4 + 0.2291\ X_5 + 0.1458\ X_6 \\
C_3 &= 0.0625\ X_1 + 0.1041\ X_2 + 0.3125\ X_3 + 0.125\ X_4 + 0.2291\ X_5 + 0.2083\ X_6 \\
C_4 &= 0.1458\ X_2 + 0.3125 X_3 + 0.125\ X_4 + 0.0625\ X_5 + 0.2708\ X_6
\end{aligned}
\tag{7}
$$

4. DESIGN EXPERT SYSTEM

The design expert system is mainly built for helping designers to easily perform web page form assessment and design. This system includes an index page which illustrates the purpose of this system, and a main page with the major functions shows how to use parameters of product form to predict the Kansei word credits whereas.

4.1. Backward KE prediction

In the main page of "Form parameters to Kansei *words," inputting suitable values of form parameters and click "Sure" button, then the results of predicted* Kanse*i word credit and its corresponding web page form will appear in the left gray zone simultaneously.*

4.2. Refinement

To complete a new product form, a final refinement is essential. Our developed design expert system provides a convenient function "Advanced Design" for users to perform their final design works. Users can click the "Advanced Design" item to operate the original HTML and CSS files of the corresponding web pages for 3C product, after redesigning in Dream weaver, users will get a newly designed and creative prototype of web page form. An example is shown in Figure 3.

Figure 3: The index and main web pages of the KE system

5. CONCLUSION

This work proposed a novel integral Kansei engineering model for effectively and accurately predicting the relationship between web-page interface elements and Kansei words. Based on the proposed model, a design expert system is also built. Followings are the conclusion of this research.

(1)The proposed methodology includes RS which may provide significance value sequence of web-page interface elements on interface images. Through the use of RS, the reluctant interface attributes can be omitted and hence enhancing the modeling speed but still maintaining prediction accuracy.

(2) The most important aspects of database analysis or data acquisition is the discovery of attribute dependencies; that is, we wish to discover which variables are strongly related to other variables. For this matter, our proposed integral method (Marjory RS) provides a satisfied result.

(3)To help product designers for further refinement and incorporation of creativity or innovation, a Kansei prediction design expert system is developed based on the mapping relationships.

(4)According to the proposed web page design expert system, designers can easily design a suitable web-page interface form which meets the customer's need, and evaluate how popular from customers' viewpoint a designed web page form should be.

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