The Semantic Approach and Emotional Engineering

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Abstract: This study compares the semantic approach and emotional engineering. The semantic approach and emotional engineering are both used for product design. The semantic approach uses Kansei engineering semantic differential scale surveys and Kansei engineering latent semantic analysis cosines to match emotional user needs to designs. The emotional engineering approach uses sensory differential scale surveys (voice sounds or facial expressions) and regression analysis to match emotional user needs to designs. Study results show that the semantic approach and the emotional engineering approach can be combined to improve matching accuracy, compared to Kansei engineering.

Key words: semantic approach, emotional engineering, Kansei engineering

1. Introduction

This study compares the semantic approach and emotional engineering. The semantic approach and emotional engineering are both used for product design. The semantic approach and emotional engineering however are fundamentally different.

The semantic approach uses Kansei engineering semantic differential scale surveys (Kansei words) and Kansei engineering latent semantic analysis cosines to match emotional user needs to designs [1-4,7-8,10-12,14-15]. Users however may communicate more emotional information by sensory means than semantic means.

The emotional engineering approach uses sensory differential scale surveys (voice sounds or facial expressions) and regression analysis to match emotional user needs to designs [5-6,9,13]. Users however may communicate more design information by semantic means than sensory means.

Section 2 describes the semantic approach. Section 3 describes emotional engineering. Section 4 presents conclusions. Study results show that the semantic approach and emotional engineering can be combined to improve matching accuracy, compared to the Kansei engineering approach.

2. The semantic approach

The semantic approach creates a KE-QT1 model, creates a KE-LSA semantic space, determines Kansei values for user needs, determines Kansei values for designs, matches Kansei values, matches KE-LSA vectors, and determines accuracies [15].

2.1 Create a KE-QT1 model

To create a KE-QT1 model, the semantic approach chooses a target product, identifies Kansei words, identifies design elements, creates sample designs, ranks sample designs, and determines ranking weights.

To choose a target product, the semantic approach surveys or interviews users, surveys or interviews designers, or analyzes documents. For an analysis of research studies on cell phones, the results show that customers need individually customized cell phones.

To identify Kansei words, the semantic approach surveys or interviews users, surveys or interviews designers, or analyzes documents. For interviews of designers and an analysis of documents on cell phones, the results show that six Kansei word pairs can be used to describe cell phone designs: ‘beautiful – plain’, ‘elegant – ordinary’, ‘simple – complex’, ‘unique – common’, ‘luxurious – basic’, and ‘high tech – traditional’.

To identify design elements, the semantic approach analyzes the target product. For an analysis of cell phones, the results show that seven design elements can be used to describe traditional cell phone designs: ‘type’, ‘screen shape’, ‘top shape’, ‘body shape’, ‘bottom shape’, ‘number keys’, and function keys’.

To create sample designs, the semantic approach builds virtual prototypes, physical prototypes, or actual products. For seven design elements and three levels, the semantic approach uses a Taguchi L_{18} array and a CAD program to create eighteen sample designs.

Sample designs

To rank sample designs, the semantic approach surveys or interviews users. For six Kansei word pairs and eighteen sample designs, the semantic approach creates a seven-point semantic differential-scale survey, with six semantic differential scales for each of the eighteen sample designs.

	1			4			7	
‘elegant’	□	■	□	□	□	□	□	‘ordinary’

To calculate ranking weights, the semantic approach uses KE-QT1 regression analysis to analyze sample design ranking results. For fifty-two users, the results show that users only consider cell phone ‘body shape’ and ‘type’ important when choosing a cell phone (p-values = 0.000, 0.025).

2.2 Create a KE-LSA semantic space

To create a KE-LSA semantic space, the semantic approach creates a ‘design by Kansei word matrix’, calculates the singular value decomposition (SVD) of the ‘design by Kansei word matrix’, and reduces KE_LSA semantic space dimension.

To create a ‘design by Kansei word matrix’ X_0, for n Kansei word pairs, the semantic approach records the KE-QT1 weights for the m designs or design elements that impact each of the n Kansei word pairs. The m rows in X_0 represent Kansei values for designs, or design elements. The n columns in X_0 represent Kansei word pairs.

To create a semantic space, the semantic approach calculates the SVD of the ‘design by Kansei word’ matrix X_0

$$X_0 = D_0 S_0 W_0' \tag{1}$$

For seven design elements, three levels, and six Kansei words, D_0 is a 21 × 6 matrix, S_0 is a 6 × 6 diagonal matrix, and W_0 is a 6 × 6 matrix. Rows in D_0 represent Kansei vectors for designs. Rows in W_0 represent Kansei vectors for Kansei words. Diagonal values in S_0 represent scaling factors.

The KE-LSA semantic space includes the three matrices. The semantic approach uses the KE-LSA semantic space to match Kansei vectors for user needs to Kansei vectors for designs. The semantic approach reduces semantic space dimension, to improve matching accuracy.

To reduce dimension, the semantic approach deletes rows and columns from the S_0 matrix and corresponding columns from the D_0 and W_0 matrices. The semantic approach chooses the reduced semantic space dimension r that gives the best matching results. The amount of information in the reduced semantic space is

$$Information = \frac{\sum_{i=1}^{r} s_i}{\sum_{i=1}^{n} s_i} \times 100\% \tag{2}$$

n is the dimension of the KE-LSA semantic space, r is the dimension of the reduced semantic space, and s_i is the i_{th} value in the S_0 matrix. For cell phones, n = 6, and *Information* > 70%, r = 2–6. The semantic approach therefore calculates results for r = 2–6.

2.2 Determine Kansei values for user needs

To determine Kansei values for user needs, the semantic approach surveys users. For cell phones, the semantic approach uses a two-part survey. Part 1 asks users to choose Kansei values for an ideal cell phone. Part 2 asks users to choose one of twelve cell phones.

	1			4			7	
‘elegant’	□	■	□	□	□	□	□	‘ordinary’
‘simple’	□	□	■	□	□	□	□	‘complex’
‘high tech’	□	□	□	■	□	□	□	‘traditional’
‘luxurious’	□	□	■	□	□	□	□	‘basic’
‘beautiful’	□	□	■	□	□	□	□	‘plain’
‘unique’	□	□	■	□	□	□	□	‘common’

1	2	3	4	5	6
					
7	**8**	**9**	**10**	**11**	**12**
					

2.3 Determine Kansei values for designs

To determine Kansei values for designs, the semantic approach chooses designs, identifies design elements, and calculates Kansei values. For the twelve cell phones, the semantic approach identifies design elements for the designs, and uses the KE-QT1 regression analysis results to calculate Kansei values for the designs.

	'elegant'	'simple'	'high tech'	'luxurious'	'beautiful'	'unique'
Phone 1	5.283	3.887	4.508	4.895	5.539	3.971
Phone 2	3.692	2.492	3.879	4.708	3.581	4.989
Phone 3	3.685	2.616	3.563	4.818	3.986	4.703
Phone 4	5.116	3.551	4.571	5.145	5.390	4.319
Phone 5	3.236	3.320	3.029	4.076	3.386	4.054
Phone 6	4.776	3.931	4.288	4.417	4.762	3.688
Phone 7	3.576	3.047	3.567	4.084	3.304	4.087
Phone 8	4.504	4.257	3.979	4.243	4.447	3.891
Phone 9	4.674	5.188	3.529	3.528	5.009	2.645
Phone10	3.156	3.500	2.717	3.745	3.357	3.674
Phone 11	2.946	3.178	3.092	3.862	3.082	3.967
Phone 12	3.218	3.580	2.979	3.543	3.207	3.601

2.4 Match Kansei values

To match Kansei values, the KE-QT1 approach calculates correlations between Kansei values for user needs and Kansei values for designs. For one user, the results show that the KE-QT1 approach chooses Phone 5 (the user's actual choice) as the 5th best match to the user's needs.

	KE-QT1	
	Rank	Corr
Phone 11	1	0.105
Phone 2	2	0.066
Phone 7	3	-0.007
Phone 3	4	-0.048
Phone 5	**5**	**-0.148**
Phone 4	6	-0.253
Phone 12	7	-0.294
Phone 6	8	-0.352
Phone 9	9	-0.358
Phone 1	10	-0.360
Phone 10	11	-0.366
Phone 8	12	-0.678

2.5 Match KE-LSA vectors

To match KE-LSA vectors, the semantic approach converts Kansei values into zero-mean, positive-reference Kansei vectors, projects the Kansei vectors into the KE-LSA semantic space, and calculates the cosine between the projected KE-LSA vectors in the KE-LSA semantic space.

	Kansei vector	Projected vector
User	[2.000, 1.000, 0.000, 1.000, 1.000, 1.000]	[2.004, -0.929, -0.345, -0.130, -0.566, 1.632]
Phone 1	[-1.283, 0.113, -0.508, -0.895, -1.539, 0.029]	[-1.900, 1.065, -0.564, -0.005, 0.096, -0.124]
Phone 2	[0.308, 1.508, 0.121, -0.708, 0.419, -0.989]	[1.182, 1.563, -0.414, 0.075, 0.117, -0.086]
Phone 3	[0.315, 1.384, 0.437, -0.818, 0.014, -0.703]	[0.897, 1.345, -0.799, -0.206, 0.244, -0.126]
Phone 4	[-1.116, 0.449, -0.571, -1.145, -1.390, -0.319]	[-1.556, 1.541, -0.539, -0.075, 0.083, -0.145]
Phone 5	[0.764, 0.680, 0.971, -0.076, 0.614, -0.054]	[1.358, -0.093, -0.646, -0.232, 0.151, -0.173]
Phone 6	[-0.776, 0.069, -0.287, -0.417, -0.762, 0.312]	[-1.084, 0.389, -0.427, 0.125, -0.126, -0.011]
Phone 7	[0.424, 0.953, 0.433, -0.084, 0.696, -0.087]	[1.177, 0.292, -0.503, 0.193, -0.112, 0.016]
Phone 8	[-0.504, -0.257, 0.021, -0.243, -0.447, 0.109]	[-0.704, 0.051, -0.156, -0.026, 0.047, -0.257]
Phone 9	[-0.674, -1.188, 0.471, 0.472, -1.009, 1.355]	[-1.572, -1.544, -0.525, -0.103, 0.134, -0.073]
Phone10	[0.844, 0.500, 1.283, 0.255, 0.643, 0.326]	[1.396, -0.688, -0.817, -0.204, 0.213, -0.131]
Phone 11	[1.054, 0.822, 0.908, 0.138, 0.918, 0.033]	[1.751, -0.234, -0.571, -0.155, 0.027, 0.055]
Phone 12	[0.782, 0.420, 1.021, 0.457, 0.793, 0.399]	[1.359, -0.796, -0.585, 0.001, 0.071, 0.005]

To project the Kansei vectors into the KE-LSA semantic space, the semantic approach multiplies each Kansei vector x by the KE-LSA semantic space matrix W_0

$$d_u S_0 = x_u W_0 \tag{3}$$

$$d_n S_0 = x_n W_0 \tag{4}$$

x_u is a Kansei vector for one user's needs, x_n is a Kansei vector for one new design, d_u is the projected Kansei vector for the user's needs, and d_u is the projected Kansei vector for the new design.

To calculate the cosine between projected vectors, the semantic approach calculates the cosine of the angle between the scaled d_u vector for each user's needs to the scaled d_n vector for each new design

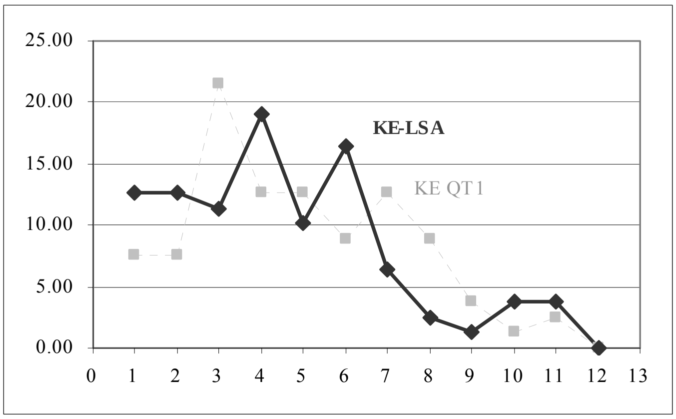
$$\frac{d_u S \bullet d_n S}{\|d_u S\| \times \|d_n S\|} \tag{5}$$

For one user and all twelve cell phones, the results show that the semantic approach chooses Phone 5 as the 4th best match to the Kansei vector for the user's needs. The results show that the semantic approach matches user needs to designs more accurately than the KE-QT1 approach.

	KE-QT1		KE-LSA		
	Rank	Corr	Rank	Cos	Angle
Phone 12	7	-0.294	1	0.764	40.2
Phone 11	1	0.105	2	0.762	40.3
Phone 10	11	-0.366	3	0.675	47.6
Phone 5	**5**	**-0.148**	**4**	**0.618**	**51.8**
Phone 7	3	-0.007	5	0.617	51.9
Phone 2	2	0.066	6	0.149	81.4
Phone 3	4	-0.048	7	0.098	84.4
Phone 9	9	-0.358	8	-0.267	105.5
Phone 6	8	-0.352	9	-0.669	132.0
Phone 4	6	-0.253	10	-0.725	136.4
Phone 1	10	-0.360	11	-0.762	139.6

Phone 8	12	-0.678	12	-0.849	148.1

For seventy-nine cell phone users, the results show that the semantic approach chooses higher ranked phones than the KE-QT1 approach. The results show that the semantic approach matches user needs to designs more accurately than the KE-QT1 approach.



Rank	1	2	3	4	5	6	7	8	9	10	11	12
KE-QT1	7.6	7.6	21.5	12.7	12.7	8.9	12.7	8.9	3.8	1.3	2.5	0.0
KE-LSA	10.1	15.2	13.9	16.5	10.1	16.5	6.3	2.5	1.3	3.8	3.8	0.0

2.6 Determine accuracies

To determine accuracies, the semantic approach determines accuracies for the KE-QT1 approach and the semantic approach. For document indexing, precision is the ratio of relevant retrieved documents (*RR*) to retrieved documents (*RET*). Recall is the ratio of relevant retrieved documents (*RR*) to relevant documents (*REL*). TRDR is the average reciprocal rank of all relevant retrieved documents [12]. For *N* trials,

$$precision = \frac{1}{N}\sum_{i=1}^{N}\frac{RR_i}{RET_i}\times 100\% \quad (6)$$

$$recall = \frac{1}{N}\sum_{i=1}^{N}\frac{RR_i}{REL_i}\times 100\% \quad (7)$$

$$TRDR = \frac{1}{N}\sum_{i=1}^{N}\left(\sum_{j=1}^{RET_i}\frac{1}{rank_j}\right)_i \times 100\% \quad (8)$$

For matching designs to user needs, precision is the ratio of retrieved designs that match user needs (*RR*) to retrieved designs (*RET*). Recall is the ratio of retrieved designs that match user needs (*RR*) to designs that match user needs (*REL*). TRDR is the average reciprocal rank of all retrieved designs that match user needs, (*N* = users).

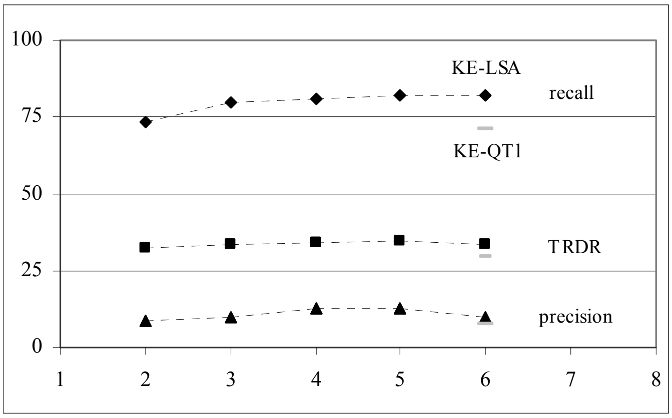
The number of retrieved designs that match user needs (*RR*) depends upon both the number of designs retrieved (*RET*) and the number of designs that match user needs (*REL*). Precision, recall, and TRDR therefore all depend upon *RET*. The semantic approach can choose *RET* values to achieve different matching results.

To calculate accuracies, the semantic approach calculates precision, recall, and TRDR, for specific *RET* values. For twelve cell phones, the design database contains twelve designs. Each user provides needs and chooses one of the designs (*REL* = 1). The approach calculates precision for *RET* = 1, recall for *RET* = 6, and TRDR for *RET* = 12.

For one user, the first new design, and the first KE-QT1 design, match the user's choice 0.0% of the time (*precision* = 0.0). One of first six semantic approach designs, and one of the first six KE-QT1 designs, match the user's choice 100% of the time (*recall* = 100.0%). The fourth semantic approach choice matches the user's choice (*TRDR* = 25.0%). The fifth KE-QT1 design matches the user's choice (*TRDR* = 20.0%).

Approach	Dimension	Information	Precision	Recall	TRDR
KE-QT1	r = 6	100.0	0.0	100.0	20.0
	r = 2	81.0	0.0	100.0	25.0
	r = 3	88.1	0.0	100.0	25.0
KE-LSA	r = 4	92.7	0.0	100.0	25.0
	r = 5	96.6	0.0	100.0	25.0
	r = 6	100.0	0.0	100.0	25.0

For all seventy-nine users, the semantic approach matches designs to users' choices with 12.7% precision, 82.3% recall, and 34.4% TRDR, and the KE-QT1 approach matches designs to users' choices with 7.6% precision, 70.9% recall, and 29.4% TRDR.



Approach	Dimension	Information	Precision	Recall	TRDR
KE-QT1	r = 6	100.0	7.6	70.9	29.4
	r = 2	81.0	8.9	73.4	32.2
	r = 3	88.1	10.1	79.7	33.3
KE-LSA	r = 4	92.7	12.7	81.0	34.3
	r = 5	96.6	12.7	82.3	34.4
	r = 6	100.0	10.1	82.3	33.3

The results show that the semantic approach improves recall 11.4%, compared to the KE-QT1 approach, (p-value = 0.028). The results show that, with five iterations, the semantic approach matches designs to users' choices with (82.3%) accuracy.

Approach	Overall	Design	Model	Matching
KE-QT1	7.6	36.7	87.4	83.5

Iterative KE-QT1	70.9	100.0	87.4	83.5
KE-LSA	12.7	30.4	87.4	94.9
Iterative KE-LSA	82.3	100.0	87.4	94.9

$$\textit{overall accuracy} = \textit{recall} \quad (9)$$

$$\textit{design accuracy} = 100\% - \textit{recall}\,|_{RET=6} + \textit{recall} \quad (10)$$

$$\textit{model accuracy} = 87.4\% \quad (11)$$

$$\textit{matching accuracy} = 100\% - 87.4\% + \textit{recall}\,|_{RET=6} \quad (12)$$

3. Emotional engineering

Emotional engineering recognizes voices, recognizes speakers, recognizes emotions, matches emotions to designs, and determines accuracies.

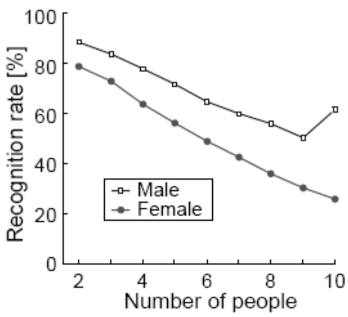
3.1 Recognize voices

To recognize voices, emotional engineering uses sound datasets and factor analysis [13]. For twenty product users, a voice dataset contains voice data, a domestic sounds dataset contains domestic sounds, and a Real World Computer Partnership (RWCP) sound dataset contains other sounds.

For Mahalanobis factor analysis, with b = 2 and fundamental frequency (f_0), variance, power, and average and variance of 12-dimension mel-frequency cepstrum coefficient as sound features, the results show that voices can be recognized at a Mahalanobis distance larger than 80.

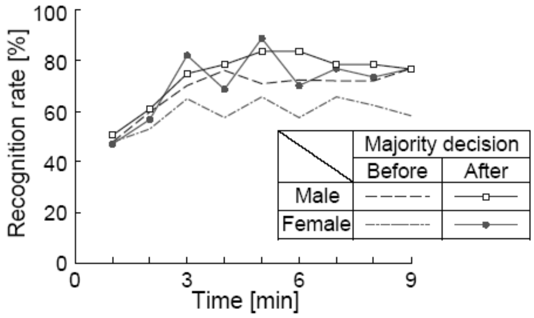
3.2 Recognize speakers

To recognize speakers, emotional engineering uses hierarchical cluster analysis to accumulate and retain speaker reference data [13]. For Ward's hierarchical cluster analysis method, with a cosine distance function, the results show that, if speakers do not speak simultaneously, speakers can be recognized with 80% accuracy.



3.2 Recognize emotions

To recognize emotions, emotional engineering classifies voice data into emotions [13]. For a reference dataset, with twenty users, twelve sentences, and three emotions (happy, angry, and sad), three minutes of voice data, with eleven users, voice recognition, speaker recognition, one-minute voice center of gravity adjustments, and majority decision classification, the results show that emotions can be recognized with 55% initial and 80% final accuracy.



3.2 Match user needs to designs

To determine match user needs to designs, emotional engineering uses regression analysis or qualitative evaluations to match classified emotional responses to designs [13]. For four users, with five hours of communication per week and qualitative evaluations, the results show that users communicated effectively.

3.3 Determine accuracies

To determine accuracies, emotional engineering compares user needs to designs [13]. For qualitative evaluations, the results show that users can communicate emotions effectively by sound.

4. Conclusions

This study compares the semantic approach and emotional engineering. The semantic approach and emotional engineering are both used for product design. The semantic approach and emotional engineering however are fundamentally different.

The semantic approach uses Kansei engineering semantic differential scale surveys (Kansei words) and Kansei engineering latent semantic analysis cosines to match emotional user needs to designs. The semantic approach can be used to improve matching accuracy, compared to the Kansei engineering approach.

The emotional engineering approach uses sensory differential scale surveys (voice sounds or facial expressions) and regression analysis to match emotional user needs to designs. Emotional engineering can be used to communicate emotions by sensory means.

Study results show that the semantic approach and the emotional engineering can be combined to improve matching accuracy, compared to Kansei engineering. The semantic approach can be used to identify user needs by semantic means. Emotional engineering can be used to identify user needs by sensory means.

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