Original paper

Research in Engineering Design 14 (2003) 119–130
DOI 10.1007/s00163-003-0032-6

Evaluation of multicultural factors from elicited customer requirements for new product development

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Abstract Globalisation has been characterised as one of the recent trends in new product development (NPD), in which multicultural factors, in particular, dominate the initial step of product development. Moreover, the voice of customers has been widely accepted as an important source of input to subsequently obtain design metrics and specifications in the early stage of product concept design. For this purpose, customer requirements elicitation and management will determine the success level of an organisation's NPD and benchmarking. Hence, multicultural factors are the most difficult issues for organisations to address, even with the assistance of today's advanced computer systems. It has, accordingly, been one of the future directions in NPD. However, in practice, there are few successful or effective techniques available for the evaluation of multicultural factors in customer requirements. This paper aims at realising a prototype system that combines the strengths of the laddering technique and the radial basis function (RBF) neural network for customer requirements acquisition and multicultural factors evaluation. The performance of the prototype system was illustrated using a case study on mobile hand phone design. The results are discussed in detail.

Keywords Voice of customers, Customer requirements acquisition and evaluation, Laddering technique, Radial basis function neural network

1 Introduction

Globalisation has been characterised as one of the recent trends in new product development (NPD). In order to gain a competitive edge and reduce the lead-time to market, product development should take into consideration sudden changes in customers' needs and economic conflicts. It should also be implemented worldwide (Yamazaki 1997). In general, product development can be regarded as a cyclical and iterative process, in which cultural factors, in particular, dominate the initial stage of product development. Thus, there is a need to examine how to convert diverse but localised cultures into a specification that can be acceptable globally (Rauner 1997). This has attracted significant attention of researchers from different fields, such as management (Elashmawi and Harris 1993), informatics (Devlin 1999), psychology (Smith and Bond 1993) and engineering (Waldegg and Scrivener 1998) to study the effect of cultural differences or multicultural issues in their domain.

In manufacturing engineering, Rauner (1997) synthesised the findings of culture research and cognitive anthropology by examining the interrelation of academic knowledge and cultural latent or tacit knowledge. The work adopts a so-called "culture-friendly" technique that requires the co-operation of scientists and operators. Further analysis reveals that this "culture-friendly" technique can be successful only if related domain knowledge of both technology providers and customers are integrated into the technology-modelling process. Yamazaki (1997) highlighted the special nature of the location factor from a cultural and a "locally-available" human resource point of view. Accordingly, a multiculture-based concept can be employed for producing products that are able to satisfy the so-called "happiness of customers", such as peace, independence and freedom. Owing to the difference of cultures, many examples indicated that a successful product for a particular geographical location could not be transferred without any modification to another.

During the early stage of product concept development, customer requirements acquisition has a direct impact on the number of design changes and unscheduled cost in NPD. This has, consequently, brought about intensive research efforts (Krishnaswamy and Elshennawy, 1992; McAdams et al. 1999) to tackle the problem. Even when reliable customer information is elicited, it can, as well, be a great challenge to transform and manage it efficiently. After examining the experiences, successful or unsuccessful, of a number of industries, Devlin (1999) concluded that culture factors are the most important, but most difficult, issues for organisations to address, even with the assistance of advanced computer systems. The successful cases revealed that the industries such as the automobile and electronic manufacturers in Japan are able to influence the cultural beliefs of customers in their potential market. Thus, the business imperative for product development of

Received: 29 September 2000 / Revised: 14 May 2001
Accepted: 12 November 2002 / Published online: 4 September 2003

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a world-class organisation should focus on "how customers do it" rather than "what customers do".

Ito and Höft (1997) proposed a novel paradigm known as "Region- and Racial Traits-Harmonised (R^2TH) product". The basic requirements of a R^2TH product include:

- Classifying the hierarchy of a R^2TH product that is dependent on the correlation between design attributes such as regional infrastructure, human and technological resources, life-style, language and customer delight.
- Establishing an evaluation method to handle cultural mindset related characteristics of a product.

It has also been established that the main barrier to realising a R^2TH product lies in the difficulties in quantifying the human-nature-related factors, which include amenity, sensitivity, mentality and performance. As nature and regional differences are unlikely to disappear in the world, the nationality of customer is a key factor in multicultural product due to political, sociological and psychological reasons (Hofstede 1983). The gap between the economic nationality and industrialisation, standardisation of products is unavoidable because of the pressure received from the world market (Latouche 1996). Based on these understandings, Trompennars (1995) identified seven perspectives after studying the behaviour of fifteen thousand managers globally and established that these perspectives would help in characterising a so-called culturalisation process of product. The seven perspectives include:

1. The universal truth versus a particular instance.
2. Individualism versus collectivism.
3. Affective versus neutral relationship.
4. Specific versus diffuse cultures.
5. Achievement versus ascription.
6. Past present or future orientation.
7. External versus internal culture (nature orientation).

The different ways in which organisations consider these perspectives will have an impact on their global strategies of NPD. As a result, they need to take advantage of the diversity through reconciliation; otherwise, a poor product conceptualisation is likely to take place.

In order to capture and handle huge quantities of customer information in the information era from different nations and various customer groups with diverse preferences, cultures or interests, and to win a competitive edge in the global market, customer requirements acquisition and management become an important issue for world-class organisations to address. The clear elicitation of multicultural factors amongst these needs, in particular, will determine the success level of specific organisation's NPD and its competitiveness and benchmarking. It involves two important steps:

1. Obtaining the "real" voice of the customer (VoC).
2. Addressing the issue concerning culture-difference in customer requirements acquisition.

This paper describes a prototype system that combines the strengths of laddering, a customer requirements elicitation technique, and neural networks for customer requirements acquisition and multicultural factors evaluation. The next section, Sect. 2, provides the details of the laddering technique and its implementation procedure. Section 3 presents a radial basis function (RBF) neural network for further customer requirements evaluation. Multicultural factors are extracted by the neural network. In Sect. 4, a case study is used to validate the prototype system. A detailed discussion on the results is provided. The last section, Sect. 5, summarises the main conclusions reached in this work.

2 Customer requirements acquisition using the laddering technique

2.1 Background

Customer requirements acquisition is frequently used as the first stage in product concept development, where affinity diagram (KJ method) and analytic hierarchy analysis (AHP) techniques are employed, in conjunction with quality function deployment (QFD) to elicit customer requirements (Burchill and Fine 1997; Fung et al. 1998). However, such an approach still possesses some limitations:

- The so-called subjective "natural grouping", to a large extent, is decided by domain experts.
- The domain elicited from customer requirements is limited in terms of coverage.
- Effective means to organise original customer requirements are scarce.

Laddering is a structured questioning methodology derived from Kelly's repertory grid technique (Kelly 1955). It was initially developed by Hinkle (1965) for classifying the relations between the constructs and organising them into hierarchical relations. Similar to other "contrived" knowledge elicitation techniques such as repertory grid and sorting techniques, it originated in psychology (Shadbolt and Burton 1989). It has also been applied with increasing frequency in the field of knowledge and requirements acquisition in recent years, as well as used as a "technique" in its original form (a predefined interview) (Boose and Bradshaw 1988) and in the form of "tools" (a computerised system) (Fransella and Bannister 1977). As such, laddering has been developed to associate with more "non-contrived" or "natural" techniques such as interviewing and self-report (McGeorge and Rugg 1992).

Compared with the aforementioned other techniques, there are a number of advantages of using the laddering technique (Corbridge et al. 1994).

- Laddering is more effective than other elicitation techniques. It is able to generate more rules and relevant clauses than sorting, that is, more "gains"; it has a wider coverage of the domain in question than interviewing, that is, more complete; and it requires less "effort" in terms of mean total time for elicitation and coding than self-report.

- Compared to self-report and interview, laddering requires less effort to transform output into alternative formats ("part-of" or "is-a" hierarchies).
- Laddering possesses more focused "control" in terms of signal/noise ratio over the direction of elicitation for process automation than other techniques.
- Laddering imposes more categorical hierarchies or discrete classes than the repertory grid.

2.2 The laddering technique

Laddering resembles a form of structured interview in which the interviewer uses a limited set of standard questions to elicit respondent (customer) requirements. It is based on the assumption that respondent requirements are organised as a polyhierarchy, that is, a multidimensional or multifaceted set of hierarchies. Laddering provides a structure for the elicitation of information using a "facet", which is a convenient way to describe individual hierarchy and decomposition requirements. Table 1 shows the definitions of terminology used in the laddering technique. Based on the work by Rugg and McGeorge (1995), an improved procedure of the laddering technique for customer requirements elicitation in product concept development is summarised as follows (Khoo et al. 2002).

Step 1. *Selecting/faceting a seed item*. An interviewer or domain expert first selects a seed item, which is a point within the domain in question, from any level within the hierarchy. For example, any facet, imposed construct or verbatim construct, can be selected as a seed item. It is recommended that several sessions be conducted, each time for a "facet" or "dimension", e.g. a specific imposed construct.

Step 2. *Preparing/phrasing the probes*. The interviewer uses probing questions to move around the structure embedding the seed item. Some of the frequently used probes or phrasings include "is-a", "has-goal" and "part-of".

Step 3. *Directing/levelling the semantics*. Different prompt is recommended to alter the direction once laddering is not possible to go any further in a particular direction, so-called "bottoming out" or "topping out".

Step 4. *Decomposing/classing the explanations*. Explanations are then decomposed recursively until terms such as classes, attributes and entities bottom out, the depth of which can be treated as an indication of requirement complexity, also known as elucidatory depth.

Step 5. *Recording/coding the sessions*. Several coding methods are available for laddering, including paper record, graphic representation and pseudo-production rule. Appropriate labelling that displays the names of classes and attributes is advisable.

Step 6. *Analysing/post-processing the results*. This enables the elicitors to gain insights into the results of laddering. Quantitative analysis can be employed to post-process the results obtained.

3 Elicitation of multicultural factors in NPD using neural networks

3.1 Framework of a prototype system

After the laddering process for customer requirements elicitation, verbatim constructs are accordingly obtained. Meanwhile, imposed constructs are also elicited due to the multilevel architecture of the laddering process. It is a well-known fact that verbatim constructs usually contain ambiguity, and subjective and qualitative inherence with overlaps and conflicts. Laddering alone is poor at handling concepts that are fuzzy and have no clear-cut boundary between sets of objects (Rugg and McGeorge 1995). As such, it is imperative to evaluate further the customer requirements information elicited from the laddering technique. However, the customer perspective is usually non-linear and overlapping. It cannot be effectively solved by a simple linear function (Nilson 1995). In this respect, neural networks present a logical alternative for recognising the patterns of customer requirements according to various multicultural factors. In this work, a neural network approach to process further the information obtained from laddering is proposed and implemented as part of a prototype system (Fig. 1).

As shown in Fig. 1, the prototype system integrates four processes, namely interview, laddering, repertory grid and neural network recognition, together. The laddering process is combined with an interview that aims at eliciting verbatim constructs of customer requirements, as well as the imposed constructs in a multilevel hierarchy (supposing that an N-dimensional respondent set exists). To allow the prototype system to perform qualitative evaluation, the repertory grid process is included. The process requires customers to define the importance ratings on each elicited verbatim construct (assumed as an M-dimensional construct array) based on some kind of predetermined scheme such as "1" stands for the least importance while "10" represents the most importance. Upon completion, an $M \times N$ matrix (with M-dimensional verbatim constructs and N-dimensional respondents) can be input into a radial basis function neural network. Thus, there are several matrices for each imposed construct, that is, the respondents should grade the same verbatim construct each time in relation to different imposed

Table 1. Definitions of terminology used in laddering technique

Terminology	Definition	Example
Verbatim Construct	An attribute used by an individual to describe something	Ease of use
Imposed Construct	The high-level attribute abstracted from the superordinate construct	Usability
Facet	The viewpoint used for a particular set of classifications	Product functionality

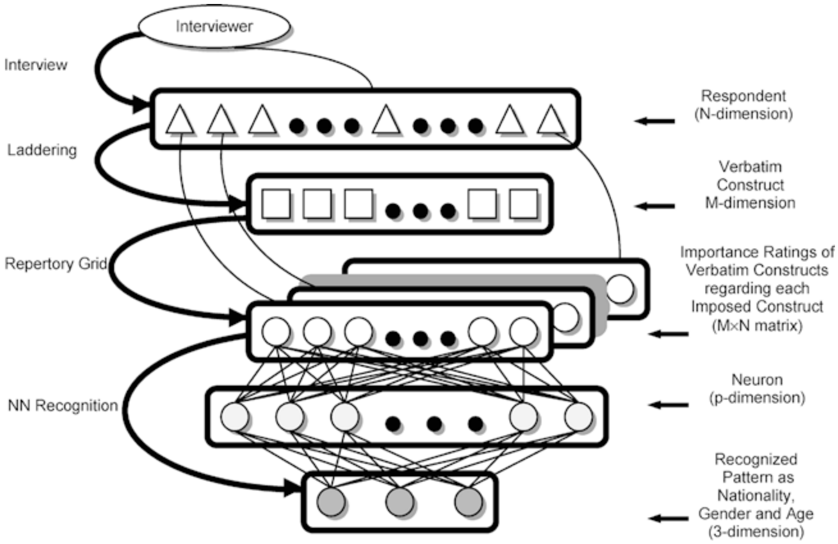

Fig. 1. Framework of a prototype system

constructs. To satisfy the multicultural evaluation, the input matrices are rearranged according to such criteria as diverse nationality, gender and age to establish various engines for culture-difference pattern recognition. The output will be a 3-dimensional pattern with low, moderate and high level of the above-mentioned criteria of nationality, gender and age, respectively.

3.2 The radial basis function neural network

Neural network has been proven to be one of the most effective artificial intelligence (AI) techniques for engineering applications, of which NPD, such as product concept development (Bahrami and Dagli 1994) and machine-part family formation (Malavé and Ramachandran 1994), is an important domain. Furthermore, researchers have paid more attentions to customer issues in product concept development such as customer segmentation (Chen et al. 2002) and marketing analysis (Chen et al. 2001). Compared with other techniques, the radial basis function (RBF) neural network algorithm is adopted because of the following advantages:

– The testing or classification results from a supervised neural network such as the RBF network can be controlled more accurately because of the predefined network training or learning rather than the automated organisation in unsupervised neural networks (Hassoun 1995).
– The RBF network can be used to handle fuzzy conditions because of its equivalence to the fuzzy inference system (FIS) (Roger and Sun 1993).
– The RBF network possesses simple input features, fast training and testing, and effective recognition results. Moreover, the trained network can easily be refined and updated by adding new inputs (Haykin 1999).

The customer feature of verbatim constructs (an $M\times N$ matrix) is used as an input to an RBF network for customer requirements evaluation. The RBF neural network is a supervised neural network, which has three layers, namely the input layer, the hidden layer and the output layer. In the RBF neural network, the mapping between the input and hidden layers is non-linear, while mapping between the hidden and output layers is linear (Fig. 2). Mathematically, the RBF neural network can be expressed using Eq. 1 as follows (Haykin 1999).

$$F(x) = \sum_{j=1}^{p} w_j \psi\left(\left\|x - t_j\right\|\right) \qquad (1)$$

where $\mathbf{x}$ is a n-dimensional customer feature vector, $F(\mathbf{x})$ is the network output and $\psi(\|\mathbf{x}-\mathbf{t}_j\|)$ is a set of p radial basis functions with Euclidean distance $\|\mathbf{x}-\mathbf{t}_j\|$ between the input vector $\mathbf{x}$ and the centre $\mathbf{t}_j$.

The design of the RBF neural network can be viewed as a curve-fitting (approximation) problem in a high-dimensional space. The learning process is equivalent to finding a hyper-plane in a multidimensional space that best fits the training data. The generalisation of the network is equivalent to the use of this multidimensional

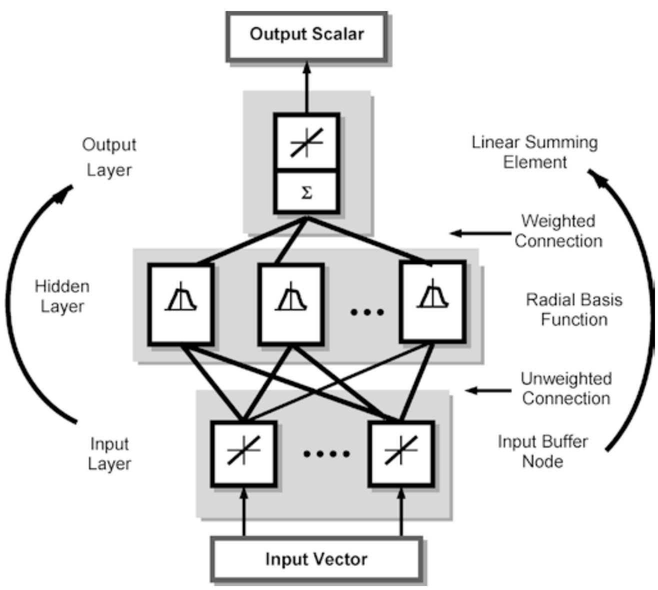

Fig. 2. Schematic of the radial basis function (RBF) neural network

surface to interpolate the test data. The mathematical justification for the RBF neural network is based on the pattern cast in the higher-dimensional space through a non-linear process that is more likely to be linearly separable (Hassoun 1995).

In the RBF neural network, different layers perform different tasks. It is therefore reasonable to separate the optimisation problem of the hidden and output layers of the networks by using different techniques and operating them at different time scales. According to how the centres of the radial basis function of the neural network are selected, a number of learning strategies have been used, e.g., supervised selection of centres such as the least-mean-square (LMS) algorithm, random selection of fixed centres such as the singular-value decomposition (SVD) algorithm and self-organised selection of centres such as the K-nearest-neighbour (KNN) rule (Haykin 1999). In this work, the weights and the centres of radial basis functions undergo supervised learning process using error-correction methods, which is commonly uses the LMS algorithm. The instantaneous value of the cost function is given by Eq. 2 as follows.

$$\varepsilon = \frac{1}{2}\sum_{i=1}^{N} e_i^2 \tag{2}$$

where N is the number of training samples and e_i is the error signal.

$$e_i = d_i - F(x_i) = d_i - \sum_{j=1}^{p} w_j G\left(\left\|x_i - t_j\right\|_{c_j}\right) \tag{3}$$

where d_i is the desired response vector in the training set and G is a radial basis function matrix. The objective is to find the free parameters w_j, $\mathbf{t}_j$ and Σ_j^{-1} related to the norm-weighting matrix C_j so as to minimise ϵ. In the minimisation process, the determination of w_j is a linear optimisation problem, whereas that of $\mathbf{t}_j$ as well as Σ_j^{-1} is non-linear.

3.3
Specifying the RBF neural network

The RBF neural network possesses the capability of representing arbitrary functions. It converges quickly, which results in rapid training. The reliability of the output, such as low, moderate or high level of multicultural factors such as nationality, gender or age, generated by an RBF neural network may be affected by the features and the volume of data used for training as each imposed construct is represented by an $M\times N$ training matrix of verbatim constructs. To assume that one kind of learning algorithm is better than another is inappropriate, since the optimal type of learning algorithm to adopt may vary depending on the pattern recognition problem and training data available (Hassoun 1995). As the RBF neural network is a kind of

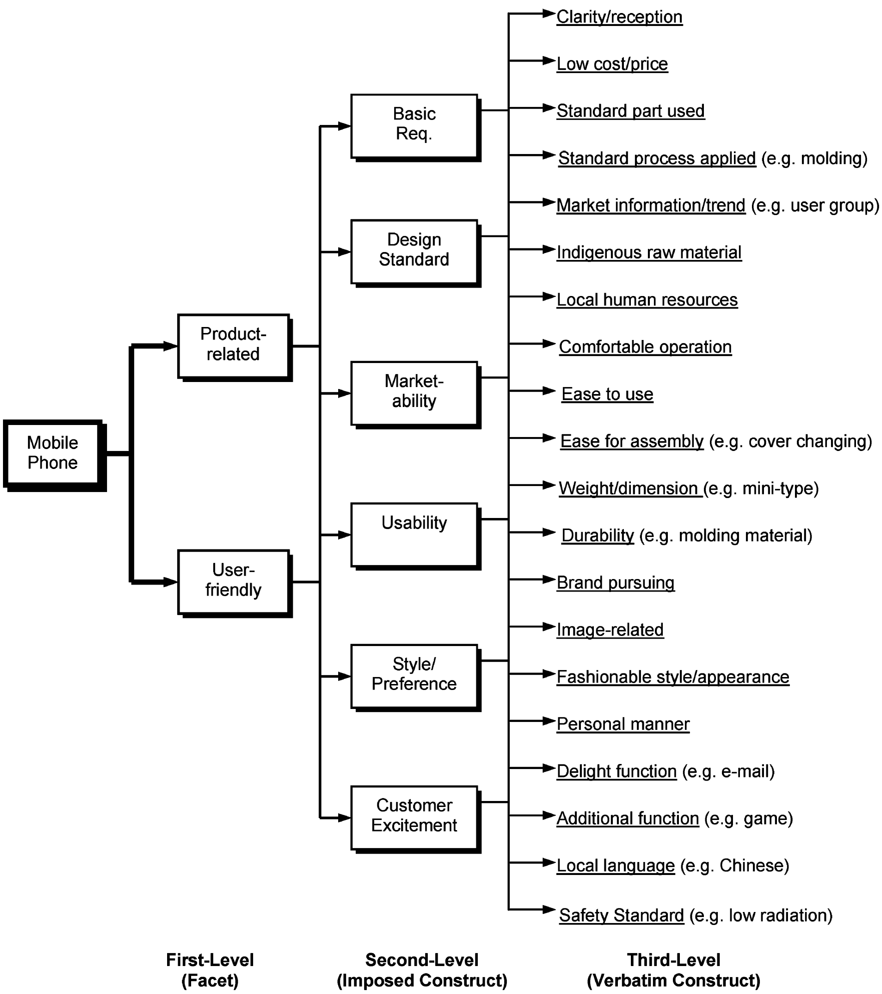

Fig. 3. Graphic representation of laddering for mobile hand phone design

supervised neural network, the pattern recognition training for output data in relation to input features proceeds under certain predetermined schemes or categories of levels for training. For example, a weak correlation between a pair of input (verbatim construct matrix) and output (the level of multicultural factors) is denoted as Pattern 0. In the same manner, a moderate correlation and a strong correlation can be denoted as Patterns 1 and 2 respectively. In addition, the training set from the respondents' ratings should be sufficient and effective, revealing that not only external respondents such as past and future customers are involved, but also internal respondents such as designers and domain experts are included.

The procedure of the RBF neural network learning and classification strategies can be summarised as follows:

Step 1. Train the RBF neural network at each point using the LMS algorithm. The weights are updated according to Eq. 4 as follows.

$$w_j(n+1) = w_j(n) + \eta \sum_{i=1}^{N} e_i(n) \exp\left(\frac{-\left\|x_i - t_j\right\|^2}{2\sigma^2}\right) \tag{4}$$

where η is the learning rate, σ is the smoothing factor ($\sigma = 1$ in this study) and n is the epoch number and $j = 1, 2, \ldots, P$.

Step 2. Evaluate the sum of square of errors (SSE) for the training set. The SSE is given by Eq. 5 as follows.

$$SSE_{train} = \sum_{n} e_n^2 < \mu \tag{5}$$

where e_n is the error of each training sample and μ is the error target.

Step 3. Test the RBF network at the end of each training epoch, then "freeze" the weights and calculate the SSE of the test data set.

Step 4. Repeat Steps 1–3, until the end condition has been satisfied. The end condition is given by Eq. 6 as follows.

$$SSE_{\text{test}} = \min \text{ and } |e_i| < \theta \tag{6}$$

where e_i is the error of each testing set. Initially, only the first condition (minimum SSE_{test}) is used, however, in the learning process, it has been found that the SSE_{test} may reach a local minimum at the initial stage of learning where the sample error is still large. Therefore, the second condition is introduced. The threshold value of error criterion θ is experimentally determined to be 0.1 or less (below this level, the global minimum of SSE_{test} can possibly be obtained).

Step 5. Classify the customer input data for pattern recognition of multicultural factors evaluation via the trained RBF network. With Eq. 7, according to the probability distribution of the classification thresholding (Zhang, 1993), the output pattern is instantiated (or fired) as desired response, viz. Pattern 0, 1 or 2, or *uncertain*.

$$\begin{cases} \text{fired} & \text{if } |e_k| < \delta \\ \text{uncertain} & \text{if } |e_k| \geq \delta \end{cases} \tag{7}$$

where e_k is the classification error of the classification sample.

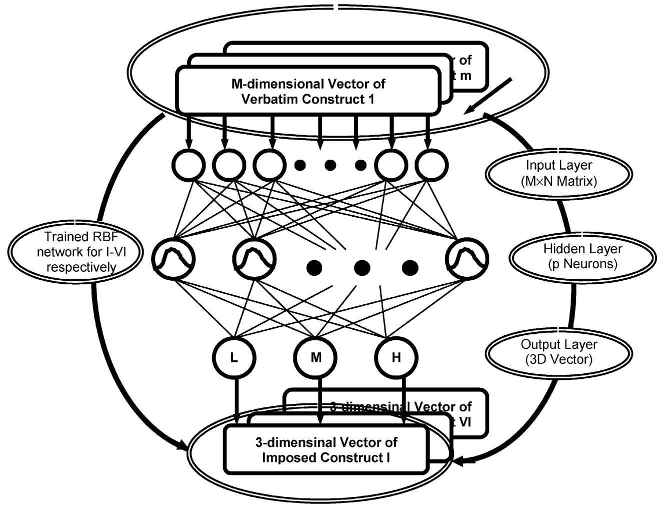

Fig. 4. Detailed architecture of the RBF network approach

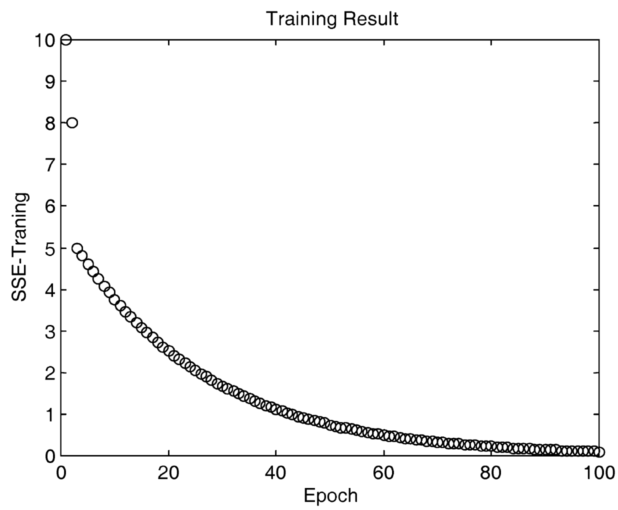

Fig. 5. Training result of the RBF network (for imposed construct I – Basic Requirements)

$$e_k = d_m - F_k \tag{8}$$

where d_m is the desired response vector, Pattern 0, 1, 2 when $k = 1, 2, 3$ respectively, F_k is the actual classification output and δ is the classification error threshold experimentally determined as 0.2.

4
A case study on mobile hand phone design

4.1
Laddering method for mobile hand phone design

This case study involved a mobile hand phone design, which was based on the assumption that the respondents have, more or less, some knowledge on a mobile hand phone, ignoring whether or not they have ever used it. A hierarchical structure is first established using the laddering technique by an interviewer (or elicitor). The interviewer first selected a seed item, for example, an imposed construct could be selected as a seed item. Subsequently, eighty (80) respondents divided into two groups

Table 2. Learning and classification parameters of the RBF network

Parameter	Value
Input Feature	20
Hidden Neuron	30
Output Pattern	3
Learning Rate	0.05
Initially Weight	0.01
Training Error Target	0.05
Testing Error Criterion	0.1
Classification Error Threshold	0.2

of different nationalities were chosen to contribute their verbatim constructs upon probes by an interviewer during a total of six sessions of laddering (each session using a specific seed item or imposed construct at one time). Each group consisted of twenty male and twenty female subjects. Furthermore, half of them are below 35 years old and the other half over 35 years old. After all the facets were bottomed out, the respondents were asked to grade the elicited constructs using a repertory grid from "1" to "10" (from the least to the most importance). As an example, a customer rating of "10" should be graded to the Verbatim Construct "Clarity/reception" with respect to the Imposed Construct "Basic Requirements" if a respondent deemed it is extremely important. A predefined session of explosive repertory grid was, beforehand, conducted for the RBF neural network training, where the respondents were selected from both external and internal ones, to grade the verbatim input constructs in relation to each imposed output construct.

4.2
Results and discussions

Figure 3 illustrates the graphical representation of laddering for mobile hand phone design, where a three-level laddering structure was obtained, together with, six (6) imposed constructs in the second-level and twenty (20) verbatim constructs in the third-level elicited from two (2)

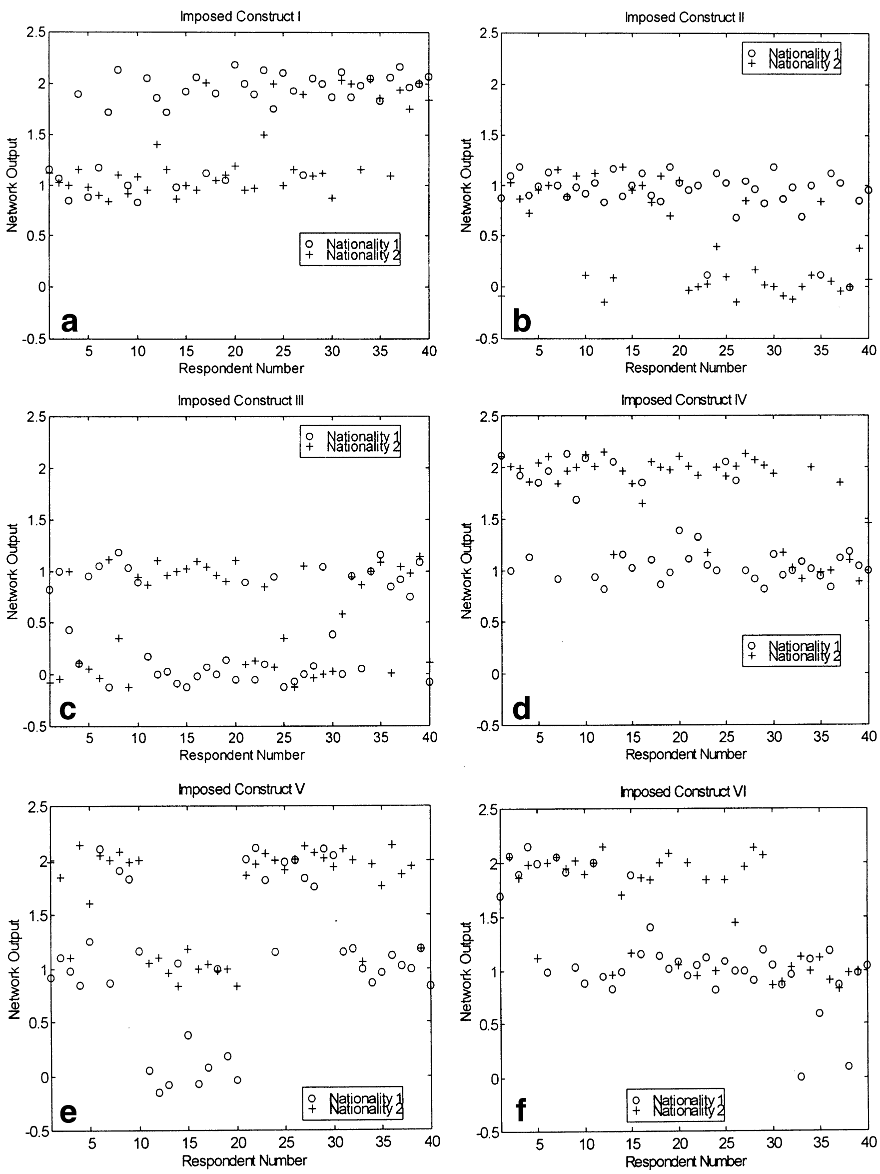

Fig. 6. Results of the RBF network classification based on nationality: (**a**) – (**f**) for output of the imposed construct *I* – *IV* (*I* – Basic Requirements, *II* - Design Standard, *III* - Marketability, *IV* - Usability, *V* - Styles/Preferences, VI - Customer Excitements)

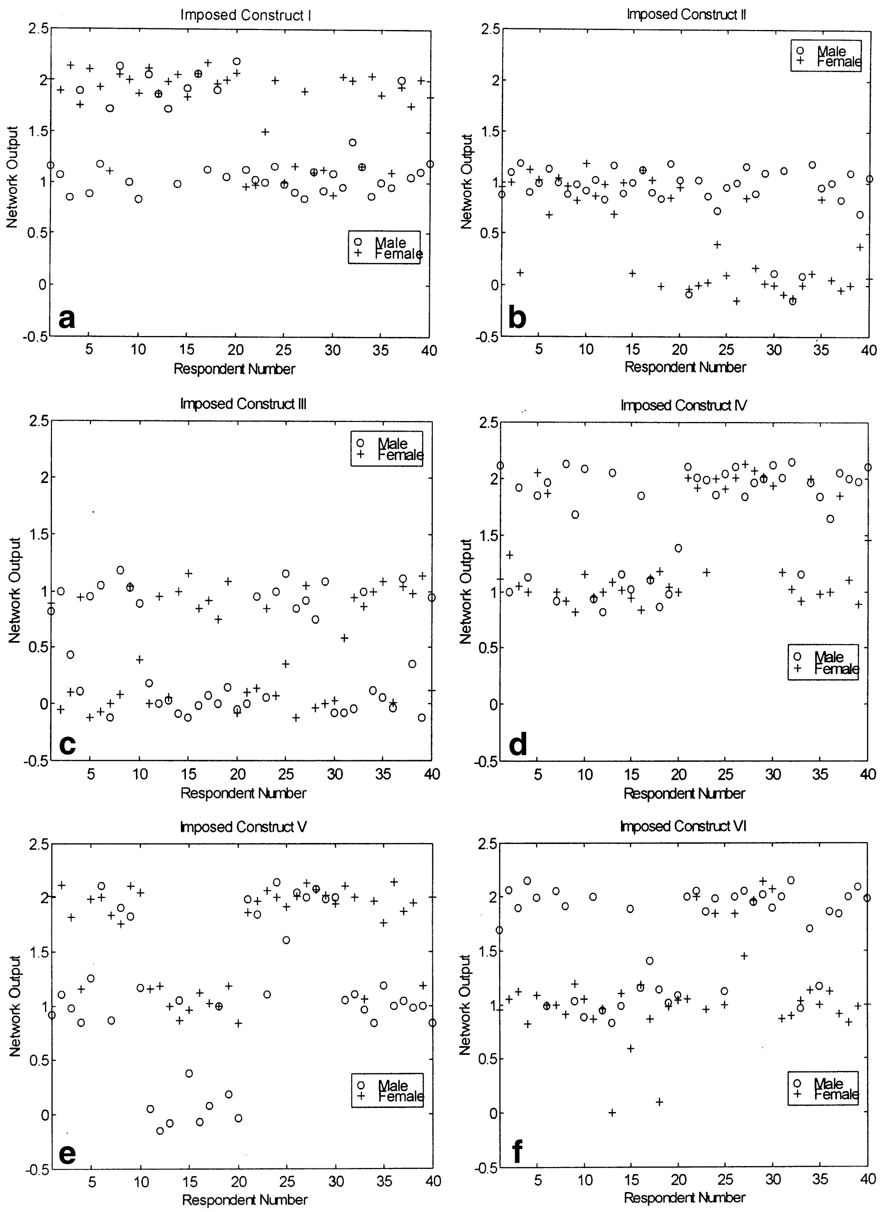

Fig. 7. Results of the RBF network classification based on gender: (**a**) – (**f**) for output of the imposed construct *I–IV* (*I* - Basic Requirements, *II* - Design Standard, *III* - Marketability, *IV* - Usability, *V* - Styles/Preferences, *VI* - Customer Excitements)

major facets in the first-level. The verbatim constructs used by the respondents contained:

– Objective ones such as the dimension of the mobile hand phone and subjective ones such as fashionable style.
– Observable ones such as good appearance and unobservable ones such as durability of the mobile hand phone.
– Concrete ones such as the material used and abstract ones such as ease of use.

It was observed that a large number of verbatim and imposed constructs elicited possess overlapping (high-commonality of distribution) facets. For example, Imposed Constructs "Marketability" and "Usability" are largely shared by both facets as "Product-related" and "User-friendly" during the laddering process. On the other aspects, the conflicts (adverse correlation) between verbatim constructs can also be detected. These include delight functions versus low price; fashionable style versus ease of use; and small dimension versus good reception. For this purpose, it appears that artificial intelligence (AI) techniques such as neural networks provide an excellent means for the identification of multicultural factors through the recognition of different patterns, such as the diversities of nationality, gender or age.

In this work, the RBF network was employed after the respondents completed the repertory grid of verbatim constructs. The graded verbatim constructs were organised as a feature vector as inputs to the RBF network learning and for classification. For instance, if twenty (20) verbatim constructs are graded by forty (40) respondents, an input matrix of 20×40 dimensions will form the input features. The network's output will be the pattern of a specific imposed construct regarding those input features of verbatim constructs, namely low correlation (Pattern 0); moderate correlation (Pattern 1); and high correlation

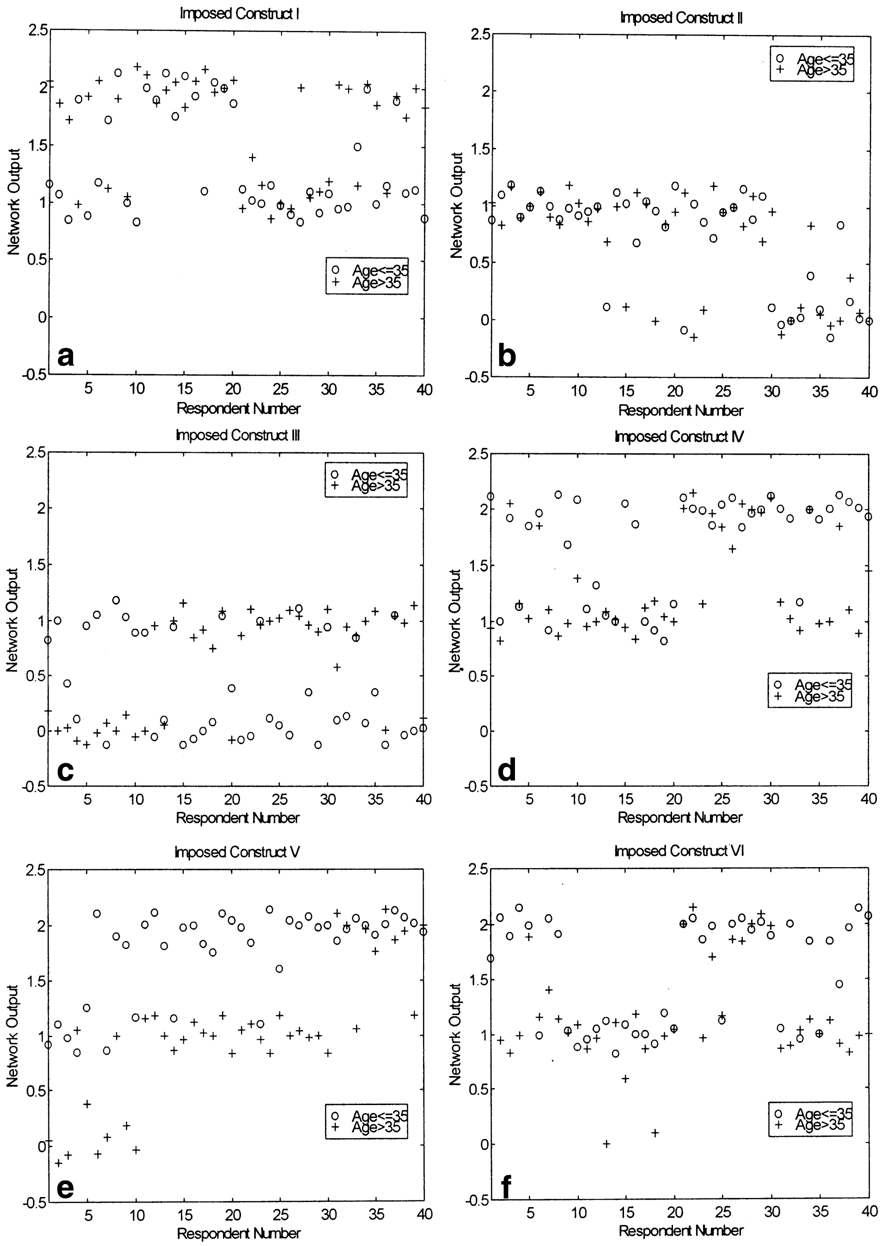

Fig. 8. Results of the RBF network classification based on age: (**a**) – (**f**) for output of the imposed construct *I–IV* (*I* - Basic Requirements, *II* - Design Standard, *III* - Marketability, *IV* - Usability, *V* - Styles/Preferences, *VI* - Customer Excitements)

Table 3. Statistical results based on nationality

Imposed Construct	Nationality 1				Nationality 2			
	Output Pattern				Output Pattern			
	0	1	2	Uncertain	0	1	2	Uncertain
I – Basic Requirements	0	11	26	3	0	27	10	3
II – Design Standard	3	35	0	2	20	16	0	4
III – Marketability	21	16	0	3	15	22	0	3
VI – Usability	0	27	10	3	0	9	28	3
V – Styles/Preferences	7	19	11	3	0	12	26	2
VI – Customer Excitements	2	27	8	3	0	18	20	2

(Pattern 2). The detailed architecture of this RBF network approach is shown as Fig. 4.

As already mentioned, the RBF neural network should be first trained using a set of predefined 20×80 input matrices of verbatim constructs each for a specific imposed construct output. Fig. 5 shows an example of the results of training and Table 2 lists the learning and classification specifications of the RBF network. In this work, the classification scheme of the RBF neural network is dependent on the multicultural factors elicited from the output patterns using the verbatim constructs, which are organised in the form of input matrices gathered from

Table 4. Statistical results based on gender

Imposed Construct	Male				Female			
	Output Pattern				Output Pattern			
	0	1	2	Uncertain	0	1	2	Uncertain
I – Basic Requirements	0	28	9	3	0	10	27	3
II – Design Standard	4	34	0	2	19	17	0	4
III – Marketability	18	20	0	2	0	11	26	3
VI – Usability	0	11	26	3	0	25	12	3
V – Styles/Preferences	7	19	11	3	0	12	26	2
VI – Customer Excitements	0	12	25	3	2	33	3	2

Table 5. Statistical results based on age

Imposed Construct	Age ≤ 35				Age >35			
	Output Pattern				Output Pattern			
	0	1	2	Uncertain	0	1	2	Uncertain
I – Basic Requirements	0	25	12	3	0	13	24	3
II – Design Standard	11	26	0	3	12	25	0	3
III – Marketability	21	15	0	4	15	23	0	2
VI – Usability	0	11	26	3	0	25	12	3
V – Styles/Preferences	0	8	29	3	7	23	8	2
VI – Customer Excitements	0	19	19	2	2	26	9	3

groups of respondents having different nationality, gender and age. It appears that the RBF neural network provides a powerful and fast means of uncovering the distribution pattern for customer requirements evaluation because:

- Only simple input matrices of graded verbatim constructs are needed. The speed of pre-processing of the input features can be improved.
- Reasonable output patterns, which are easy for subsequent statistical analysis, can be acquired.
- It involves only quantitative evaluation.

Figures 6, 7 and 8 show the classification results obtained from the RBF neural network based on nationality, gender and age, respectively. As previously mentioned, Eq. 7 in Sect. 3.3 shows that there are two diversities within the output patterns: one is selected from any of the three states (Pattern 0, 1 or 2); the other is uncertain due to the predefined threshold value. The results obtained are organised according to the three multicultural factors, namely nationality, gender and age in Tables 3, 4 and 5 respectively. Figure 9 shows the 3D graphical representations of the statistical results.

It appeared that the outputs under each nationality, gender and age grouping exhibited some kind of patterns: either Patterns 0 and 1 or Patterns 1 and 2 were instantiated for most imposed constructs. "Uncertain pattern", though not significantly prominent, was also observed in the distribution due to the probability distribution of the classification thresholding. Some form of similarities (commonality of distribution) can be observed between two different nationality, gender and age groups. For example, all the customer groups emphasised Imposed Constructs "Basic Requirements", "Styles/Preferences" and "Customer Excitements", because the majority of output patterns was linked to Pattern 2 (high correlation) as well as Pattern 1 (moderate correlation). Hence, differences (adverse correlation) can still be spotted as different groups possessed different distribution patterns for some imposed constructs.

- It was detected from Figs. 6 and 9(a) and Table 3 that Group 1 focused on "Basic Requirements" much more than Group 2, as 26 out of 40 responses in Group 1 were linked to Pattern 2 (high correlation) as compared to only 10 out of 40 in Group 2. As for Imposed Constructs "Usability", "Styles/Preferences" and "Customer Excitement", it is obvious that Group 2 paid more attention to them as more than half of the responses of each imposed construct are linked to Pattern 2 compared to about a quarter of the responses of each imposed construct from Group 1.
- In the same way, it was found from Figs. 7 and 9(b) and Table 4 that, in different gender groups, male respondents were more interested in "Usability" and "Customer Excitement" while female respondents were more concerned with "Basic requirements", "Marketability" as well as "Styles/Preferences".
- By the same token, it was observed from Figs. 8 and 9(c) and Table 5 that respondents below 35-year-old paid more attentions to "Usability" and "Styles/Preferences" whereas those who are over 35-year-old were more interested in features such as "Basic Requirements".

5 Conclusions

A novel approach based on the laddering technique and the radial basis function (RBF) neural network has been investigated and implemented as a prototype system for

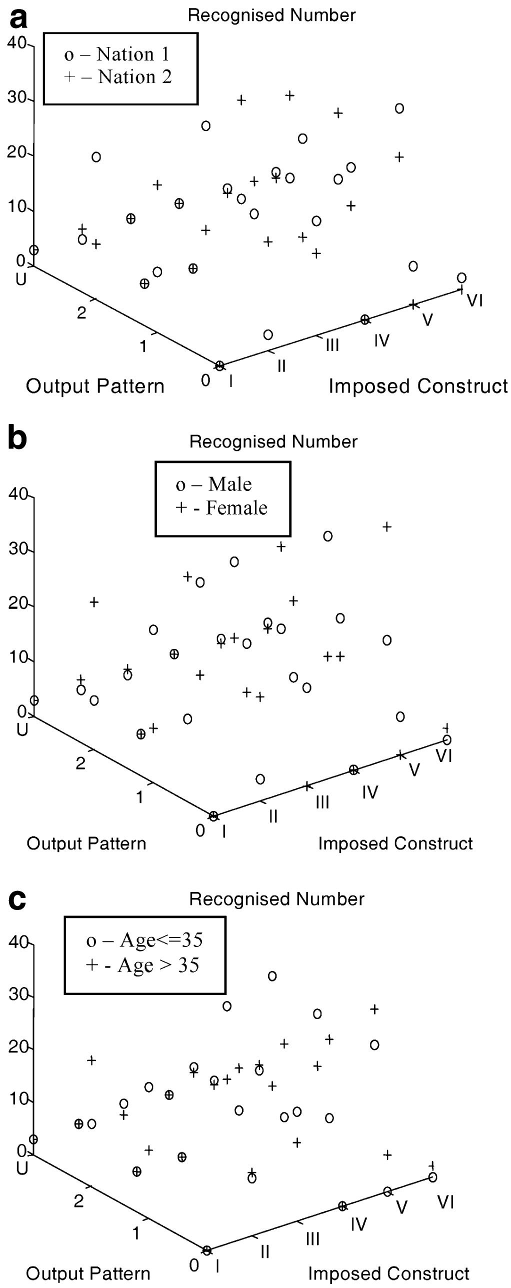

Fig. 9. Summary of statistical results: **a**, **b** and **c** for nationality, gender and age respectively (Imposed Construct *I* - Basic Requirements, *II* - Design Standard, *III* - Marketability, *IV* - Usability, *V* - Styles/Preferences, *VI* - Customer Excitement)

NPD. Based on such a prototype system, customer requirements are first elicited using a three-level hierarchical laddering technique. Subsequently, various verbatim and imposed constructs were obtained in relation to different facets. To overcome the qualitative nature of the imposed constructs and assess the effects of multicultural factors on them, an RBF neural network has been established to evaluate the imposed constructs quantitatively. The prototype system enables the similarity and difference between different respondent groups to be studied psychologically and computationally. More specifically, the advantages of employing both laddering and RBF network include:

- Compared with other knowledge or requirements acquisition techniques, laddering, which was originally developed from psychology, can systematically elicit the customer requirements due to its wider coverage of domain, less mean total time for elicitation and coding, and a more controllable process.
- As laddering alone cannot identify the uncertainty and fuzziness amongst customer requirements, the RBF network, which is theoretically equivalent to a fuzzy inference system, presents a logical alternative to integrate with the laddering technique during multicultural factor analysis. It can effectively recognise multicultural patterns due to its simple input features, fast network training, controllable network testing and classification, and easy network updating.

A case study on mobile hand phone design was used to illustrate performance of the prototype system. From the case study, the laddering technique has demonstrated its effectiveness in eliciting customer requirements in the early stages of NPD. The RBF neural network which requires simple input matrices of graded verbatim constructs provides an efficient means of evaluating the effects of multicultural factors in customer requirements statistically. It is envisaged that with the genuine voice of customers and the effects of multicultural factors on customer requirements identified, organisations can gain a competitive edge in NPD.

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