INTERNATIONAL CONFERENCE ON ENGINEERING DESIGN, ICED'07
28 - 31 AUGUST 2007, CITE DES SCIENCES ET DE L'INDUSTRIE, PARIS, FRANCE

A RULE MINING APPROACH TO EMOTIONAL DESIGN IN MASS CUSTOMIZATION[1]

Si Jie Phua[2], Wee Keong Ng[2], Haifeng Liu[2], Bin Song[3] and Xiang Li[3]
[2]Nanyang Technological University, Singapore
[3]Singapore Institute of Manufacturing Technology, Singapore

ABSTRACT
In the current manufacturing environment of intense competition, mass customization becomes a crucial capability for a company to survive. Acquiring and identifying customer needs is an important aspect of mass customization. Emotional terms are often included in the description of customer needs and customer evaluations. At the same time, products that consider emotion responses and evoke positive emotions tend to attract customers. Thus, emotional design has been proposed to incorporate customer emotional needs into design elements to deliver customer emotional satisfaction. The main challenge of emotional design originates from difficulties in mapping customers' subjective emotions to perceptual design elements. This paper proposed an association rule mining approach to provide emotional design decision support where the basic requirements can be identified. This approach applies rule mining on customer evaluations and product specifications. Three main steps—data preprocessing, association rule mining, and rule evaluation—are involved in this approach. Data preprocessing extracts critical emotional terms and perceptual design elements from data sources. Data provided by similar customers are grouped. For each customer group, association rule mining is applied on the emotional terms and associated design elements to find out implicit relationships between them. Support level, confidence level and freshness of supporting data of the rules are used to evaluate and rank the applicability of the rules. The proposed approach is illustrated by a case study on emotional design for a series of mobile phones.

Keywords: Association Rule Mining, Emotional Design, Emotional Needs, Mass Customization

1 INTRODUCTION
Nowadays, the over-capacity of mass-produced products results in intense competition [1]. In order to maintain competitive advantage, providing products to meet individual requirements at near mass-produced price and time-to-market is emerging as a crucial capability. This capability is called mass customization.

In order to reach the goal of mass customization, manufacturers should be able to identify the diversity in costumer needs during product development. Diversity is a characteristic that differentiates objects and groups similar ones together [2]. Customers may have diverse needs towards certain products arising from different culture, age groups, social climates, nationality, and so on. In mass customization, a product platform is developed based on common factors of customer needs to allow further customizations to meet individual requirements [3]. The proper development of a product platform saves cost and design effort. Thus, understanding diversity of needs adds value in product design.

However, satisfying customers' true needs is not an easy task. Norman suggested that emotion plays an important role in customers evaluating the products that meet their needs [4]. Emotional design proposes that design elements lead to three levels of emotional responses: visceral, behavioral and reflective. Visceral responses are concerned with aesthetic measures. Behavioral responses relate to the pleasure and effectiveness of use. Reflective responses are stimulated by the rationalization and intellectualization of a product. These three levels interact with one another, each modulating the

---

1 This work is supported in part by grant P0520095 from the Agency for Science, Technology and Research (A*STAR), Singapore.

other. To deliver customer emotional satisfaction, product design should incorporate customer emotional needs such as “good-looking”, “feature-rich”, and so on, into perceptual design elements, such as “round” in visceral design and “3G” in behavioral design. The main challenge of emotional design originates from difficulties in mapping subjective emotional terms to definite values or structures of design elements.

Kansei Engineering has been developed as a customer-oriented technology that supports emotional design in new product development [5]. ‘Kansei’ is a Japanese word that means human sensibility. Kansei engineering, as a form of human ergonomic technology, is used to translate human psychological factors such as emotion evoked by products into appropriate perceptual design elements.

Kansei Engineering has attracted much attention since the 1970s. As an effective tool for customer-oriented product development, it has been applied to various sectors such as clothes, vehicles, kitchen and electronic products in Japan and Korea. Various approaches, such as category classification [5], sorting technique and Kohenen’s self-organizing map [6], rule-based inference model [7][8] have been developed as models of Kansei Engineering.

In the category classification approach [5], physical design details are determined by recursively breaking down the kansei categories in the planned target. Using this approach, a tree structure of kansei categories is formed where the leaf nodes are physical design details. To use this approach, the product development team should understand how customers’ kansei can be elicited by design elements and conduct surveys or experiments when necessary.

Chen *et al.* have applied sorting techniques and Kohenen’s self-organizing map [6] to transform customer emotional requirements into product concepts. In this approach, the first step is to let customers identify their emotional requirements using picture sorting methods. Then, a session is conducted to obtain importance rating on each emotional requirement from a large group of customers. Using the self-organizing map algorithm, these customers are grouped into a few prototypes based on the importance rating vectors of emotional requirements provided by them. The resultant prototypes assist designers to develop product concepts according to the importance ratings on emotional requirements of the prototype.

Rule-based inference models [7][8] have been suggested to assist designers by identifying rules between kansei words and design elements. The model usually comprises three important portions: kansei words collection, rule-based inference procedure, and rule evaluation. Kansei words collection identifies kansei words for specific product by collecting them from various sources such as newspaper and magazine. A rule-based inference procedure conducts a survey to evaluate a variation of the specific product for each kansei word using a semantic differential scale. After this, a rule-mining approach is applied to find out the relationship between kansei words and design elements. Rule evaluation measures the applicability of rules based on their support and confidence level. The set of rules obtained serves as design guidelines to predict appropriate values for design elements when a set of customer needs are given.

We propose an association rule-mining approach to provide emotional design decision support. This approach is similar to a rule-based inference model. However, instead of collecting data from survey, the customer evaluations on existing products are used as data sources. A related work has proposed feature-based opinion summarization of customer evaluations to discover the opinions to product features that the customers have commented on [9]. Different from theirs, our approach intends to discover perceptual design elements, i.e. values of product features, which are implied by the opinions. In our approach, the first step collects emotional words from these evaluations and identifies critical perceptual design elements from corresponding product specifications. After applying association rule mining on these data, the discovered rules show the implicit relationship between customers’ emotional needs and design elements. These rules evaluated by our proposed “freshness weights” together with confidence levels may assist designers to identify critical design elements for given customer needs from specific customer groups. A case study on mobile phone is used to illustrate the proposed approach.

2 PROBLEM DESCRIPTION

Customer-oriented product development usually involves a mapping process from customer needs in the customer domain into perceptual design elements in the design domain. We propose using a set of rules to rationalize the mapping process where the emotional terms are extracted from customer evaluations and combined with critical design elements of the evaluated product to form a transaction record. The problem in this work is to identify rules that support decision making in product development such that designers may select the set of rules according to the desired market segment and apply the rules to identify critical design elements from given customer needs. Note that the transaction records are partitioned according to market segments so that valuable rules may be found. We formulate the problem as follows:

Given some customer needs towards a series of products represented by a set of emotional terms $E = \{e_k \mid k=1,2,\ldots,N_E\}$ where e_k is the k^{th} emotional term and N_E is the total number of emotional terms, and a set of design elements $D = \{d_k \mid k=1,2,\ldots,N_D\}$ satisfying E extracted from the product specifications where d_k is the k^{th} design element and N_D is the total number of design elements, relying on the historical transaction records where each transaction record t is defined as a hybrid set of emotional terms and design elements, i.e., $t = \{i_k \mid i_k \in E \text{ or } i_k \in D, k=1,2,\ldots,N_t\}$ (N_t is the number of elements within the record), the task is to discover a set of rules $R = \{r_k \mid r_k : P(E) \rightarrow P(D), k=1,2,\ldots N_R\}$ where $P(E)$ and $P(D)$ is the power set of E and D respectively, and each rule r inferences a subset of D that satisfies a specific subset of E.

3 APPROACH

We proposed a rule-mining approach to solve the problem defined in Section 2. As shown in Figure 1, the approach comprises three main steps; namely, data preprocessing, association rule mining, and rule evaluation. These steps are performed in sequence. At the end of the whole process, a set of rules with evaluation rating is generated for each market segment. These rules are expected to provide guidelines for designers in the identification of critical design elements.

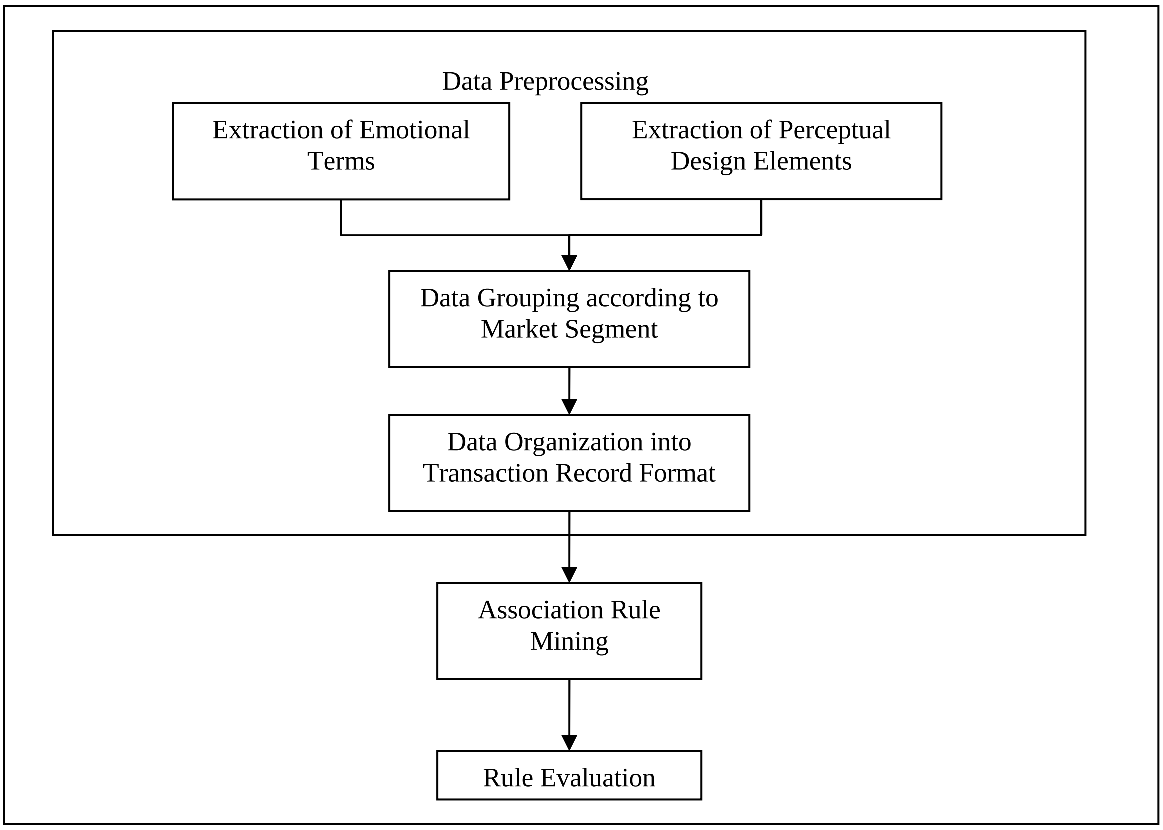

Figure 1. Procedures of our rule-mining approach

3.1 Data Preprocessing

The whole processes of data preprocessing consists of the extraction of emotional terms, the extraction of perceptual design elements, data grouping according to market segment and data organization into transaction record format.

Extraction of Emotional Terms

In this approach, customer evaluations are the source of emotional terms. In general, customer evaluations are collected in the form of free text. This enables customers to freely express what they feel about the product. Valuable information may be embedded in these customer evaluations.

In order to identify the embedded information, these customer evaluations are organized so that data mining algorithms can be applied. First, all the emotional description in the customer evaluations are extracted where a lot of descriptions may mean the same. These descriptions which has similar semantic meaning are then be summarized using a set of emotional terms $E^*\subseteq E$. We build up a semantic mapping table so that similar descriptions share the same representation (emotional terms).

The construction of semantic mapping table is done either manually or statistically. When done manually, the emotional description may be summarized according to preferences and needs. However, expert knowledge is essential to apply the manual method. Affinity diagrams and interviews may assist the manual process. To use statistical methods, questionnaires should be arranged to ask customer which emotional terms are important to them. This is often done on a seven-point scale where emotional descriptions are rated according to participants' preferences. Emotional descriptions that have similar results in the process can be grouped together. This process requires statistical background and the arrangement of questionnaire.

Extraction of Perceptual Design Elements

Perceptual design elements are those product properties that have direct impact to customers such as "round" for size, "black" for colour and "3G" for function. A consistent way for identification of perceptual design elements is missing in the literature.

Customers usually mention what they perceive. As a result, we propose to take customer evaluations as a reference when extracting critical perceptual design elements from product specifications. For the purpose of association rule mining, design elements which have the same values on almost all products in the series should be omitted in order to derive valuable rules.

Data Grouping According to Market Segment

The diversity of customer profiles results in the diversity of customer needs. Customers tend to prefer products that satisfy their specific needs instead of obtaining an average product. Thus, it is important to analyze customer data separately according to market segments so that specific needs can be met.

Market segments may be formed according to several customer profiles. As an alternative, customer evaluations can also be used to classify customers into market segments. We suggest that customers that select similar products should form a market segment. The descriptions in their evaluations also reflect their characteristics. It is suggested to handle positive descriptions and negative descriptions separately.

Data Organization into Transaction Record Format

For each customer evaluation, its mapped emotional terms $E^*\subseteq E$ are used to form a transaction record $t=\{i_k \mid i_k\in E$ or $i_k\in D$, $k=1,2,\ldots,N_t\}$ together with the associated set of perceptual design elements, $D^*\subseteq D$. As a result, a list of transaction is formed so that association rule mining could be applied on the data.

3.2 Association Rule Mining

Association rule mining is a data mining method to find frequent patterns from a reasonably large dataset. Traditional association rule mining assumes that all items belong to the same itemsets in the transaction data. However, rules of the form $E^* \rightarrow D^*$, where E^* and D^* are from different itemsets, are of our interest. In our case, $E^*\in P(E)$ is a set of emotional terms while $D^*\in P(E)$ is a set of design elements. Each rule has a support of s% and a confidence of c% in the transaction database defined as follows:

$$s\% = \frac{count(E^*\cup D^*)}{count(Transaction)}\times 100\% \tag{1}$$

$$c\% = \frac{count(E^*\cup D^*)}{count(E^*)}\times 100\% \tag{2}$$

where the $count(E^* \cup D^*)$ is the number of transaction records that contains all items in $E^* \cup D^*$, *count*(*Transaction*) is the total number of transaction records, *count*(E^*) is the number of transaction records that contains all the items in E^*. As a result, the general form of an association rule in this approach is of the form:

$$E^* \rightarrow D^* \; [Support = s\%, Confidence = c\%]. \tag{3}$$

Equation (3) indicates that the inference from a list of emotional terms E^* to a list of perceptual design elements D^* has a confidence of c% and a support of s% from the transaction database. Given the list of emotional requirements E^*, the rule implies that resultant products should contain the list of design elements D^*; in other words, D^* serves as a basis for setting product specification. The inference is associated with a c% confidence.

Large numbers of efficient algorithms for mining association rules have been proposed [10][11][12][13]. In our approach, the Apriori algorithm [10][11] is adopted to extract the frequent rules. Apriori is an influential algorithm for mining frequent itemsets. It uses prior knowledge of frequent itemset properties and employs an iterative approach known as a level-wise search, where k-itemsets are used to explore ($k+1$)-itemsets. Once the frequent itemsets are identified from transaction database, it is straightforward to generate association rules with high confidence levels from them.

3.3 Rule Evaluation

Each association rule indicates a particular mapping between emotional terms and perceptual design elements. Such a mapping must be useful to suggest the underlying inference mechanism of emotional design. In this approach, the association rules are refined to keep the most meaningful rules in the knowledge base. Therefore, each rule should be evaluated to find the relevant and valuable ones.

In this paper, support level, confidence level and the freshness of supporting data serve as the measures to evaluate and rank the rules. The freshness of supporting data is in the form of weight assigned to rules according to the occurrence time of most recent supporting data. It is included to handle the ever-changing customer needs over time. The rules generated from the most recent data are assigned higher weights than those from older data so that priorities are given to rules generated from recent data. The weight assignment is proposed to be a function of time with the most recent data occurrence time as input. The weight assignment function for different products should be different as the speed of their developments differs.

Suppose there is a rule $E^* \rightarrow D^*$ in the form of Equation (3). The following equation is an example to assign rating to rule:

$$rating = c \times u(s - min\_support) \times freshness\_weight \tag{4}$$

where c is confidence level, s is support level, *min_support* is user-specified minimum support level, $u(x)$ is step function, and *freshness_weight* is the weight assigned to rule according to occurrence time of supporting data. Below is an example of *freshness_weight* computation:

$$freshness\_weight = 100 - a \times (recent\_t_{non\text{-}support} - recent\_t_{support}) \tag{5}$$

where $recent\_t_{support}$ is the most recent occurrence date of transaction record that contains itemset $E^* \cup D^*$, $recent\_t_{non\text{-}support}$ is the most recent occurrence date that contains itemset E^* and a is a user-specified parameter to represent the speed of change of requirements on desired products. An appropriate function for *freshness_weight* assists to discard outdated rule.

4 CASE STUDY

The potential of association rule-mining approach has been tested using customer evaluations on a series of mobile phones found on the Internet. The customer evaluations from a specific market segment are selected to give a simple illustration. These data are organized manually to extract emotional terms and perceptual design elements. A C# implementation of Apriori algorithm is applied on these data to discover underlying rules. These rules are ranked based on the confidence level, support level and freshness weight defined in the previous section.

4.1 Data Preprocessing

Customer evaluations of mobile phones are extracted from the website of CNET Asia [14] while the perceptual design elements are extracted from the website of CNET Asia and Nokia [15]. A specific market segment is chosen for simple illustration. After the data preprocessing, a total of 126 evaluations on 11 models of mobile phones are used for analysis.

Selection of Market Segment

The data on Nokia's mobile phone is chosen as the candidate data source because Nokia is one of the leading companies in the mobile phone industry. For simple illustration, only the mobiles that satisfy the following conditions are selected:

- Price is between S$500 and S$1,000.
- The mobile phone is available on the market for less than 2 years.
- The mobile phone receives more than one customer evaluations.

The reason for choosing middle price range mobile phones is that the buyers of middle price range mobile phones would select the best choice for themselves as they have sufficient purchase. The time of market availability is also used as filter condition of data sources because the inclusion of outdated products in analysis may lead to error results. If a mobile phone receives too few customer evaluations, the phone may have a bad configuration and thus, is not considered in analysis. As a result, 11 models of Nokia mobiles are selected.

Extraction of Emotional Terms

The customer evaluations found on CNET Asia website is in free text. The extraction of emotional terms is performed manually as no efficient automatic extraction algorithm is available. The emotional descriptions which are similar to each other, such as "big screen", "big display", are represented in database by only one of them, "big display" in this case. Only positive responses are collected for this case study. As shown in Table 1, a total of 25 emotional terms are collected.

Table 1. List of emotional terms extracted

Big display	Good-looking	Nice display	Nice sound	Slim
Business phone	Great build	Nice interface	Nice video	Solid
Fantastic	Multimedia phone	Nice memory	Overall good	Stylish
Fast interface	Nice battery life	Nice packaging	Perfect	User-friendly
Feature-rich	Nice camera	Nice reception	Rocks	Worth

Extraction of Perceptual Design Elements

The perceptual design elements are extracted from product specifications available on CNET Asia website and Nokia website. A total of 25 perceptual design elements (as shown in Table 2) which are probably related to customer evaluations are extracted manually from the specifications.

Table 2 shows the perceptual design elements with their categories and numbers of supporting models. The design elements such as "At least 320x240 pixels", "At least 2M camera" are used to reflect the ordinal property of their categories. This representation enhances the efficiency of rule mining as no split on the associated category is required to be found.

Not all the design elements in Table 2 are included in the transaction database. The design elements that have either too large or too small number of supporting models are omitted. The design elements that have 10 or 11 supporting models are already served as a minimum requirement for the product platform and thus can be excluded. The design elements that have only 1 supporting model are also excluded because the opinions towards it may be specifically belonged to its supporting model. As a result, only 17 perceptual design elements are included.

Table 2. List of perceptual design elements extracted

Category	Perceptual Design Element	Number of Supporting Models
Form	Candy bar	7
	Slider	4
Cover	At least 2 choices for colour	3

Resolution	At least 320x240 pixels	6
	More than 100000 pixels	2
Colour display	At least 18-bit colour display	10
	24-bit colour display	1
User interface	Camera key	6
	Multimedia key	5
	Scroll key	6
	Joystick	1
	Music key	1
	User-configurable soft key	1
Embedded OS	S40	1
	S60	8
Camera resolution	At least 2M camera	8
	3M camera	4
Music Player	Integrated music player	11
	Integrated FM radio	11
Special function	Visual radio	8
	3G	10
Battery life	3+hrs talk time	8
	3.5+hrs talk time	5
	4+hrs talk time	3
Package	Included memory card	6

4.2 Association Rule Mining

The well-known Apriori algorithm is chosen for association rule mining. A C# implementation found on website of "Free Data Mining Source Code" [16] is modified to be used for this approach. The implemented interface is shown in Figure 2. The general properties of desired rules such as minimum support level, minimum confidence level and maximum number of items can be configured in this interface.

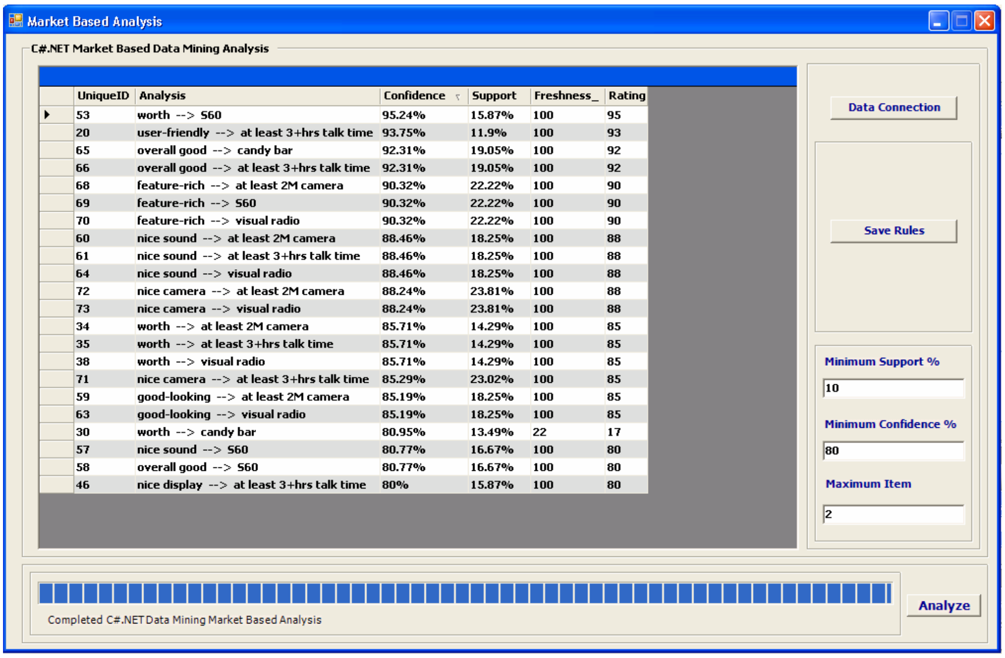

Figure 2. Interface for association rule mining

The columns of "Freshness_Weight" and "Rating" are added to serve as applicability measures of the rules. As a result, each rule has a confidence level, a support level, a freshness weight, and a rating from the transaction database. Table 3 shows the table of rules derived with minimum support of 10%, minimum confidence of 80%, and a maximum of 10 items while Table 4 shows the table of rules derived with minimum support of 5%, minimum confidence of 70%, and a maximum of 2 items, where *C* stands for confidence; *S* stands for support; *W* stands for "freshness weight". In this case study, "freshness weight" is computed using Equation (5) with *a*=1.

4. 3 Rule Evaluation

The generated rules in Table 3 and 4 are ranked according to "Rating" which is computed using Equation (4). As an example, the first rule in Table 3 can be used to claim that an embedded OS of S60 should be included if customers wish to get a mobile that is "worth". The rating of 95 can be used to serve as confidence of such claims.

All the rules found in Table 3 are quite reasonable. For instance, the rule "User-friendly → 3+ hrs talk time" indicates that the battery life of mobile phone should exceed 3+ hrs talk time so that it is user-friendly to customers. Noted that the rules are not totally mutual exclusive such as the design elements implied by the rules for given customer emotional needs may be combined together to serve as requirements on the product platform. As a result, the rules that are probably spurious, such as "Nice sound→At least 2M camera", also assist to identify the minimum requirement on the product platform as "At least 2M camera" has become a common design element of mobile phones.

Table 3. Rules table with minimum support of 10%, minimum confidence of 80% and a maximum of 10 items

ID	Rule	C	S	W	Rating
1	Worth→ S60	95.2%	15.9%	100	95
2	User-friendly → 3+hrs talk time	93.8%	11.9%	100	93
3	Overall good→ Candy bar, 3+hrs talk time	92.3%	19.1%	100	92
4	Feature-rich → At least 2M camera, S60, Visual radio	90.3%	22.2%	100	90
5	Nice sound → At least 2M camera, Visual radio	88.5%	18.3%	100	88
6	Nice sound → 3+hrs talk time	88.5%	18.3%	100	88
7	Nice camera → At least 2M camera, Visual radio	88.2%	23.8%	100	88
8	Worth → At least 2M camera, S60, Visual radio	85.7%	14.3%	100	85
9	Good-looking → At least 2M camera, Visual radio	85.2%	18.3%	100	85
10	Nice camera → 3+hrs talk time	85.3%	23.0%	100	85
11	Worth → 3+hrs talk time, S60	81.0%	13.5%	100	80
12	Nice sound → At least 2M camera, S60, Visual radio	80.8%	16.7%	100	80
13	Overall good → S60	80.8%	16.7%	100	80
14	Nice display → At least 3+hrs talk time	80.0%	15.9%	100	80

From Table 4, we can observe the benefit to rank the rules using freshness weight as one of the measure. The 15^{th} rule that sounds not so reasonable has a confidence of 92.3% where the 16^{th} rule and the 17^{th} rule that sounds more reasonable have lesser confidence. However, the "freshness weight" of 15^{th} rule is only 15. As a result, the 15^{th} rule obtains a rating of 14 and should be discarded.

Table 4. 2-item rules of "Big display" with minimum support of 5%, minimum confidence of 70%

ID	Rule	C	S	W	Rating
15	Big display → 3+hrs talk time	92.3%	9.5%	15	14
16	Big display → At least 18-bit color display	84.6%	8.7%	100	85
17	Big display → At least 2.4-inch screen	76.9%	7.9%	100	77

5 CONCLUSION

In this paper, an association rule mining approach is applied to emotional design in mass customization. This approach applies on customer evaluations that are available on many websites to gain valuable knowledge to assist in future emotional design work. Through the case study, it is shown that this approach can provide rational rules. The inclusion of "freshness weight" as a measure of rule applicability is able to discard some meaningless rules.

For given customer emotional needs, the rules discovered can be used to infer the minimum requirements on product platform. In addition, this approach may be easily integrated into enterprise software such as PLM to find valuable knowledge on vast data.

This approach involves lots of manual information extraction and filtering. For future work, we plan to integrate our approach with the feature-based opinion summarization of customer reviews [9]. The integration aims to provide more efficient decision support for design.

REFERENCES

[1] B. Song, X. Li and W. K. Ng. A Framework for an Intelligent Design-support System Based on Product Lifecycle Data. *PLM: Going beyond product development and delivery*, 2006.

[2] Khalid H. M. Embracing diversity in user needs for affective design. *Applied Ergonomics*, 2006, 37, 409-418.

[3] Xuehong Du, J. J. and Mitchell M. Tseng. Architecture of Product Family: Fundamentals and Methodology. *Concurrent Engineering: Research and Application*, 2001, 9(4), 309-325.

[4] Norman D. A. *Emotional Design: Why Do We Love (or Hate) Everyday Things*. Basic Books, New York, 2004.

[5] Nagamachi M. Kansei Engineering and its Applications in Automotive Design. *SAE Technical Paper Series*, 1999-01-1265.

[6] Chun-Hsien Chen, L. P. K. and Wei Yan. An investigation into affective design using sorting technique and Kohonen self-organising map. *Advances in Engineering Software*, 2006, 37, 334-349.

[7] Sun-mo Yang, M.N. and Soon-yo Lee. Rule-based inference model for the Kansei Engineering System. *International Journal of Industrial Ergonomics*, 1999, 24, 459-471.

[8] Jianxin Jiao, Y. Z. and Martin Helander. A Kansei Mining System for Affective Design. *Expert Systems with Applications*, 2006, 30(4).

[9] Minqing Hu and B. L. Mining Opinion Features in Customer Reviews. In *Proceedings of Nineteeth National Conference on Artificial Intelligence (AAAI-2004)*, 2004.

[10] Argrawal R., I. T. and Swami A. N. Mining Association Rules between Sets of Items in Large Databases. *SIGMOD*, 1993, 22(2), 207-216.

[11] Agrawal R. and S. R. Fast Algorithms for Mining Association Rules. *VLDB*, 1994, 487-99.

[12] Mannila H., T. H. and Verkamo A. I. Efficient algorithms for discovering association rules. *AAAI Workshop on Knowledge Discovery in Databases (SIGKDD)*, 1994, 181-192.

[13] Zaki M. J., Parthasarathy S., Ogihara M. and Li W. Parallel Algorithms for Discovery of Association Rules. *Data Mining and Knowledge Discovery*, 1997, 1(4), 343-373.

[14] CNET Asia. http://asia.cnet.com/reviews/mobilephones/ .

[15] Nokia. http://www.nokia.com.sg/ .

[16] Free Data Mining Source Code. http://www.kdkeys.net/forums/ .

Contact: Si Jie Phua
Nanyang Technological University
Centre for Advanced Information Systems, School of Computer Engineering
50 Nanyang Avenue
Singapore 639798
Tel: Int +65 97548019
Fax: Int +65 67926559
E-mail: SJPhua@ntu.edu.sg
URL: http://www.cais.ntu.edu.sg/~phuasj/