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Analytical affective design with ambient intelligence for mass customization and personalization

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Abstract The fulfillment of individual customer affective needs may award the producer extra premium in gaining a competitive edge. This entails a number of technical challenges to be addressed, such as the elicitation, evaluation, and fulfillment of affective needs, as well as the evaluation of affordability of producers to launch the planned products. Mass customization and personalization have been recognized as an effective means to enhance front-end customer satisfaction while maintaining back-end production efficiency. This paper proposes an affective design framework to facilitate decision-making in designing customized product ecosystems. In particular, ambient intelligence techniques are applied to elicit affective customer needs. An analytical model is proposed to support affective design analysis. Utility measure and conjoint analysis are employed to quantify affective satisfaction, while the producer affordability is evaluated using an affordability index. Association rule mining techniques are applied to model the mapping of affective needs to design elements. Configuration design of product ecosystems is optimized with a heuristic genetic algorithm. A case study of Volvo truck cab design is reported with a focus on the

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customization of affective features. It is demonstrated that the analytical affective design framework can effectively manage the elicitation, analysis, and fulfillment of affective customer needs. Meanwhile, it can account for the manufacturer's capabilities, which is vital for ensuring a profit margin in the mass customization and personalization endeavor.

Keywords Mass customization · Affective design · Customer needs · Product ecosystem

1 Introduction

Manufacturers nowadays are competing in a marketplace where the demand for low-volume, high-customization products is becoming increasingly evident. Rapid response to diversified customer needs at affordable cost presents a constant challenge to manufacturers. The traditional mass production paradigm is inadequate to meet this challenge because the actual production volume usually cannot defray the huge investments in product development, equipment, tooling, maintenance, and training. Mass customization lends itself to be a paradigm shift for manufacturing industries to provide products that best serve individual customer needs while maintaining near mass production efficiency (Tseng and Jiao 1996). At the front-end, it caters to the requirements of individual customers or customer groups by developing product families that cover a spectrum of product performance requirements. At the back-end, production efficiency is ensured by developing product platforms that leverage upon commonality, standardization, and modularity across different products, along with process platforms that accommodate flexibility and reusability of the production systems (Meyer and Lehnerd 1997).

An important factor to be considered in mass customization is the fulfillment of individual preferences of customer needs, referred to as personalization. Apart from offering market-focused products, which corresponds to an average satisfaction of customer requirements, companies are pursuing a strategy of offering customer-focused products with a large degree of individuality (Tseng and Piller 2003). This is essential for a company to gain a competitive edge over its competitors owing to the high premium possibly gained from the personalized products. Hence, designing personalized products or product systems suggests a new stream of business success. However, extreme personalization is not necessarily desired because such a practice inevitably leads to high complexity and costs in product fulfillment (Child et al. 1991). Moreover, making a wide variety of products available and letting customers 'vote' on the shelf may constrain customers' ultimate satisfaction, leading to mass confusion (Huffman and Kahn 1998). Therefore, it becomes imperative for the manufacturers to determine how to offer the right product variety to the target market.

Among the spectrum of customer needs, affective needs, which focus on customers' emotional response and aspirations, are arousing more and more attention in comparison to the functional needs, which focus on the product performance and usability factors (Jordan 2000; Khalid 2001). Affect is a basis for the formation of human values and human judgment. For this reason, it might be argued that models of product design that do not consider affect are essentially weakened (Helander and Tham 2003). In addition, product technologies have turned to be mature such that design for performance and design for usability can no longer empower a competitive edge (Khalid and Helander 2004). Moreover, diversity of customer groups calls for an understanding of individual user's emotions and affective needs, which is a prerequisite of predicting successful product design that can address these needs (Khalid 2006). Therefore, it is essential for manufacturers to incorporate affective aspects in their mass customization and personalization implementation in order to gain competitive advantages. However, until recently, the affective aspects of designing and design cognition have been substantially absent from formal theories of design (Helander et al. 2001).

Customers' affective needs basically imply an issue of addressing the customer perceptions with context-awareness. In particular, the aim of affective design is to address human's emotional responses and aspirations, and to achieve aesthetic appreciation and pleasurable experience through human-product-ambient interactions. In this regard, the major challenges are (1) how to elicit the affective needs from latent customer perceptions, (2) how to establish a logical relationship between affective needs and design elements, and (3) how to achieve affective design in terms of design elements to leverage customer satisfaction and the producer affordability. Towards this end, this paper proposes a framework of affective design for mass customization and personalization. The aim is to develop an analytical model that incorporates various technologies to facilitate decision-making in product planning and development. The organization of the paper proceeds as follows. Section 2 presents the background research related to affective design for mass customization and personalization. The major challenges and key research issues are formulated in Sect. 3. In Sect. 4, a decision framework is proposed to address the major research issues. The implementation of the framework to facilitate affective design of the Volvo truck cab is discussed in Sect. 5. The merits and limitations of the research are discussed in Sect. 6, and conclusions are drawn in Sect. 7.

2 Related work

From a business perspective, mass customization and personalization aim at maximization of the overlap of the producers' capabilities with the window of customers' needs in the marketplace. This can be achieved either through expanding producers' capabilities by developing the company's portfolio, including products, services, equipments, and skills that market demands, or through channelling customers to the total capacity of the company so that customers are better served.

The former strategy is largely the research focus of product planning and platform-based product development, where strategic development of product and process platforms gives the producer an advantage of improved resource utilization. Many researchers seek to categorize or map the evolution and development of product families. For example, Meyer (1997) emphasizes the importance of establishing product platforms for the product strategy and corporate success.

Sanderson (1991) introduces a notion of 'virtual design.' Wheelwright and Clark (1992) suggest designing 'platform projects.' Rothwell and Gardiner (1990) advocate 'robust designs' as a means to generate a series of different products within a single product family. A direct consequence of product customization is the proliferation of process variations in production. Accordingly, producers strive to reduce the incurred cost through efficient process variety management. For example, development of process platforms has been extensively studied in Meyer and Lehnerd (1997), Sanchez (1994), and Jiao et al. (2003, 2005).

At the front-end, to direct market needs to the capacity of a producer, a clear understanding of customer needs and subsequent fulfilment of the customer needs with the appropriate design elements suggest themselves to be critical issues. A major difficulty for affective design is the elicitation of customer needs. In most cases, it is difficult to capture the customers' affective needs due to their linguistic origins. Therefore, the elicitation of customer needs emphasizes the transformation of customer verbatim constructs, which are often tacit and subjective, into an explicit and objective statement of customer needs. Appropriate elicitation techniques that are able to offer a compromised solution between the extensiveness of expertise and the genuineness of the Voice of the Customer (VoC) are necessary for effective acquisition of customer needs (Yan et al. 2002).

A wide range of research has been geared toward investigating means by which the needs of customers can be captured more effectively (Stauffer and Morris 1992). Customer needs may originate from diverse customer groups in various market segments through different channels, such as interviews, questionnaires, feedback from sales agents and retailers, customer comments and complaints, as well as field maintenance reports. Kano et al. (1984) distinguish among three types of requirements that affect customer satisfaction in different ways, including must-be requirements, one-dimensional requirements, and attractive requirements. Such a differentiation of customer satisfaction helps identify the customers' expected, high-impact, low-impact or hidden requirements, and thus guides through their fulfilment process. Other approaches for customer needs elicitation include psychology-based approaches (Nagamachi 1989; Burchill and Fine 1997), artificial intelligence-based approaches (Turksen and Willson 1992; Jenkins 1995; Hauge and Stauffer 1993), and knowledge recovery approaches (Tseng and Jiao 1998; Chen et al. 2002; Du et al. 2003). Despite these efforts, the consideration of ambience where the behaviors of customers are contextualized is generally lacking during the elicitation process. To achieve reliable and efficient customer needs elicitation, it is desirable to render the customers with the actual product ambience and study their response in an unobtrusive way.

Mapping the customer needs to design elements constitutes another important research topic. Quality Function Deployment (QFD) has been widely adopted to translate customer requirements to technical design requirements. A key component of QFD is the customer requirement framework to aid the designer's view in defining product specifications (Clausing 1994). While QFD excels in converting customer information to design requirements, it is limited as a means of actually discovering the VoC (Hauge and Stauffer 1993). To empower QFD with market aspects, Fung et al. (1998) propose to pre-process the customer needs prior to their being entered as customer attributes into the House of Quality (HoQ). In this process, the VoC is categorized using an affinity diagram. Fung et al. (2002) extend the QFD-based customer requirement analysis method to a non-linear fuzzy inference model. Researchers at IBM have applied structured brainstorming techniques to build customer requirements into the QFD process (Byrne and Barlow 1993). McAdams et al. (1999) propose a matrix approach to identify the relationships between customer needs and product functions. Kansei engineering has been well recognized as a technique of translating consumers' psychological feelings about a product into perceptual design elements (JSKE 2003). Nagamachi (1996) proposes six technical styles of Kansei engineering methods with applications to the automobile industry, cosmetics, house design, and sketch diagnosis. Nadia (2001) adopts Kansei modeling to reduce the uncertainty and complexity involved in the mapping between visual expressions and impressive words used to convey them. Hajime (2002) explores a unique field of food Kansei engineering. Sedgwick et al. (2003) adopt semantic differential techniques to inform the customers of the surface's physical characteristics for their packaging to enhance their emotional engagement with the products. Ishihara et al. (1995) apply neural network techniques to enhance the inference between Kansei words and design elements in Kansei design systems. Matsubara and Nagamachi (1997) propose to develop hybrid expert systems for Kansei design support.

While the aforementioned methods are useful from various perspectives, a designer must be aware that prospective customers may respond in a survey what they like to buy, but regret and decline the purchase at the time of the sale. There is a long mental step between intention and behavior (Fishbein and Ajzen 1972). Hence, the information on customer needs may be sketchy, and designers may proceed by ignoring customer needs and estimate functional requirements as much as they can. The mapping from the affective customer domain to the design domain will have to be inferred based on incomplete information.

Fulfillment of affective customer needs is mainly concerned with product portfolio planning considering both producer affordability and the customer-perceived value. An optimal product portfolio has to account for both the consumer surplus (i.e., the amount that customers benefit by being able to purchase a product for a price that is less than that they would be willing to pay) and the producer surplus (i.e., the amount that producers benefit by selling at a market price that is higher than that they would be willing to sell for) (Jiao and Zhang 2005b).

Product portfolio planning has been traditionally dealt with in the management and marketing fields with the focus being on portfolio optimization based on customer preferences. The objective is to maximize profit, share of choices, or sales (Urban and Hauser 1993). Consequently, the measurement of customer preferences among multi-attribute alternatives has been a primary concern in marketing research. Analysis of customer needs involves the understanding of customer preference and relevant target markets, along with requirement prioritization and classification. Customer preference has been investigated using market analysis techniques, such as conjoint analysis (Green and DeSarbo 1978; Tseng and Du 1998), discrete choice experiments (Green and DeSarbo 1978), fuzzy systems (Turksen and Willson 1992), etc. Prioritizing customer preference with respect to a set of customer requirements is achieved through assigning different importance weights to customer requirements. Typical prioritization approaches include Analytic Hierarchy Process (AHP) (Saaty 1990; Akao 1990; Armacost et al. 1994), fuzzy AHP (Van Laarhoven and Pedrycz 1983), neural networks techniques (Chen et al. 2003), conjoint analysis (Gustafsson and Gustafsson 1994), etc. Requirement classification helps guide the designer in compiling, organizing, and analyzing product design issues (Rounds and Cooper 2002). Various taxonomies have been developed to facilitate the process (Morris and Stauffer 1994; Lin et al. 1996; Gershenson and Stauffer 1999). However, the effectiveness of these methods in affect evaluation is limited because the interpretation of the customer needs and derivation of quantitative customer satisfaction is always absent. Such a quantitative measure is essential for developing a comprehensive decision-making framework for designing product portfolios.

On the other hand, cost commitment at the production stage constitutes the major concern of the producer surplus, where the cost of the customization results from process variations due to product variety (Tseng and Jiao 2004). Estimation of an absolute figure of production costs is deemed to be very difficult, if not impossible. The major difficulty lies in the reliance on a detailed knowledge of product design and process plans (Jiao and Tseng 1999). A complete description of product design, however, is rarely available at the early product planning phase, nor does there exist any well-defined relationships, at this stage, between various attribute levels and the cost figures for their manufacture. More difficult is the allocation of variable and fixed costs among products (Dobson and Kalish 1993), although a linear-additive fixed cost function is always employed (Moore et al. 1999). Accordingly, a general consensus in mass customization and personalization is that design and manufacturing admit resources (and thus the related costs) to be shared among multiple products in a reconfigurable fashion, as well as per-product fixed costs (Moore et al. 1999). Furthermore, the cost advantages in mass customization and personalization lie in the achievement of mass production efficiency, rather than the absolute dollar value of the costs. As a matter of fact, what is important is to justify optimal product offerings in terms of their relative magnitudes of the deviations from existing product and process platforms due to design changes and process variations in relation to product variety. Towards this end, various indices have been introduced to measure or indicate the cost effects. Collier (1981) proposes the Degree of Commonality Index (DCI) as a metrics of commonality underlying a product architecture based on the company's Bill of Materials (BOM). Wacker and Treleven (1986) extend the DCI and develop the Total Constant Commonality Index (TCCI), which distinguishes commonalities within a product from those between products. Furthermore, Treleven and Wacker (1987) explore the process commonality based on set-up time, flexibility in sequencing, and flexibility expediting decisions. Jiao and Tseng (2000) develop the commonality index, which incorporates component commonality and process commonality, into a unified formulation. Kota et al. (2000) establish a product line commonality index to assess the commonality levels of a product family based on various manufacturing factors, such as size, shape, material, processes, assembly, etc. Siddique (2000) proposes two measures, namely, component commonality and connection commonality, and applies them to modularity analysis of automobile under bodies. Jiao and Tseng (2004) propose to model the cost consequences of providing variety by varying the impacts on process capabilities. The process capability index has been extended to be an instrument for handling the sunk costs that are related to the product families and shared resources.

3 Problem formulation

Customer affective needs involve not only the customers' interactions with the product, but also with the environment where the product is operating, referred to as the ambience. The consideration of human-product-ambience interactions is consistent with the wisdom of 'product ecosystems,' which essentially entail a scenario of affective design of the entire system with customer perception and experience in the loop, as shown in Fig. 1. Products can interact with its ambience, and such an interaction influences the customer's perceptions due to the particular context created. Hence, affect consist of two elements, namely, customer perception and customer experience. Accordingly, the aim of affective design is to address humans' emotional responses and aspirations, and to achieve aesthetic appreciation and pleasurable experience through human-product-ambience interactions. Likewise, affective product design attempts to define the subjective emotional relationships between consumers and products and to explore the affective properties that products intend to communicate with the ambience through their physical attributes.

Figure 2 shows an affective design process transforming affective customer needs into configurations of product ecosystems. This process is represented in the form of mapping relationships between the customer domain and the design domain. In general, the process involves three technical issues as elaborated below. It should be noted that the design process presented here is not restricted to affective design. It is a generic process that can be applied to address the functional requirements as well. Accordingly, the methodology presented in the subsequent sections can be extended to product design in general, which involves customization and

Fig. 1 Affective needs through human-product-ambience interactions

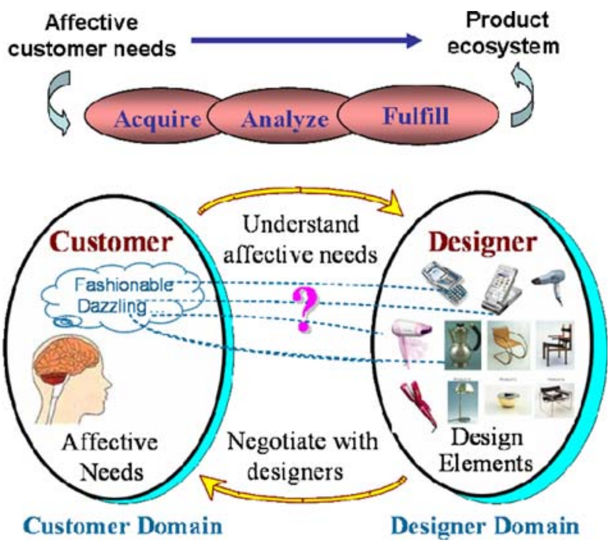

Fig. 2 General process of affective design

personalization. This paper presents the deployment of the methodology for the particular case of affective design.

3.1 Acquisition of customer needs

Acquisition of affective needs is deemed to be the starting point of affective design. It is important at this stage to establish a set of qualitative and quantitative affective descriptors that are of interest to describe customer perceptions. Rather than describing individual customers, definitions of affective needs should be representative for diverse customer groups and market segments.

3.2 Analysis of customer needs

An analytical model should be developed to explicitly signify the affordability of the producer and to channel the customer needs to the producer affordability based on certain mapping schemes. In particular, the following issues have to be addressed: (1) identify the design elements that constitute the configuration of the product ecosystem, (2) identify the mapping relationship between affective needs and the corresponding design elements, (3) quantify customer satisfaction with respect to the affective needs, and (4) quantify the producer affordability in terms of production costs.

3.3 Fulfilment of customer needs

This is achieved by determining optimal product ecosystem configurations for given customer affective needs. The configuration of the product ecosystem involves combinations of different design elements to achieve the desired affective expectation as quantified in the previous stage. The major concerns include (1) define objective functions that leverage both the consumer surplus and the producer surplus and (2) develop efficient solution algorithms to deal with the large search space of the configuration design problem.

4 Methodology

Figure 3 shows a framework of affective design. It is consistent with the general process of mapping given affective needs to a specific configuration of the product ecosystem. There are five major steps involved in this model, as elaborated below.

(1) Affective needs elicitation defines the process of extracting the affective descriptors that can be used to define customer groups. Semantic ontology is developed to categorize affective descriptors according to different customer groups and market segments. Ambient intelligence techniques are adopted to facilitate the elicitation process owing to its power of creating a context-rich environment.

(2) Affective mapping is concerned with the identification of design elements and the mapping relationship from affective needs to design elements. This is enabled by analyzing historical data using data mining techniques. In this research, association rule mining techniques are employed to discover the patterns of mapping mechanisms (Jiao and Zhang 2005a).

(3) User satisfaction is quantified based on a part-worth model, for which conjoint analysis is used to establish the relationship between individual affective descriptors and the cohort impression/satisfaction of a particular customer on a specific configuration of the product ecosystem.

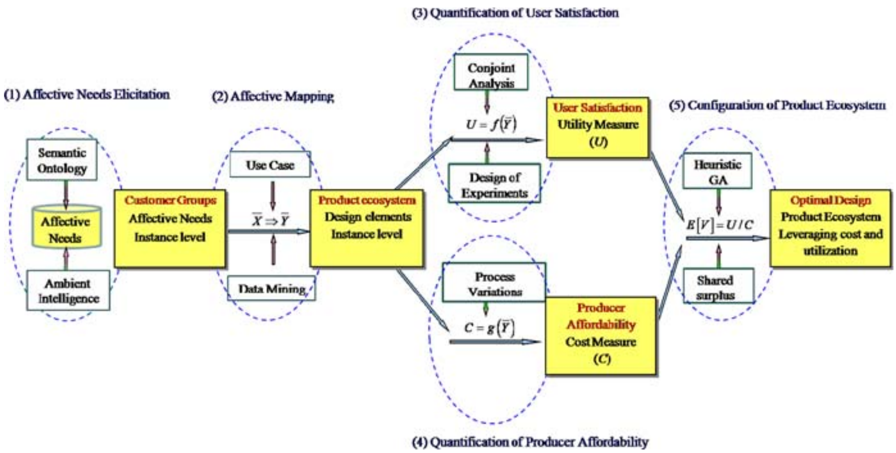

Fig. 3 An analytical model of affective design

(4) For a specific planned set (configuration) of design elements, the producer affordability is measured according to their consequence on existing design and production capabilities. As such, an affordability index is introduced (Jiao and Tseng 1999).
(5) An optimal product configuration is generated through an optimization process with the shared-surplus as the objective function. Essentially, configuration design entails a combinatorial optimization problem. In this research, a heuristic genetic algorithm (GA) is developed for this purpose.

4.1 Affective needs elicitation with ambient intelligence

Affective needs are difficult to capture due to its qualitative and intangible nature. To tackle such a problem, this research proposes to apply ambient intelligence techniques to explore customer needs and to develop semantic ontology to describe and categorize the affective needs explicitly.

4.1.1 Ambient intelligence

Ambient intelligence suggests itself to be a new paradigm of information and communication technologies, taking the integration provided by ubiquitous and pervasive computing one step further to realize context-aware environments that are sensitive and responsive to the presence of people (Ducatel et al. 2001). The strength of ambient intelligence is to support affective design with context-aware adaptive applications. In particular, it can facilitate the elicitation of affective needs from two perspectives. Firstly, ambient intelligence can generate an environment that simulates the actual scenario of the respective product ecosystems. Technology advancements in hardware and software have made it possible to place a customer in a virtual reality (VR) or augmented reality (AR) environment that closely matches the actual environment of a customers' experience with product ambience. In addition, an ambient intelligence-enabled environment can be easily reconfigured to reduce costs of imitating a real environment. Secondly, with ambient intelligence embedded in the product ecosystem, the behaviors and reactions of the customers can be captured in real time without interrupting the customers' normal activities. Unlike traditional survey approaches, where customers have to follow predefined procedures and express their feelings depending on their own reflection and imagination, customers enjoy more freedom in interacting with the product ecosystem and expressing their feelings spontaneously. Moreover, the surveillance system embedded in the ambience intelligence environment can capture customer responses throughout the investigation process for offline analyses afterwards.

This research proposes to apply VR and AR technologies to construct an ambient intelligence-enabled environment. In a VR environment, various digital product models are built, which consist of a number of customizable product features. On the other hand, the AR environment comprises an actual product with the basic product features, a set of virtual models of customizable features, and a projection system that superimposes the virtual models onto the actual product so as to render the desired visual effects. The advantages of a VR environment include lower costs and simpler operations for reconfiguring product ecosystems. However, it lacks the rich information of the real world, such as haptic feedback, which is available in an AR environment (Boud et al. 1999). Constructing an AR environment, on the other hand, is technologically more demanding, because is requires more accurate registration and object tracking techniques (Azuma 1997). Moreover, surveys are carried out such that each customer is situated in the environment and is guided through a series experience of interacting with the product, while changing the configuration of products. The feedback of the customers, including voices, expressions, and behaviors, are recorded throughout the survey process. The preliminary set of customers' affective needs is extracted from the descriptive words that the customers have used during the survey.

4.1.2 Semantic ontology

The purpose of semantic ontology is to describe and categorize the affective needs that are communicable among customers and designers from different sectors using a limited number of terminologies that are as small as possible yet comprehensive enough to cover the major aspects of affective design. Each type of product ecosystem is supported by a set of affective terminology and taxonomy based on different customer requirements with respect to the particular product systems (e.g., automobile, living room, shopping mall, etc.). The development of semantics starts with the customer survey. Next, semantic scales can be constructed for affect evaluation, which involves the collection of a large number of descriptive words for the product ecosystem and the clustering of the words that are similar in meaning into categories according to diverse customer groups (Karlsson et al. 2003). From each category, one or several words are chosen to represent the category along with the associated semantic scales in order to characterize the market segment-level affective assessment on the product ecosystem. Finally, the assessment semantic scales can be interpreted by domain experts to delineate the usage of the terminology.

Based on the semantic ontology, all customer affective needs can be described using a set of affective descriptors, represented as $\overline{X} = \{x_m\}_M$, where $x_m \equiv \left\{x^*_{mi}\right\}_I$ denotes each affective descriptor along with its scale instances, M is the total number of affective descriptors, and I is the number of scale instances related to a particular affective descriptor. Assume that there are multiple market segments, $\{\Lambda_s\}_S$, each containing homogeneous customers. The respective affective needs category can be represented as $\left\{\left\{x^*_{mis}\right\}_{M\times I}\right\}_S$, where $M \times I$ is the total number of affective words (i.e., instances of affective descriptors) used for representing the sth customer group. The set of scale instances of affective needs related to a particular customer group is denoted as $\overline{X^*_s} = \left\{x^*_{mis}\right\}_{M\times I}$.

4.2 Analytical model of affective satisfaction

4.2.1 Translation of affective needs into design elements

Product ecosystem design yields many design alternatives that are desired by different customers. Each design entails a set of design elements, $\overline{Y} = \{y_n\}_N$, where $y_n = \left\{y^*_{nj}\right\}_J$ stands for a design element and its individual specifications, N is the total number of design elements, and J is the number of individual specifications related to a particular design element. Organized based on the rationale of product family design, these design elements are actual customizable features that facilitate the fulfillment of respective affective needs. Typically, these features are determined by engineers based on their knowledge of the importance of the elements and the ease with which these elements can be changed. Typically, the specification of a design element includes such attributes as dimension, color, material, auxiliary components, and so on.

Given that affective needs are fulfilled by a certain set of design elements, the set of design elements used to address the affective needs belonging to the sth customer group can be denoted as $\overline{Y^*_s} = \left\{y^*_{njs}\right\}_{N \times J}$. Differentiation between the affective needs and design elements is consistent with the fact that customers' affective impressions are associated with the gestalt design rather than individual elements. The customers do not know what their affective needs mean by mapping to specific design elements. This is a typical 'data-rich yet knowledge-sparse' decision-making problem. Kansei engineering and data mining techniques have been adopted to deal with this type of problem (Jiao and Zhang 2005b; Jiao et al. 2006). A prerequisite for carrying out data mining is that a set of sales records is available that contains information of the affective customer needs and the actual selection of design elements that characterize the product variants delivered to the customers.

In this research, an association rule mining mechanism is developed to reveal the mapping from various affective needs to different product and ambience parameters (referred to as design elements of the product ecosystem), i.e., $\overline{X^*_s} \Rightarrow \overline{Y^*_s}$, where an association rule, $\Rightarrow$, indicates an inference from the precedent ($\overline{X^*_s}$) to the consequence ($\overline{Y^*_s}$). The association rules are extracted from transaction data that contain order information corresponding to the customers and products. Each set of transaction data indicates a particular mapping relationship from the customer needs to the design elements. Such transaction data are available from the company's sales records and product documentation, usually constituting a large data set.

The general form of an association rule in association rule mining is given as:

$$\alpha_1 \wedge \alpha_2 \cdots \wedge \alpha_k \cdots \wedge \alpha_K \Rightarrow \beta_1 \wedge \beta_2 \cdots \wedge \beta_l \cdots \wedge \beta_L \; [Support = p\%; Confidence = c\%] \quad (1)$$

where $\alpha_k = exist\left(x^*_{mis}\right), \forall k = 1, \ldots, K \leq M$, $\beta_l = exist\left(y^*_{njs}\right), \forall l = 1, \ldots, L \leq N$, and $p\%$ and $c\%$ refer to the support and confidence levels for this rule, respectively. Equation 1 states that whenever a set of customer needs exist, a particular set of design elements must be available to accommodate these needs. The confidence denotes the strength of an association, and the support indicates the frequency of the occurring patterns contained in the rule.

4.2.2 Quantification of affect satisfaction

It is important to discern the cohort customer satisfaction (U) on the entire product ecosystem from the customer satisfaction on individual design elements ($\overline{Y_s^*}$). As shown in the above roadmap, this essentially implies a mapping between two domains, i.e., $U = f\left(\overline{Y_s^*}\right)$. Obviously, this process is highly subjective and intangible. The affect satisfaction does not mean the summation (e.g., a weighted sum) of individual assessments at the design element level per se. Rather, it is a holistic impression on the cohort of all the design elements involved in a product ecosystem, namely, an overall consequence of individual measures regarding $\overline{Y_s^*}$.

To derive such a conjoint effect on the overall satisfaction (U) by a number of customer impressions on individual design elements ($\overline{Y_s^*}$), this research applies conjoint analysis techniques that are widely used in marketing research (Jiao et al. 2006). Conjoint analysis starts with the construction of product profiles. Due to the numerous product configurations that can be constructed based on the design elements, the Design of Experiment (DOE) (Nair et al. 1995) technique is useful to construct orthogonal testing profiles in order to minimize the collection of response data and the effort in setting up focus groups for interviewing with respondents. Customer satisfaction levels with respect to each product configuration are collected from the experiment. For example, a respondent is asked to evaluate a product configuration and give a mark based on a 9-point scale, where '9' means the maximum satisfaction level, and '1' means the minimum satisfaction level.

Because different groups of customers may exhibit quite diverse expectations of product ecosystem design, the above satisfaction measure must be related to different market niches. In addition to demographic data, a number of other dimensions should be taken into account in relation to particular customer profiles. A set of market segmentation models based on fuzzy clustering techniques has been reported in consumer electronics products (Jiao and Zhang 2005b). This can be readily extended to explore customer experience regarding affects.

Following the part-worth model, the utility of the sth segment for the dth design, U_{sd}, is assumed to be a linear function of the part-worth preferences (utilities) of the design elements of dth design, i.e.,

$$U_{sd} = a_d + \sum_{n=1}^{N} u_{sn} y_{dn}, \quad \forall s \in \{1, \ldots, S\}, \forall d \in \{1, \ldots, D\} \tag{2}$$

where u_{sn} is the part-worth utility of *the* sth segment for the nth design element, D denotes the total number of design alternatives, a_d is a constant associated with the derivation of a composite utility from part-worth utilities with respect to dth design, and y_{dn} is a binary variable such that $y_{dn} = 1$ if the nth design element is contained in dth design and $y_{dn} = 0$ otherwise.

4.2.3 *Quantification of producer affordability*

To circumvent the difficulties inherent in estimating the actual cost figure of launching the product variants, this research adopts an affordability index to indirectly evaluate the cost of producing the design elements. The affordability index is a measure of the economic latitude of production process variations due to product customization (Jiao and Tseng 1999). It is formulated based on the legacy process capability, which is an instrument for handling the sunk costs that are related to the product families and shared resources. In particular, the expected cycle time can be used as a performance indicator of variations in process capabilities (Jiao and Tseng 1999). The characteristic for the cycle time is of 'the smaller the better' type. The cycle time demonstrates the distinctions between variables that differ as a result of random error and are often well described by a normal distribution. Hence, the one-side specification limit affordability index (A^{IN}) can be formulated as:

$$A^{IN} = \frac{\mu^T - LST^T}{3\sigma^T} \tag{3}$$

where LST^T, μ^T, and σ^T are the lower specification limit, the mean, and the standard deviation of the estimated cycle time, respectively. Variations in the cycle time are characterized by μ^T, and σ^T, reflecting the compound effect of multiple products on production in terms of process variations. The LST^T can be determined ex ante based on the best-case analysis of a given process platform, in which standard routings can be reconfigured to accommodate various products derived from the corresponding product platform (Jiao et al. 2003).

Based on the affordability index, the cost of launching a product variant (the dth design) is estimated as:

$$C_d = \lambda \exp\left(\frac{1}{A_d^{IN}}\right) \tag{4}$$

where λ is a constant indicating the average dollar cost per variation of process capabilities. The meaning of λ is consistent with that of the dollar loss per deviation constant widely used in Taguchi's loss functions. It can be determined ex ante based on the analysis of existing product and process platforms. Such a cost function produces a relative measure, instead of actual dollar figures, for evaluating the extent of overall process variations among multiple products.

4.3 Product ecosystem configuration design

The design of the optimal product ecosystem can be explored for target market niches. To leverage both the cost of product ecosystem development and the corresponding affective satisfaction, a shared-surplus model is proposed, where the objective function is formulated as the ratio of the customer-perceived utility (U_{sd}) and the costs (C_d) to produce it, i.e.,

$$\max\ E[V] = \sum_{s=1}^{S}\sum_{d=1}^{D}\frac{U_{sd}}{C_d}P_{sd}Q_s y_d \tag{5}$$

where $E[V]$ denotes the expected value of the shared-surplus, V, which is defined as the utility (U_{sd}) per cost (C_d), modified by the probabilistic choice model, $\{P_{sd}\}_{S\times D}$, and the market size, $\{Q_s\}_S$. y_d is a binary variable such that:

$$y_d = \begin{cases} 1 & \text{if the manufacturer decides to offer product } d, \\ 0 & \text{otherwise} \end{cases}$$

The underpinning principle of the shared-surplus coincides with the implications of customer values in marketing, i.e., the customer's expectations of product quality in relation to the actual amount paid for it. This is different from the consumer surplus, which is usually defined as a function of utility minus price (Green and Krieger 1985). It is also different from the producer surplus, which is defined as a function of price minus cost (Dobson and Kalish 1993). In essence, the customer-perceived utility (U_{sd}) indicates the customers' willingness to buy the product, and the costs (C_d) reflect the affordability of producers to launch the product.

The conjoint-based search for an optimal product ecosystem always results in combinatorial optimization problems because typically discrete parameters are used in conjoint analysis (Zeithaml 1988). Nearly all of these problems are known to be mathematically intractable or NP-hard, and thus mainly heuristic solution procedures have been proposed for the various problem types (Kaul and Rao 1995). Comparing with traditional calculus-based or approximation optimization techniques, GAs have been proven to excel in solving combinatorial optimization problems. In this regard, a heuristic GA is developed to solve such a combinatorial optimization problem (Jiao and Zhang 2005b).

5 A case study

The proposed affective design model has been applied to mass customize a series of Volvo truck cabs. In particular, the interior of four basic truck models are to be designed to address different market niches, as shown in Fig. 4 (http://www.volvo.com). The customization involves both functional requirements (e.g., storage, overnight accommodation, etc.) and affective needs (e.g., comfort, uniqueness, etc.).

Fig. 4 The Volvo FH series truck cab variants

Both types of requirements are fulfilled as a number of design elements of the cab. Nevertheless, this case study emphasizes the affective design aspect only.

5.1 Affective needs elicitation

The affective needs are acquired from truck drivers with different demographic backgrounds. To ensure that the affective descriptors reflect the actual needs of the users, surveys have been carried out in both AR and VR environments. The AR environment was installed onto a few basic truck cab models, as shown in Fig. 5. Each respondent (a mock-up truck driver for the experiment) is situated in the truck cab with a head-mounted display device, and the expected customizable features can be superimposed onto the actual truck cab ambience. The user can easily select and modify the features according to his/her preferences and see right away what they look like in such an ambience intelligence-enabled environment. In addition, four surveillance cameras are mounted into the system to inspect the drivers' responses in real time, which are analyzed offline afterwards. The voice of customers and their perceptions on experiencing with the truck cab configurations are recorded during the investigation process. Figure 6 shows a two-side immersive VR interface of the truck cab ambience intelligence environment. The customer

Fig. 5 Ambient intelligence environment of a truck cab

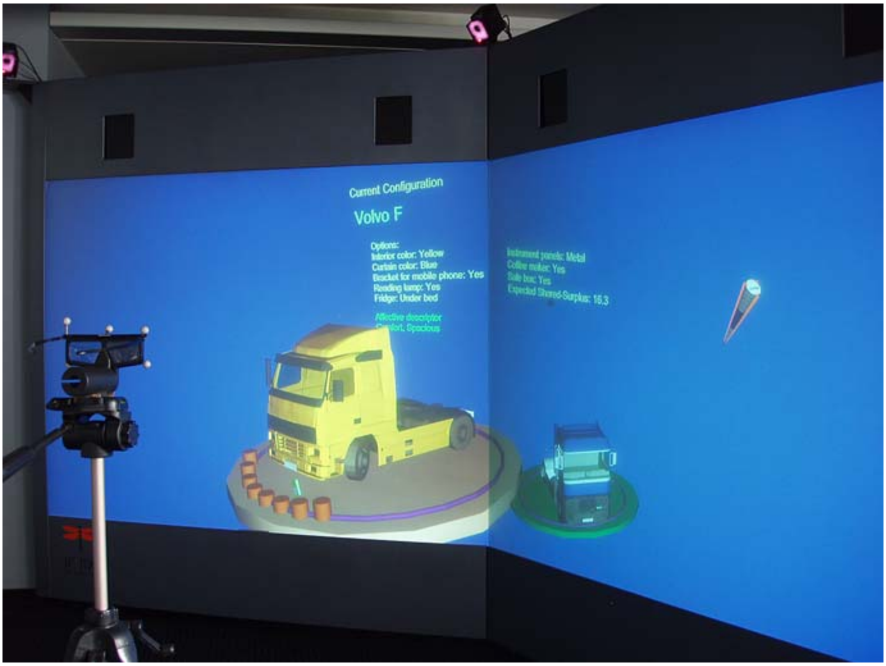

Fig. 6 VR user interface layout

experience is also explored through the truck cab configuration process. Based on customers' inputs of their preferences, changes of design elements and/or their parameter values are presented in both environments in real time.

Based on the survey and experiments, a number of affective needs are extracted. These affective needs are categorized into different groups, forming the semantic ontology. For purpose of illustration, ten affective descriptors are shown in Table 1 for describing affect information as perceived by different truck users. The major design elements that influence the affective needs are identified by senior design engineers from the respondents' reactions during the survey and experiment. A total of 15 design elements are recognized as the ambience parameters that characterize a truck cab ecosystem, as shown in Table 2.

Table 1 Affective descriptors for truck cabs

Descriptor	Code	Descriptor	Code
Ease	X1	Silent	X6
Comfort	X2	Spacious	X7
Simple	X3	Genuine	X8
Relaxed	X4	Luxurious	X9
Clean	X5	Good smelling	X10

Table 2 Truck cab affective design elements

Code	Description	Figure	Code	Description	Figure	Code	Description	Figure
Y1	Interior color_blue		Y6	Panel for switches		Y11	Instrument panels_wood	
Y2	Interior color_yellow		Y7	Bracket for mobile phone		Y12	Instrument panels_metal	
Y3	Interior color_grey		Y8	Reading lamp		Y13	Top storage	
Y4	Curtain color_blue		Y9	Fridge under bed		Y14	Coffee maker	
Y5	Curtain color_yellow		Y10	Fridge in rear shelf		Y15	Safe box	

5.2 Affective mapping

Based on the identified affective needs and design elements, 350 sales orders are organized into a transactional database, where each transaction record denotes the presence of a set of affective needs and the corresponding customers' selection of design elements. In this case, the transactional data are organized in two segments, which are identified based on established market research of the company. A data mining tool, Magnum Opus (Version 2.0) (http://www.rulequest.com), is employed to find the mapping relationships between affective needs and design elements. The mining process terminates with a set of rules containing 186 association rules, as shown in Table 3.

5.3 Quantification of user satisfaction and producer affordability

Conjoint analysis is applied for evaluating the part-worth utility of the design elements. Given all design elements as shown in Table 2, a total number of $3 \times 2 \times 2^3 \times 2 \times 2 \times 2^3 = 1{,}536$ combinations may be constructed, representing 1,536 possible product configurations. To overcome such an explosion of configurations by enumeration, orthogonal product profiles are generated based on the principle of DOE (Nair et al. 1995). Using the Taguchi orthogonal array selector provided by SPSS software (http://www.spss.com), a total number of 36 orthogonal product profiles are generated, as shown in Table 4. In the table, the columns under 'Conjoint Test' indicate the specification of offerings that are

Table 3 Identified association rules of affective mapping

Rule no.	Inference relationship	Support	Confidence
1	X1 ⇒ Y7	0.170	0.228
2	X2 ⇒ Y2	0.271	0.423
3	X3 ⇒ Y11 & Y15	0.267	0.320
4	X4 ⇒ Y5	0.167	0.427
5	X6 ⇒ Y14	0.233	0.512
6	X7 ⇒ Y10	0.233	0.460
7	X8 ⇒ Y1	0.362	1.000
8	X9 ⇒ Y13	0.532	0.757
9	X10 ⇒ Y14	0.365	0.365
180	X1 & X6 ⇒ Y4 & Y7	0.264	0.575
181	X3 & X7 & X8 ⇒ Y11 & Y12 & Y15	0.206	0.743
182	X1 & X10 ⇒ Y15	0.263	0.282
183	X5 & X6 & X9 ⇒ Y3 & Y8	0.112	0.864
184	X5 & X9 & X10 ⇒ Y2 & Y5 & Y8 & Y12	0.204	0.624
185	X2 & X8 ⇒ Y1 & Y9	0.227	0.955
186	X3 & X5 & X6 ⇒ Y3 & Y13 & Y14	0.372	0.653

Table 4 Response surface experiment design

Conjoint test															Satisfaction scale
Choice	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	…	V14	V15	1 … 9
1	1	0	0	1	0	1	0	1	1	0	0	…	1	0	5
2	0	0	1	1	0	0	1	0	0	1	1	…	0	1	5
3	1	0	0	0	1	0	1	0	1	0	1	…	1	0	8
…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…
34	1	0	0	1	0	1	0	1	0	0	0	…	0	0	7
35	0	0	1	0	1	0	1	0	1	1	1	…	1	1	9
36	0	1	0	1	0	0	1	1	0	1	1	…	0	1	3

involved in the profiles, and the ‘Satisfaction Scale’ column collects the satisfaction level given by the respondents.

A separate group of 30 truck drivers were invited to act as the respondents for conjoint analysis. The same ambience intelligence-enabled environment used for affective needs elicitation is reconfigured to simulate the truck cab ambience according to diverse choices of design elements. Each respondent is asked to evaluate all 36 profiles one by one and give a mark based on a 9-point scale, where ‘9’ means the user prefers a product most and ‘1’ least. This results in 30 × 36 groups of data. For each respondent, 36 regression equations are obtained by interpreting his/her original choice data as a binary instance of each part-worth utility. With these 36 equations, the part-worth utilities for this respondent are derived. By averaging the part-worth utility results of all respondents belonging to the same market niche, a segment-level utility is constructed for each design element. Columns 2 and 5 in Table 5 show the part-worth utilities of two segments with respect to every design element.

Table 5 also shows the affordability indices for design elements based on empirical studies. The company fulfills customer orders through assembly-to-order production while importing all components and parts via global sourcing. With assembly-to-order production, the company has identified and established standard routings as basic constructs of its process platform. The affordability index of each design element is established based on time and motion studies of the related assembly and testing operations.

5.4 Optimal truck cab configuration

Based on the established truck cab semantic ontology, a customer order is interpreted as a set of affective needs (ease, comfort, clean, silent, good smelling). Based on the affective mapping rules in Table 3, the corresponding design elements are identified as Y2, Y4, Y7, Y8, Y9, Y12, Y14, and Y15. To determine an optimal truck ecosystem configuration for this customer, the heuristic GA procedure is applied to search for a maximum of expected shared-surplus among all possible combinations of these design elements (Jiao and Zhang 2005b). In the GA, a

Table 5 Part-worth utilities

Segment 1			Segment 2		
Code	Part-worth utility	Affordability index	Code	Part-worth utility	Affordability index
Y1	0.21	103	Y1	0.28	137
Y2	0.45	132	Y2	1.28	168
Y3	0.33	115	Y3	0.21	143
Y4	1.21	52	Y4	0.84	52
Y5	2.40	46.5	Y5	1.44	48.5
Y6	0.23	19	Y6	0.46	16.5
Y7	1.43	33	Y7	2.15	40
Y8	1.03	120	Y8	1.14	137
Y9	0.14	9.5	Y9	0.38	8
Y10	0.63	66	Y10	0.11	65
Y11	0.13	20	Y11	0.67	23
Y12	0.63	22	Y12	1.86	25
Y13	1.72	56	Y13	1.03	68
Y14	1.13	68	Y14	0.63	70
Y15	2.00	87	Y15	1.32	65

chromosome string consists of 15 genes, each represented as a bit that denotes the presence of a design element. A gene may assume a value ‘1,’ indicating that a design element is selected in the product configuration; otherwise, a bit with a value ‘0’ indicates that the design element is not selected. For each generation, the population size is set to be 30, meaning that only the top 30 fit product configurations are kept for reproduction. The GA solver returns the near-optimal configuration as shown in Table 6, which achieves an expected shared-surplus of 16.3. The shared surplus value is a performance indicator that leverages the customer satisfaction and producer affordability. It should be noted the absolute value of the share surplus is not significant. But rather, it suggests the relative superiority of a product configuration.

Table 6 The optimal truck cab design for the given customer order

Design element	Parameter value
Y2: Interior color	Yellow
Y4: Curtain color	Blue
Y7: Bracket for mobile phone	Y
Y8: Reading lamp	Y
Y9: Fridge	Under bed
Y12: Instrument panels	Metal
Y14: Coffee maker	Y
Y15: Safe box	Y
Expected shared-surplus	16.3

6 Discussion

The difficulty in affective needs elicitation could be effectively alleviated with the support of an ambient intelligence environment. Previously surveys have been carried out to tackle affective needs using paper- or electronic-based questionnaires, where the design elements are presented separately in pictures or sample objects. However, this method is both inefficient and ineffective. The respondents are slow in response because it usually involves a long mental process for the customer to correlate the design elements with their ambiences. Moreover, the respondents suffer a general difficulty of expressing their feelings using linguistic words because they may be easily misled by the way the questions are presented. Within an ambient intelligence environment, design elements are rendered in its entirety such that a respondent can easily evaluate a design element in relation to the ambience. The customer behaviors recorded during the probing process can be further analyzed to extract useful affect information. One drawback of the current application of ambient intelligence is that it involves additional costs of setting up the environment with an initial investment on hardware and software. However, such an investment can be compensated by the savings in carrying out the survey. This is because the VR or AR environment can be easily reconfigured to present diversified design alternatives without building expensive mockup models.

The analytical model is an important tool for understanding the affective design process with consideration of the producer's affordability. A mapping scheme between affective needs and design elements can be represented as a set of mutually compatible association rules. It involves a bottom-up process of discovering possible patterns and then applying these patterns to facilitate decision-making in the future. This is advantageous over those methods that depend solely on the designer's experience. On the other hand, a few precautions for using the data mining method have been identified. Firstly, the original data for rule mining must be up-to-date; otherwise the rules could not reflect the current market trend and technology advancement. This is because the validity of data ultimately determines the validity of the rules. Secondly, the data mining tools themselves cannot determine whether the rules are valid and useful or not. Sometime, it requires additional effort to interpret the outcome and to judge the validity of the outcome by domain experts. The post-process of discovered patterns is deemed to be important and cannot be overlooked.

The configuration of product ecosystems must be optimized in terms of both customer satisfaction and producer affordability. It is expected that the shared-surplus formulation is important for the manufacturer's interest, because customer-perceived utility alone cannot ensure the manufacturer's business success. Ultimately, the manufacturer has to launch the product at an affordable cost so as to gain a profit margin. The proposed system does not require a huge investment that extends the manufacturer's production capacity. Instead, it focuses on directing the customers' needs to the existing capacity of the manufacturer. Such a practice is more practicable for a company because a huge investment or a radical change of the company's structure will inevitably meet managerial barriers. Moreover, an analysis of different customer groups in terms of the shared surplus may reveal useful economical implications. For example, a larger shared-surplus value indicates a higher profit margin. Hence, the company can identify which customer groups may provide the largest return of investment, which can be further used as a basis for projecting future market strategies.

7 Conclusions

From a business perspective, the fulfilment of affective needs is an important enabler of product added value. However, a few major challenges have to be addressed, such as the acquisition and understanding of the affective customer needs and the fulfilment of affective needs at affordable costs. The proposed framework of affective design presents an effort to enhance customer satisfaction based on the manufacturer's existing capabilities. Within this framework, ambient intelligence provides an effective means to elicit affective customer needs by incorporating ambience factors into the customer experiences. It is advantageous over traditional customer survey methods because it facilitates the study of customer behaviors through exploring extensive interactions among the customer, the product, and the ambience. Moreover, this research extends affective design analysis and modeling techniques to the downstream product design and production stages. To map affective needs to design elements, this research adopts the association rule mining technique, which features a bottom-up process of finding possible patterns and the application of these patterns to facilitate decision-making in the future. A shared-surplus model is proposed based on an analysis of user satisfaction and producer affordability. Accordingly, the configuration of product ecosystems is optimized according to the manufacturer's capacity to fulfill the affective needs. The affective design method with analytical affect modeling and evaluation sheds light on answering such questions as (1) how to measure an affective design with respect to different customers' preferences, (2) how to incorporate the ambience in evaluating customer affective perceptions, and (3) how to predict affective design in terms of customer-perceived utility and producer affordability.

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