AFFECTIVE-COGNITIVE DESIGN OF PRODUCT ECOSYSTEMS FOR USER EXPERIENCE

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ABSTRACT

As industry sectors mature, a critical challenge confronting many companies is how to provide users with engaging experiences within a product ecosystem (e.g., a subway station ecosystem). User experience goes far beyond cognitive aspects to encompass affective aspects, where the former accommodates users' cognitive capabilities, tendencies, and limitations while the latter concerns how to elicit desirable emotional responses from users. Both aspects have major impacts on each other and importantly influence user satisfaction.

Although companies have long been concerned with users in the product design and development process, the emphasis has been on the cognitive aspects to support users' cognitive processes through human-product interactions, demonstrated as usability studies in the areas of human factors and human-computer interaction. Further, traditional usability studies often consider interactions between the user and a single object (product), ignoring the kind of user interactions in a context of product ecosystems that consist of multiple interdependent products, users, and ambient factors (e.g., environmental settings and cultural factors). On the other hand, user pleasure has been considered in the new development of human factors and ergonomics; affective human-computer interaction is also gradually being recognized. From a holistic perspective, it is imperative to study user experience design incorporating its two essential dimensions, i.e., the affective dimension and the cognitive dimension, in the context of product ecosystems.

This research develops a conceptual model that elaborates the operational mechanism of key factors underlying product ecosystems for user experience design while leveraging both affective and cognitive dimensions of users. In addition, a technical framework is proposed to drive product ecosystem design for user experience with rigorous engineering methods. The

technical framework has three consecutive and iterative steps, i.e., affective-cognitive need elicitation, affective-cognitive analysis, and affective-cognitive fulfillment.

Toward this end, multiple physiological measures acquired from wearable sensors are applied to support affective need elicitation and prediction with three different types of models for comparison. A system based on case-driven ambient intelligence is developed to address cognitive need acquisition and analysis for elderly in-home assistance applications. To deal with affective-cognitive analysis, a technique named fuzzy reasoning Petri nets is proposed, considering product ecosystem formation, user experience modeling in terms of affective responses and cognitive task processes, as well as operational cost for a subway station ecosystem design. A hybrid data mining and refinement system is put forward to leverage both forward and backward affective mapping for affective need fulfillment in the context of a truck cab interior ecosystem design. The results of these endeavors towards the *affective-cognitive design of product ecosystems for user experience* suggest the significance of the research problem as well as the feasibility and potential of the proposed framework.

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List of Abbreviations

AC: Affective-Cognitive
ACM: Affective-Cognitive Mapping
ACN: Affective-Cognitive Need
ACTA: Applied Cognitive Task Analysis
ACT-R: Adaptive Control of Thought – Rational
ADLs: Activities of Daily Living
AI: Artificial Intelligence
AmI: Ambient Intelligence
AMR: Association Mining and Refinement
AUX: Affective User eXperience
BACM: Backward Affective-Cognitive Mapping
BAM: Backward Affective Mapping
BVP: Blood Volume Pulse
C-AmI: Case-driven Ambient Intelligence
CBR: Case-Based Reasoning
CDM: Critical Decision Method
CS: Corrugators Supercilii
CTA: Cognitive Task Analysis
CUX: Cognitive User eXperience
DR: Decision Rule
DT: Decomposition Tree
ECG: Electrocardiogram
EDA: Electro Dermal Activity
EEG: Electroencephalography
EHA: Elderly in-Home Assistance
EMG: Electromyography
FACM: Forward Affective-Cognitive Mapping
FAM: Forward Affective Mapping
fMRI: functional Magnetic Resonance Imaging
FN: False Negative
FP: False Positive
FRPN: Fuzzy Reasoning Petri Net
GOMS: Goals, Operators, Methods, and Selection rules
HCI: Human-Computer Interaction
HFE: Human Factors and Ergonomics
HSD: Honestly Significant Difference
HTA: Hierarchical Task Analysis
IAPS: International Affective Picture System
ILP: Inductive Logic Programming
KE: Knowledge Elicitation
k-NN: *k*-Nearest Neighbor
LDA: Linear Discriminant Analysis
LSA: Latent Semantic Analysis
NPD: New Product Development
OLR: Ordinal Logistic Regression
PET: Positron Emission Tomography
PN: Petri Net
PSD: Power Spectral Density
QFD: Quality Function Deployment
RFID: Radio-Frequency Identification
SAM: Self-Assessment Manikin
SCR: Skin Conductance Response
SOAR: State Operator and Result
TM: Ticketing Machines
TP: True Positive
UX: User eXperience
WSN: Wireless Sensor Network
ZM: Zygomaticus Major

PUBLICATION LIST

As a result of the work carried out in this research, the following papers have been submitted and published.

Journal Paper

1. **F. Zhou**, R. J. Jiao, S. Chen, and D. Zhang, 2010, "A Case-Driven Ambient Intelligence System for Elderly in-Home Assistance Applications", *IEEE Trans. Systems, Man, and Cybernetics*, *Part C: Applications and Reviews*, 41(2): 1-11.
2. **F. Zhou**, X. Qu, M. Helander, and R. J. Jiao, 2011, "Affect Prediction from Physiological Measures via Visual Stimuli", *International Journal of Human Computer Studies*, 69(12):801-819.
3. **F. Zhou**, R. J. Jiao, Q. Xu, and K. Takahashi, 2011, "User Experience Modeling and Simulation for Product Ecosystem Design Based on Fuzzy Reasoning Petri Nets", *IEEE Trans. Systems, Man, and Cybernetics*, *Part A: Systems and Humans*, 99, 1-12.
4. **F. Zhou**, Q. Xu, R. J. Jiao, and M. Helander, "Emotion Prediction from Physiological Signals: A Comparison Study between Visual and Auditory Elicitors", *Interacting with Computers*, under revision.

Conference Paper

1. Q. L Xu, **F. Zhou,** and J., Jiao, "Design for User Experience: An Affective-Cognitive Modeling Perspective", in The 5th IEEE International Conference on Management of Innovation and Technology (ICMIT), June 2-5, 2010, Singapore.
2. **F. Zhou**, R. J. Jiao, Q. Xu, S. Chen, X. Qu and M. Helander. "An Affective-Cognitive Framework of Product Ecosystem Design" in The IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), Dec. 8-11, 2009, Hong Kong.
3. **F. Zhou**; K. Takahashi, Q. Xu; R. J. Jiao, D. Zhang, "Affective-Cognition Modeling of Product Ecosystems Using Timed Colored Petri Nets", 16th International Conference on in

Industrial Engineering and Engineering Management, 2009. (IE&EM), 21-23 Oct. 2009, Beijing, China.

4. **F. Zhou**, R. J. Jiao, S. Chen, D. Zhang, “A Context-Aware Information Model for Elderly Homecare Services in a Smart Home”, in ASME 2009 International Design Engineering Technical Conferences (IDETC) & Computers and Information in Engineering Conference (CIE), Aug. 30-Sept. 2, 2009, San Diego, USA.
5. **F. Zhou**, R. J. Jiao, D. Schaefer, S. Chen, “Rough Set Based Rule Mining for Affective Design”, in The 17th International Conference on Engineering Design, (ICED), 24 - 27 August 2009, Stanford University, CA, USA.
6. **F. Zhou**, D. Wu, X. Yang, and R. J. Jiao, “Ordinal Logistic Regression for Affective Product Design,” in The IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 2008, Singapore.
7. X. Yang, D. Wu, **F. Zhou**, and R. J. Jiao, “Association Rule Mining for Affective Product Design,” in The IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), 2008, Singapore.
8. **F. Zhou**, H. B. L. Duh, and M. Billinghurst, “Trends in Augmented Reality Tracking, Interaction and Display: A Review of Ten Years of ISMAR,” in The 7th IEEE and ACM International Symposium on Mixed and Augmented Reality (ISMAR), 2008, Cambridge, UK.
9. **F. Zhou**, A. Tan, and R. J. Jiao, “Emergency Logistics using Graph Theory and Abstraction Hierarchy,” in The 4th IEEE International Conference on Management of Innovation and Technology (ICMIT), 2008, Bangkok.

CHAPTER 1
INTRODUCTION

This chapter provides an overview of the background knowledge leading to this research. Based on the discussion of research motivation, the research problem is identified as affective-cognitive (AC) design of product ecosystems for user experience (UX), which suggests itself as an important strategy to achieve high value-added user satisfaction. Accordingly, research objectives and scopes are defined, along with an outline of a technological roadmap for this research.

1.1 Background

When all mobile phones produced by different companies can connect people with their friends and family globally, what is the key factor that makes a person select one mobile phone over another? Here is where the concept of user experience (UX) comes into play. Some phones are easy to operate, others are fancy, cool, or elegant, while others are just right to hold and touch. These experiences define how the connection between two people is realized and unfolds. This is well reflected in iPhone's slogan: 'Touching is Believing'. Many other companies, such as 3M, Google, Philips, have also echoed the importance of UX as a key success factor for product design.

In academia, research on UX is situated at the intersection of several scientific disciplines, such as human factors and ergonomics (HFE), human-computer interaction (HCI), psychology, mechanical and material engineering, consumer and marketing research, and product and system design, and so on. For a long time, HFE mainly focuses on the understanding of the design, development, and deployment of systems and services based on humans' physical and cognitive capabilities and limitations (Wickens *et al.*, 1998). Despite the fact that user pleasure and affective aspects are considered in the new development of HFE (Jordan, 2000a; Helander and Tham, 2003), efforts are rarely put on multiple interrelated products that collectively influence UX.

The discipline of HCI is the study, planning and design of the interaction between people (users) and computers. Traditional practice in HCI limits itself to the studies on usability of hardware and software products and systems, and reflects an awareness of the importance of human-computer interface design (Carroll, 2000; Kramer *et al.*, 2000). Designers are persistently exploring new functionalities and interaction possibilities that can be created with new technologies (Moggridge, 2007). A shift from usability studies to UX studies has been witnessed in terms of both cognitive and affective aspects, such as efficiency, presence, trust and engagement (e.g., de Rosis, 2002; Picard and Klein, 2002; Scheirer *et al.*, 2002; Hassenzahl and Tractinsky, 2006).

In the field of psychology, affect and cognition were separately studied for a long history. Nevertheless, researches have recently demonstrated that affect and cognition not only interact with each other, but also that their integrative operation is necessary for adaptive functioning, ranging from decision making to memory (Oschsner and Phelps, 2007). For example, the theory of affect heuristic is about that a human being's affect can influence their decision-making (Slovic *et al.*, 2002). Kahneman (2002), a Nobel laureate, emphasizes that he would have reformulated the Prospect Theory, if he had known about the emotional basis for decision making. Emotion theorists have also argued for the role of emotion as a powerful motivator, influencing perception, reasoning, memory, coping, and creativity in important ways (e.g., Norman, 2004; Ahn and Picard, 2005).

Mechanical and material engineering has long been concerned with products in terms of physical structures of devices, forms and shapes, materials and their effects on durability, reliability, production, and technical performance (Ashby and Johnson, 2002). However, this perspective has been expanded. A prominently seen trend is to study the relationships between design elements and subjective feelings. For example, Kansei engineering aims to map a consumer's feelings for a product into design elements (Nagamachi, 1995) and has been widely applied in various industries (see Nagamachi, 1996; Ishihara *et al.*, 2001; Jiao *et al.*, 2006; Jiao *et al.*, 2007).

Studies on marketing and consumer are mainly concerned with how to bring the product to market in a profitable way by leveraging product, price, promotion, and distribution (Malhotra, 2002). Nevertheless, as a customer, purchasing decisions are not merely the result of pure logic — other factors come in, such as emotions, which often have more to do with the heart than the head (Hammond and Beck, 2003). Customers' emotional responses to a product, however, so far have mainly been addressed from an advertising perspective. This has led to the dilemma that what customers expect from a product based on the way it is advertised always deviates from what it actually 'feels' like in a variety of aspects (Millard, 2005). Therefore, in order to be successful, companies must also understand the constancy and power of emotion in the decision-making process, and leverage that power to improve customer satisfaction directly from the products and services themselves (Hammond and Beck, 2003).

System design refers to the definition, analysis, and modeling of complex interactions among many components that comprise a natural system or an artificial system, and the design and implementation of the system with proper and effective use of available resources (Ulrich and Eppinger, 2000). The process of system design requires being able to skillfully divide complex processes and phenomena into meaningful and intelligible subcomponents (Suh, 2001). However, a lesson learned repeatedly by industrial designers is that design problems (especially for complex systems with several products) have a context, and that the overly narrow optimization of one part of the design can be rendered invalid by the broader context of the problem (Hewett, 1992). Therefore, it is imperative to have a system thinking that considers multiple components of the overall system. Consistent with this notion, the concept of product ecosystem design is emerging that highlights a paradigm of human-product-ambience interactions where the ambience indicates ambient factors that influence the traditional human-product interactions (Jiao *et al.*, 2007).

In summary, UX study encompasses research from different disciplines. However, to fully understand UX incorporating both cognitive and affective aspects, it is imperative to come up with approaches that bridge the gaps among these various fields.

1.2 Research Motivation

Designers' ability to create meaningful UX goes far beyond usability. It is also indispensible to consider other cognitive, socio-cognitive, and affective aspects of UX in the interaction process, such as users' enjoyment, aesthetic experience, brand loyalty, and enhanced mental models (Law and van Schaik, 2010). Depending on the context in which designers work, they can utilize the latest technologies, combine multi-media platforms with services, or make use of sensory information to create meaningful UX (Hekkert and Schifferstein, 2008). As so many products are no longer islands of their own to fulfill self-contained functionality, the most impressed means is probably a product ecosystem vision, where multiple interdependent products are considered as a consistent whole to create unique UX, and importantly, to achieve high economic value (Jiao *et al.*, 2007). One good example is the iPhone ecosystem where a central smart phone product is upholstered by a suite of software, hardware, services, retailing stores, and developer and user groups. All of them form an iPhone ecosystem that contributes to such a great UX and a high economic margin that other more disjointed offerings could not match. The concept of the product ecosystem is also consistent with that of experience economy, where strategic business advantages depend less on the power of technology embedded in a given product, but more on UX within a product ecosystem (Pine and Gilmore, 1999).

On the other hand, UX always results from some interaction the user has with a product and the interaction is clearly product-dependent. However, the processes that are activated during the interaction are similar over products and, thus, it should be possible to develop an overall theoretical framework that guides the study of how people experience products and to gain much support from empirical research (Hekkert and Schifferstein, 2008). Hassenzahl and Tractinsky (2006) define UX as a dynamic, context-dependent, internal state of users, which consists of both instrumental and emotional aspects. In the design community, these two aspects correspond to cognitive design and affective design, respectively. Although affective and cognitive design for UX have received much attention, most of the current work has been conducted in their respective areas, lacking an integration of the affective and cognitive dimensions (e.g., Roth *et al.*, 2002; Helander and Khalid, 2006; Jiao *et al.*, 2007). Therefore, AC design of product ecosystems for UX suggests itself as an important research topic for high value-added user satisfaction.

1.3 Research Objective and Scope

The primary objective of this research is to formulate a systematic framework for AC design of product ecosystems for UX. Accordingly, it is decomposed into several sub-objectives that are to answer the following key research issues:

(1) How to formulate product ecosystems systematically;

(2) What are the essential dimensions of UX in the context of product ecosystems;

(3) What are the key factors and the operational mechanism leading to desirable UX;

(4) How to construct relationships between design elements and UX;

(5) How to test principles of product ecosystem design under different scenarios with rigorous, transparent and replicable methodologies.

Towards this end, corresponding research tasks are proposed:

(1) Examine the entities and relationships in a product ecosystem and define it with mathematical models, in particular,

- Identify design elements of a product ecosystems, including users, products, and the ambient factors where the products are collectively operating;
- Analyze interactive relationships between these entities, including user-product, user-user, user-ambience, and product-product relationships;
- Define product ecosystems and discussed implications of product ecosystem design;

(2) Model UX explicitly and develop a conceptual model of product ecosystem design for UX, including

- Explore essential dimensions of UX as well as possible relationships between them;
- Identify typical factors and their rationales underlying UX design;

(3) Propose a technical framework to develop rigorous methodologies for product ecosystem design that links relationships of design elements to UX in terms of affective needs and cognitive needs. The framework consists of three consecutive and iterative steps, i.e., AC need elicitation, AC analysis, and AC fulfillment. Corresponding research tasks have been conducted below:

For affective need elicitation and prediction:

- Develop a systematic method to elicit and predict affective needs using wearable sensors with physiological measures;

- Investigate the influence of ambient factors, specifically culture and gender on affective need elicitation and prediction;
- Validate the affective need elicitation and prediction method with comparison studies;

For cognitive need acquisition and analysis:

- Develop a systematic procedure and method for cognitive need acquisition and analysis with case-driven ambient intelligence (C-AmI);
- Validate the system and method based on the results of a case study;

For AC need analysis:

- Develop AC analysis and modeling techniques with fuzzy reasoning Petri nets (FRPNs);
- Validate the model based on the simulation results of a case study;

For affective need fulfillment:

- Develop affective need fulfillment with a hybrid mining and refinement system;
- Validate the system based on the results of a case study.

The first two tasks demonstrate the basic research objectives while the last two show both the technical objectives that are used to fulfill the sub-objectives and the research scope with perspectives from different disciplines (e.g., psychology, engineering design, HFE, HCI) and case studies.

1.4 Organization of This Thesis

Figure 1-1 presents the roadmap of this thesis, including motivation & significance, problem formulation, methodology & solution, and application & validation.

The motivation and significance are discussed in Chapters 1 and 2. Chapter 1 discusses the general background and a holistic view of this research. Chapter 2 provides a comprehensive review in terms of two essential aspects of UX design, i.e., affective and cognitive design.

Chapter 3 formulates the key problems of this research. It first presents the fundamental issues underlying product ecosystem design for UX. Discussed in details are the product ecosystem formulation, UX modeling, key research issues along a proposed technical framework, as well as the respective solution strategies. AC design of product ecosystems for UX implies three consecutive and iterative steps, namely, AC need elicitation, AC analysis, and AC fulfillment. However, the boundary among them is actually blurred. Elicitation techniques are usually driven by the choice of analysis schemes, and vice versa: many modeling schemes in the analysis task imply the use of particular kinds of elicitation techniques as well as the fulfillment task (Nuseibeh and Easterbrook, 2000). Therefore, Chapters 4, 5, 6, and 7 emphasize these topics, respectively, but may cover more than one topic.

In Chapter 4, regarding affective need elicitation and prediction, experimental studies are conducted using wearable sensor-based physiological measures for affect prediction models with data mining methods. Meanwhile, factors of gender and culture are also introduced to investigate their influences on affective need elicitation and prediction.

Chapter 5 reports the development of a C-AmI system for cognitive need acquisition and analysis. It synthesizes various ambient and wearable sensors for data collection, a rough-set based activity recognition module, a case-based reasoning module for context understanding, along with discussions on HCI issues for assistive actions, within a coherent framework. A case study of elderly in-home assistance in a smart home ecosystem is presented to illustrate the feasibility and potential of the proposed system.

Chapter 6 is devoted to AC analysis and modeling in the context of product ecosystems with FRPNs. Product ecosystem design with regard to UX and cost optimization is systematically formulated. A case study of a subway station ecosystem is used to demonstrate the proposed techniques and a simulation method is employed for the purpose of validation.

Chapter 7 focuses on affective need fulfillment via forward and backward affective mapping with a hybrid data mining and refinement method. The *K*-optimal rule discovery method and a rule importance measure based on the rough set theory are proposed to extract and refine forward affective mapping relationships, respectively. Ordinal logistic regression is proposed for backward affective mapping while weighted ordinal logistic regression based on conjoint analysis is contrasted with the basic model for refinement. A case study of interior cab ecosystem design is presented to validate the potential and feasibility of the proposed method.

The last chapter, Chapter 8, summarizes the achievements in addressing the research objectives and tasks. A critical assessment is given to highlight the limitations and possible improvements of the thesis work, along with recommendations for future work.

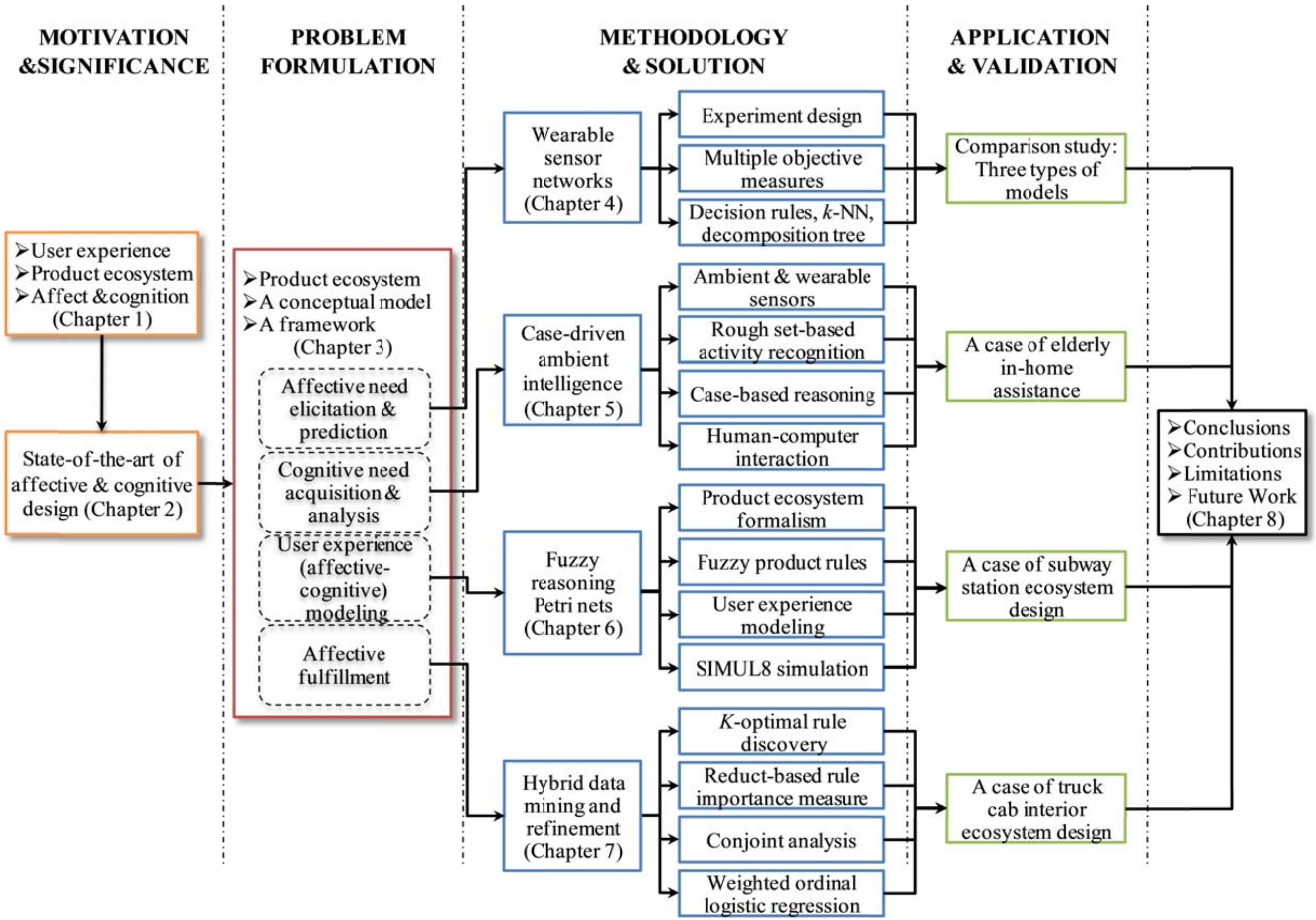


Figure 1-1 Organization of this thesis

CHAPTER 2
LITERATURE REVIEW

UX consists of both instrumental and emotional aspects, which are corresponding to cognitive design and affective design, respectively, in the design community. This chapter is dedicated to the state-of-the-art review for affective and cognitive product design. Introduction to the affect and cognition perspectives in product design is offered. Particular emphasis is placed on various issues related to the design process, such as affective and cognitive need elicitation, affective and cognitive analysis, as well as affective and cognitive fulfillment. Potential directions for future research are also discussed.

2.1 The Affect Perspective

2.2.1 Definition of Affect

Affect or affective response (state) is an encompassing term that includes emotions, feelings, moods, and evaluations (Simon, 1982). Among them, emotion is the most important one. However, the emotion theories in psychology may be considered as a '*very confused and confusing field of study*' (Ortony *et al.*, 1988). Therefore, the summary of emotion that incorporates the key elements of previous definitions by Kleinginna and Kleinginna (1981) is given:

(1) Emotions give rise to affective experiences, such as pleasure or displeasure.

(2) Emotions stimulate us to generate cognitive explanations – to attribute the cause to ourselves or to the environment, for example.

(3) Emotions trigger a variety of internal adjustments in autonomic nervous system, such as increased heart rate and decreased skin conductance response.

(4) Emotions elicit behaviors that are often, but not always, expressive (laughing or crying), goal-directed (approaching or avoiding), and adaptive (removal of a potential threat).

Based on this summary, emotions occur as a result of an interaction between subjective factors, environmental factors, and neural and hormonal processes.

Feelings are the subjective representation of emotions (Davidson *et al.*, 2003). Feelings are often consciously accessible and thus operationalized as verbal self-reports for most current studies (Grandjean *et al.*, 2008).

The term mood refers to a longer-term affective state (Picard, 1997). Russell (2003) also defines it as prolonged core affect with no directed object (simple mood). The precise duration is not well-defined, although moods can apparently last for hours, days, and maybe longer. In contrast, prototypical emotional episodes are said to begin and then, after a short time (up to a few minutes), end (Russell, 2009). A mood may arise when an emotion is repeatedly activated. For example, a bad mood may arise during a half hour of reinforced negative thoughts or actions, or may be induced by taking drugs or medication (Picard, 1997).

Evaluation is a kind of affective response that enables categorization of positive and negative reactions (Simon, 1982). It is the aspect of affect that is used to assess a situation or a product whether it is attractive, pleasurable, or disgusting. In this thesis, the term affect, affective response, or affective state mainly concerns emotions, feelings, and evaluations.

2.2.2 Affective Design

Evidence has revealed that affect plays an important role in human information processing. Zajonc (1980) argues that affective reactions constitute the primary and determining response to social stimuli and consequently influence human judgments substantially. Affect also plays a significant role in decision making. Damasio (1994) demonstrates that without emotions, the ability of decision-making would be impaired. Further, Nobel laureates Simon (1967) and Kahneman (2002) emphasize that a general theory of thinking and problem solving must incorporate the influence of emotion. Therefore, even a small change in one's affective state can significantly impact creativity and problem solving (Picard and Klein, 2002). Besides, affect also influences a variety of other cognitive functions (Picard, 1997).

While the interaction process between humans and products is considered as an information processing activity (Wickens and Hollands, 1999), affect is one of the key factors in this interaction process (Picard, 1997). In some instances, optimal performance requires an appropriate affective state (Yerkes and Dodson, 1908), such as in aviation safety where a state of high vigilance is desirable (Wickens and Hollands, 1999). At other times, it is often necessary to maintain or prevent particular affective states to have optimal performance and pleasurable UX (e.g., the flow state (Csikszentmihalyi, 1990)). As a result, appropriately capitalizing on the affect perspective in product design is deemed to improve task performance and human satisfaction (Helander and Tham, 2003), in such areas as marketing and consumer research, engineering design, HFE, HCI, and so on.

In marketing and consumer research, a large number of studies focus on consumers' affective responses to advertisements and brands (e.g., Morris *et al.*, 2002), as well as the role of affect in consumer behavior, such as purchase decision making and judgment (e.g., Yeung and Wyer, 2004). Kansei engineering can "measure" the feelings of users toward certain product properties. In consequence, products can be designed to bring forward the intended feelings (Nagamachi, 1995). It has been applied to various industries, such as cosmetics, garment, automotive, and electronics industries (Nagamachi, 1996; Ishihara *et al.*, 2001; Jiao *et al.*, 2006; Jiao *et al.*, 2007). Researchers in HFE explore both practical problems and theoretic issues, such as affective need elicitation, analysis, and fulfillment (Jiao *et al.*, 2007), as well as affect semantic space construction, measurement, and model construction (Helander and Tham, 2003; Norman, 2004; Helander and Khalid, 2006). The group led by Picard at MIT Media Lab advocates affective computing in the HCI domain. It is the computing that relates to, arises from, or deliberately influences emotions or other affective phenomena (Picard, 1997). In affective computing, user needs are defined in a broader perspective that includes emotional and social needs and technology's emerging capability is examined to address and support such needs (Picard and Klein, 2002).

The perspective of affect in various disciplines has stimulated many research opportunities for the design community to understand the radical meanings of interactions between humans and systems, socially, emotionally, and culturally, such as design for Kansei (Nagamachi, 1995), hedonic pleasure (Jordan, 2000a; Helander and Khalid, 2006), aesthetics (Liu, 2003), and emotional responses and aspirations (Jiao *et al.*, 2007). In this thesis, these endeavors are referred to as *affective design*, with the aim to improve affective UX.

2.2 The Cognition Perspective

2.2.1 Definition of Cognition

Neisser (1967) in his book *Cognitive Psychology* defines cognition as 'all processes by which the sensory input is transformed, reduced, elaborated, stored, recovered, and used. It is concerned with these processes even when they operate in the absence of relevant stimulation, as in images and hallucinations'. Such terms as sensation, memory, attention, perception, action, problem solving, and mental imagery, among many others, refer to aspects of cognition. These mental processes described as cognitive or cognitive processes are thought to be necessary to perform a cognitive task (Wickens and Hollands, 1999). Cacciabue and Hollnagel (1995) coin the term 'macrocognition' to indicate descriptions of cognitive functions that are performed in natural (versus artificial laboratory) decision-making settings. Such cognitive functions involve joint attention, anomaly recognition, replanning, sense making and others that are situated in the context of human goals, desires, activity, and work (Klein *et al.*, 2003). On the other hand, microcognition focuses on mental processes, skills, and reasoning strategies that happen only in the head and is believed to act as building blocks for more complex information processing (Klein *et al.*, 2003; Woods and Roesler, 2008). While cognitive phenomena can be described at a microcognitive level, they can also be described at a macrocognitive level, such as those shown in Table 2-1 (Klein *et al.*, 2003). Both types of descriptions are complementary.

Table 2-1 Important macrocognitive phenomena and traditional microcognitive lab research

Macrocognition phenomena of concern	Parallel traditional microcognition topics
Planning and problem detection	Puzzle solving
Using leverage points to construct options	Strategies for searching problem spaces
Attention management	Serial versus parallel processing models
Uncertainty management	Estimating probabilities or uncertainty values

Human is thought of as an active information processor in which some information is consciously manipulated while other processing takes place outside of conscious awareness (Styles, 2005). Regardless of different cognitive processes, according to Huitt (2003), however, there are four basic principles regarding human cognitive information processing presented below:

(1) The cognitive system has limited capacities, that is, bottlenecks or restrictions in the flow and processing of information, occur at very specific points;

(2) A control mechanism is required to oversee the encoding, transformation, processing, storage, retrieval, and utilization of information. This control mechanism requires itself processing power, depending on the difficulty level of the task;

(3) There is a two-way flow of information. Sensory input is combined with information stored in memory in order to construct meaning;

(4) The human organism has been genetically prepared to process and organize information in specific ways.

2.2.2 Cognitive Design

Cognitive design takes considerations of human capabilities and limitations in the information processing tasks to lower cognitive workloads, reduce errors, and improve efficiency and UX (Wickens and Hollands, 1999). This perspective has burgeoned in HFE since 1960s and has been widely applied to areas, such as HFE, HCI, software engineering, systems engineering, and product design (Helander, 2005). Cognitive design has tremendous potential to influence the most difficult aspects of systems with increased complexities, including the vast amount of available data, the pressure to make timely decisions, and the reduced manpower and cost goal (Perry *et al.*, 1999).

When Woods and Roesler (2008) discuss the relationships between design and cognition, they categorize design on microcognitive level and macrocognitive level. The former is concerned with the impact of design on the mental costs by carrying out the details of specific tasks. For example, a design can act as external memory aids to help people recall relevant knowledge, while poor designs create or exacerbate bottlenecks in elemental cognitive processes. Thus, the microcognitive perspective in design can identify bottlenecks (e.g., memory, attention, and workload bottlenecks) with regard to specific design and suggest repair methods for new designs.

Among many others, usability testing is one of the most prevailing practice in terms of microcognitive design (e.g., Juristo *et al.*, 2007), especially by consumer electronics companies. Usability is a quality attribute that assesses how easy user interfaces are to use (Nielsen, 2003). Critical dimensions have been identified as follows (Nielsen, 1994):

(1) Learnability: The process by which users figure out how to use the design and complete the task for the first time;

(2) Efficiency: Once the users have learned the design, how quickly can they perform the task?

(3) Memorability: When users return to the design after a period of time, how easily can they reestablish proficiency?

(4) Errors: How many errors do users make, how severe are these errors, and how easily can they recover from the errors?

(5) Satisfaction: How pleasant is it to interact with the design?

Other dimensions, such as simplicity, consistency, and locus of control, are also proposed (Kim and Han, 2008). There are plenty of cognitive engineering methods to improve usability and thus to address cognitive needs. For example, one of the classical paradigms is user-centered design that keeps user needs central to the design process (Norman and Draper, 1986).

The macrocognitive perspective in design emphasizes how design (usually more complex systems) can support people actively to explore and find meaning in the world (Gibson, 1979). For example, one of the focuses is how systems are designed to help examine what constitutes an anomaly, how to recognize an anomaly, and how it influences information search, explanation building, and revision, i.e., anomaly recognition (Woods and Roesler, 2008). Woods and Roesler (2008) suggest three advantages gained from macrocognitive design:

(1) It provides directions to explore in the conceptual and ideation phases of design,

(2) Produces criteria to see if early design work is a promising direction that merits further investment rather than generating a prototype to be well specified to begin testing, and

(3) Offers a guide to create concrete scenarios that instantiate challenges for macrocognitive processes as relevant to the scope of the design project.

For example, Smith *et al.* (2007) demonstrate a good example of designing air traffic management systems to support macrocognition functions, enabling greater flexibility in tailoring and modifying flight plans.

2.3 General Process of Affective and Cognitive Design

The affective and cognitive design process starts with effective discovering, eliciting and understanding affective and cognitive needs (compared with traditional functional requirements) of users in the user domain. Subsequently, it aims to document these needs in a form that is amenable to analysis, communication, and finally implementation for fulfilling these needs for respective stakeholders with consideration of marketing and engineering concerns in the designer domain. The process of affective and cognitive design has three tasks, i.e., (1) affective and cognitive need elicitation, (2) affective and cognitive analysis, and (3) affective and cognitive fulfillment.

Affective and cognitive need elicitation. This task is to systematically acquire affective and cognitive needs of users. It also needs to identify target stakeholders, including users and producers. In such a way, the goals, tasks, use scenarios and cases can be defined and corresponding constraints can be obtained (Nuseibeh and Easterbrook, 2000).

Affective and cognitive analysis. This task is to interpret affective and cognitive needs and derive explicit requirements that can be understood by marketing and engineering folks. Hence, this task involves representational formalisms to synthesize and communicate acquired results in the user domain and design implications in the designer domain.

Affective and cognitive fulfillment. This task is to explicitly explore the relationships between affective and cognitive needs in the user domain and concrete product specifications in the designer domain. While it is human-centered design in terms of users, it needs to consider many engineering and marketing concerns (Du *et al.*, 2003), such as cost, product technologies, manufacturability, reliability, and environmental safety, to name but a few (Prudhomme *et al.*, 2003).

These tasks are closely related and share a commitment to (1) acquiring and analyzing the affective quality and the cognitive demands in the user domain, (2) informing subsequent information and decision support in the designer domain, and (3) linking the two domains with considerations of engineering and marketing concerns.

2.4 Affective and Cognitive Need Elicitation

Like the functional requirement elicitation process, the elicitation task stresses the transformation process that usually converts subjective and tacit verbatim constructs into explicit and objective statements of affective and cognitive needs (Jiao and Chen, 2006). In order to effectively elicit affective and cognitive needs, numerous perspectives have been proposed. For example, segmentation of different users in terms of demographic factors (e.g., Zhang *et al.*, 2006b), classification or hierarchies within affective or cognitive needs (e.g., Kano *et al.*, 1984), laddering (Chen *et al.*, 2006)), and analysis of users and their tasks in a particular workplace (e.g., Johnson and Turley, 2006) are all valuable approaches. Nevertheless, elicitation of affective and cognitive needs is discussed with regard to the techniques used in different disciplines in this review.

2.4.1 Knowledge Elicitation

Knowledge elicitation (KE) is the transfer and transformation of problem-solving expertise and domain knowledge from a source into a program (McGraw, 1992). Various KE techniques have been applied to investigate cognitive needs, such as interviews (structured, unstructured, and semi-structured), self-reports, observation, process tracing methods (e.g., think-aloud, critiquing), and conceptual methods (e.g., hierarchical sort, laddering) (Crandall *et al.*, 2006). For example, Johnson and Turley (2006) apply a think-aloud protocol to investigate cognitive requirements of nurses and physicians for designing healthcare software. Coffey and Carnot (2003) employ structured interviews to develop concept maps in rocket science. Laddering techniques are widely used in eliciting goals and underlying values (Rugg and McGeorge, 1995). For instance, through laddering interviews, Wansink (2003) develops a "mental map" that visually links to brand attributes, the benefits or consequences of using it, and the personal values it satisfies.

To elicit affective needs, the most frequently used method is described as follows: Above all, a large amount of affective adjectives that are representative of users' feelings on a product are collected from user interviews (Jiao *et al.*, 2007), journals and magazines related to the product, and words used by marketing and design personnel (Nagamachi, 1995; Zhang *et al.*, 1996). Subsequently, the most relevant and appropriate words are selected by domain experts using focus groups, affinity diagrams, factor analysis, cluster analysis (e.g., Tague, 2004; Lanzotti and Tarantino, 2008), etc. In HFE and product design, plenty of methods have been employed to elicit affective needs, including interviews (Jordan, 2000b), Philip's Questionnaire (Jordan, 2000b), self-reports about one's emotional state, be it instantaneous or retrospective (Rosenberg and Ekman, 1994), affect grid techniques based on subjective feelings (Russell *et al.*, 1989), a non-verbal product emotion measurement instrument (i.e., PrEmo) (Desmet, 2003), etc.

2.4.2 Cognitive Task Analysis

Although KE techniques provide a rich source of information, they often result in a large set of data that are difficult to interpret (Crandall *et al.*, 2006). Cognitive task analysis (CTA) is defined as the extension of traditional task analysis techniques to yield information about the knowledge, thought processes, and goal structures that underlie observable task performance (Schraagen *et al.*, 2000). In performing CTA, two mutually reinforcing perspectives need to be considered, i.e., fundamental characteristics of the domain and the cognitive demands they impose (Pfautz and Roth, 2006). Hence, these methods are particularly suitable for mining cognitive needs.

Typical CTA techniques encompass applied cognitive task analysis (ACTA), hierarchical task analysis (HTA), cognitive field observation, critical incident analysis, critical decision methods (CDMs), and so on (see Crandall *et al.*, 2006). ACTA adopts three structured interview methods (i.e., task diagram, knowledge audit, and simulation interview) in order to extract information about the critical cognitive elements and skills required for a task (Militello and Hutton, 1998). For example, Takeshi *et al.* (1998) use ACTA to identify cognitive requirements of Microsoft Word 95 and Excel 95 for usability evaluation. HTA decomposes a task into a hierarchy of goals, supporting sub-goals, and the actions performed to accomplish those goals (Shepherd, 2000). Thus it helps identify cognitive workloads and potential errors for achieving sub-goals and goals (Stanton, 2006). Cognitive field observation has been used to examine performance in actual environments and high-fidelity simulators (Woods and Roth, 2006). Critical incident analysis relies on retrospection to investigate actual past cases, such as firefighting experience (Dekker, 2002).

On the other hand, CTA techniques are also applicable to elicit affective needs, especially in the consumer decision making process, such as CDMs. CDMs take advantage of cognitive probe questions to determine the bases for situation assessment and decision making in a non-routine incident (Klein *et al.*, 1989). Crandall *et al.* (2006) employ CDM interviews to examine consumers' decision-making process in brand shift, especially the subtle cues, to understand their loyalties to brands. CDMs, together with knowledge audit for marketing research applications (Readinger, 2004), are also designed to elicit incidents of a particular type of purchase, use, and surprise about different aspects of product performance (Crandall *et al.*, 2006).

2.4.3 Artificial Intelligence-Based Approach

Generally speaking, to run CTA techniques, domain experts equipped with knowledge of cognitive engineering and cognitive psychology are needed (Schraagen *et al.*, 2000). Further, subjective factors and intensive statistical analysis involved during user requirements elicitation may complicate the problem and even lead the elicitors astray (Jiao and Chen, 2006). Many techniques in artificial intelligence (AI), such as computational cognitive architectures and models can accommodate cognitive needs by simulating complex cognitive tasks. Such results can provide *a priori* performance predictions of how easy the system will be learned and used, the workload it imposes, and the propensity for errors (Lamoureux *et al.*, 2006). For example, ACT-R (Adaptive Control of Thought – Rational) is used to model driving while the user is concurrently performing other cognitive tasks, revealing cognitive issues in developing new in-vehicle devices (Salvucci *et al.*, 2005). Marinier *et al.* (2008) integrate emotion with cognition in the SOAR (State Operator and Result) architecture to model simple cognitive behavior and emotional states of an agent.

Although basic intelligence is incorporated in ACT-R and SOAR, these architectures or models are still missing some important aspects of intelligence (e.g., episodic and semantic memories) (Laird, 2008), and thus are not widely used in product design. Nevertheless, other techniques, such as fuzzy systems (Yan *et al.*, 2006) and expert systems (Delin *et al.*, 2007) have been developed, mainly for eliciting affective needs. Due to the subjectivity of affective needs, these methods might elicit more accurate and genuine results (Jiao and Chen, 2006). For example, Delin *et al.* (2007) employ expert systems to automatically retrieve a large number of affective adjectives and then reduce it to an acceptable number using a rule-based system, yet still cover major aspects of affective needs. Chen *et al.* (2006) and Yan *et al.* (2006) investigate integrated approaches to elicit affective needs by combining sorting techniques, fuzzy evaluation, and Kohonen self-organizing map.

2.4.4 Physiological Methods

Basically, need elicitation methods can be divided into two categories: subjective and objective. The methods mentioned above are typically subjective and susceptible to linguistic ambiguity and dependable on expert skills. It is reported that affect and cognition ought to be considered as multi-level phenomena, which must be dealt with simultaneously from physiological, psychological, behavioral, and social points of view (Cosmelli and Ibáñez, 2008; Grandjean *et al.*, 2008). Therefore, objective methods, such as physiological and behavioral measures obtained either directly or indirectly, are also used to elicit affective and cognitive needs (Helander and Khalid, 2006). Typical physiological measures consist of skin conductance response (SCR), blood volume pulse (BVP), electrocardiogram (ECG), respiration, peripheral temperature, electromyography (EMG), heart rate, electroencephalography (EEG), neuroimaging measures (e.g., positron emission tomography (PET)), and functional magnetic resonance imaging (fMRI)), and so on.

Evidence has shown that physiological signals can access to and differentiate among different affective states with pattern recognition methods (e.g., Picard *et al.*, 2001; Peter and Herbon, 2006). For example, Bos (2008) and Li *et al.* (2009) apply EEG to examine emotion recognition. However, it is also suggested one physiological measure alone is not adequate to give a coherent picture of what an affective state is occurring within the user (Scheirer *et al.*, 2002). This is because the relationship between psychology and physiology is not entirely all one-to-one (Cacioppo and Tassinary, 1990). Thus, multiple physiological measures are usually incorporated in most of the studies. Picard *et al.* (2001) build predictive models based on physiological data, including SCR, EMG of the jaw, BVP, and respiration rate of a single subject. The best model obtains 81% accuracy when recognizing eight affective states. Li and Chen (2006) capitalize on ECG, skin temperature, SCR, and respiration using canonical correlation analysis and achieve 85.3% classification accuracy among three emotions. Liu *et al.* (2008) collected a large set of physiological indices (ECG, photoplethysmogram, heart sound, bioimpedance, electro dermal activity (EDA), facial EMG, peripheral temperature) to predict three targeted affective states for six children with autism spectrum disorders. They developed a support vector machine-based affective model which yielded reliable predication with 82.9% success.

To address cognitive requirements by physiological measures, most of the researchers explore cognitive workloads and fatigue. This is due to the fact that extraneous cognitive loads (compared with intrinsic cognitive loads inherent in the work itself) are generated by the manner in which information is presented to users and are under the control of instructional designers (Chandler and Sweller, 1991). Further, reliable measures can set limits on workloads for establishing work allowance. For example, Trejo *et al.* (2007) explore the EEG-fatigue relationships using multichannel spectral measures and have a range of accuracy from 91% to 100%. PET and fMRI have also shown that cerebral blood flow in regions of the prefrontal cortex can quantify attentional resources and cognitive workloads (Parasuraman and Caggiano, 2005). Fredericks *et al.* (2005) find that both cognitive and physical tasks have a significant effect on the product of heart rate and systolic blood pressure.

While physiological measures are fruitful, it is important to consider problems of invasiveness, temporal resolution, and sensitivity (Helander and Khalid, 2006): (1) Physiological measures vary widely in how invasive they are. EEG with dozens of channels could be invasive while heart rate and SCR measured by wearable sensors are less obtrusive. (2) The temporal resolution of various physiological measures also varies to a large extent. Some measures are instantaneous – such as SCR, while, for example, impedance cardiography requires longer duration for reliable measurement (Larsen and Fredrickson, 1999). (3) Different measures vary broadly in terms of sensitivity. Depending upon the affective states and the cognitive states that are being recorded, it is preferable to validate the particular physiological measure to understand if it is sensitive enough to record differences in the intensity of each state.

2.4.5 Behavioral Methods

Behavioral measures are also objective and have been widely applied to the fields of computer engineering, affective computing, and HCI. These measures include facial expressions, vocal characteristics, actions, daily objects, location, ambient information, and so on.

Facial expression recognition. Facial expressions are able to differentiate different affective states and cognitive states (Ekman, 1982). Ekman and his colleagues (Ekman and Friesen, 1978; Ekman, 1982) develop a facial action coding system. It consists of 46 action units based on the movements of the face and some characteristics are believed to be the results of certain emotions. Ekman’s work inspires many researchers to analyze facial expressions by means of image and video processing. These methods usually take advantage of statistical and pattern recognition methods with a range of accuracy from 55% to 98% for a number of emotion categories (e.g., three to eight) (Cowie *et al.*, 2001; Fasel and Luettin, 2003). For example, Essa and Pentland (1997) use an optical flow region-based method to recognize facial expressions. Chen (2000) applies a suite of static classifiers to recognize facial expressions, reporting on both person-dependent and person-independent results. Cohen *et al.* (2003) describe classification schemes for facial expression recognition in two types of settings: dynamic and static classification. Another measure that is able to characterize affective and cognitive states is facial EMG. It measures the nerve impulses to muscles fired by facial changes or expressions (Helander and Khalid, 2006). For instance, Bailenson *et al.* (2008) apply facial EMG and other physiological measures for real-time facial recognition. More information about facial recognition can be referred to (Pantic and Rothkrantz, 2000; Cowie *et al.*, 2001; Fasel and Luettin, 2003) for a review.

Vocal emotion recognition. Vocalization is a bodily process sensitive to emotion-related changes (Larsen and Fredrickson, 1999). Therefore, vocal characteristics, such as pitch, loudness, tone, and timing, can convey information about the speaker's emotional state (Helander and Khalid, 2006). Similar to human, automated vocal affect analyzers have prediction accuracy ranged from 55% to 70% when recognizing two to eight emotions with sentences having a length of one to twelve words (Pantic and Rothkrantz, 2003). For example, Petrushin (1998) compares human with machine with regard to recognition of emotions in speech and achieves similar rates around 65% for both. Maffiolo and Chateau (2003) investigate the emotional quality of speech messages used by the France Telecom Orange. Lee and Narayanan (2005) apply three sources of information, i.e., acoustic, lexical, and discourse, to improve speech emotion recognition. In order to improve recognition accuracy, it is natural to combine multiple modalities. For example, combinations of facial expressions and vocal characteristics (Chen, 2000; Fragopanagos and Taylor, 2005; Mower *et al.*, 2009), and of facial expressions and physiological measures (Bailenson *et al.*, 2008) have been witnessed. More information can be referred to (Pantic and Rothkrantz, 2003; Ververidis and Kotropoulos, 2006) for a comprehensive review about vocal emotion recognition.

Activity recognition. To acquire cognitive needs, activity recognition has emerged based on the activity theory. Activity theory implies that any high eventual satisfaction of a need can be predicted from the low level operations and actions that form the activity (Leont'ev, 1977). This notion is consistent with the macrocognitive perspective in design where cognitive processes are externalized from an 'in-the-head' view to an 'in-the-world' view in order to construct meaning and explore the environment (Woods and Roesler, 2008). Activity recognition is achieved by capturing and recognizing the actions and goals of one or more users from a series of observation on users' behavior (e.g., actions, gaits) and contextual conditions (e.g., objects the users interact with) (e.g., Gu *et al.*, 2009). Since 1980s, activity recognition has captured much attention from computer engineering and HCI, owing to its strength in providing personalized support for many different applications, including activity-based actuation (e.g., dimming lights when a movie is being watched), prompting (e.g., providing directions when using unfamiliar facilities), and notification (e.g., informing caregivers when an elderly person fails to perform key activities of daily living (ADLs)) (Perkowitz *et al.*, 2004).

There are two major types of activity recognition, namely, logic-based and probabilistic-based methods (Hu and Yang, 2008). The latter one is dominant in this area and can be grouped into vision-based and sensor-based methods. As for vision-based methods, either pre-stored templates (e.g., Sul *et al.*, 1998) or spatiotemporal characteristics (Niu and Abdel-Mottaleb, 2004) are used to recognize activities. Although such systems can represent a variety of activities in principle, the activities are usually simple, such as walking and running. The main problem lies in the fact that the features robustly detectable from vision are coarse, though vision is a very general sensor (Perkowitz *et al.*, 2004). The researchers soon realize that the easiest way for a computer to deduce what activity one is performing is by identifying the objects he/she is interacting with using RFID techniques (Pentney *et al.*, 2006). Meanwhile other contextual information is also valuable for activity recognition, such as motion and sound information (Ward *et al.*, 2006), as well as location and environmental information (Favela *et al.*, 2007; Gu *et al.*, 2009). A combination of such sensors forms a dense sensor network that has distributed sensing capabilities, from which the system can recognize and infer what people are doing for various ADLs. For example, Pentney *et al.* (2006) apply RFID techniques and common sense mined from the web for recognizing 13 ADLs with 88% accuracy. Ward *et al.* (2006) apply audio and motion sensor data for assembly task recognition. Favela *et al.* (2007) draw on the information about the location, artifacts being used, the people collaborated, and the time of the day to infer activities in a hospital environment, and achieve accuracy for 75% of the time for 196 hours using neural networks. Recently, data mining methods have been reported to excel in activity recognition. The gist of these methods is to treat activity recognition as a pattern-based classification problem. For instance, Gu *et al.* (2009) formulate activity models using emerging patterns for activity recognition.

2.5 Affective and Cognitive Analysis

Extensive studies have put efforts into the analysis task such that affective and cognitive needs are represented in some form that is more concrete, immediate, communicable, and accessible. Many elicitation methods actually have analysis processes and representational formalisms contained within an overall methodology (e.g., HTA) (Crandall *et al.*, 2006). Due to the qualitative nature of affect and cognition, it is natural to approach the analysis task with qualitative methods. However, unlike qualitative methods which are usually time-consuming and less systematic, quantitative methods make use of computerized tools to reduce the time and complexity with large data sets.

2.5.1 Qualitative Methods

Qualitative methods might yield representations of textual descriptions, tables, graphs by cataloguing cues and patterns, identifying themes, concepts, and key issues, as well as coding and classifying data, and so on.

Textual representation. Usually the elicitation task yields a large amount of data. The simplest, most flexible but most demanding approach is to search major themes, cues, and patterns by domain experts (Crandall *et al.*, 2006). Pfautz and Roth (2006) apply CTA methods to identify major themes and to display concepts and decision support elements in software system design. Crandall *et al.* (2006) apply CDMs to identify cues among the chronology of incident events in consumer behavior of brand shift in order to uncover decision making processes with regard to brand loyalties.

In the analysis task, it is imperative to deal with conflicts and differences of affective and cognitive needs among different types of users. Johnson and Turley (2006) divide medical staff into nurses and physicians for designing healthcare software. They also code audio data about patient diagnosis into different propositions and concepts to understand the differences of their reasoning processes. Kano *et al.* (1984) propose a model to distinguish four basic drivers of user satisfaction i.e., must-be, one-dimensional, attractive, and indifferent drivers. Kim and Han (2008) categorize usability dimensions into three groups, namely, product, product-user, and product-user-task, for usability evaluation. Delin *et al.* (2007) group affective needs into three groups, i.e., highest, medium, and least concept coverage, in order to facilitate selection of appropriate affective adjectives describing different user groups.

Graphical representation. Graphical representations excel in conveying knowledge and representing mapping relationships from the user domain to the designer domain. Among many others, concept maps and cognitive maps are widely used. A concept map is a diagram, showing the relationships (i.e., concept mapping) among concepts, connected with labeled arrows (marked with "give rise to", "consist of", etc.) in a downward-branching hierarchical structure (Novak and Cañas, 2006). Furthermore, conceptual, methodological linkages can be constructed for affective and/or cognitive analysis in a particular domain (Crandall *et al.*, 2006). For example, NASA retiring engineers' expert knowledge is represented by concept maps, facilitating knowledge learning and preservation for novices (Coffey and Carnot, 2003). Hoffman *et al.* (2000) apply concept maps to build a knowledge model in weather forecasting, including URLs linked to up-to-date data.

Cognitive maps are used to represent concepts linked by causal links among them (Pidd, 1996). These causal links help show decision-making processes and perspectives of different actors with regard to that decision (Carbonara and Schiuma, 2004), helping to reach a consensus among different actors. For example, Carbonara and Scozzi (2006) employ cognitive maps to analyze new product development (NPD) process, particularly understanding different perspectives with regard to different actors involved in NPD. Fuzzy cognitive maps introduce fuzzy degrees of interrelationships between concepts (Miao and Liu, 2000). They have been widely used to capture the causal reasoning process present in geographic information systems (Liu and Satur, 1999), urban design (Xirogiannis *et al.*, 2004), and fault detection and troubleshooting systems (Perusich, 2008), and the like.

2.5.2 Quantitative Methods

Highly structured and systematic analysis processes that produce quantified data can be attractive, particular for those who are trained to consider statistical methods are the desirable legitimate path to locate what is important in the data (Crandall *et al.*, 2006).

On the one hand, one difficulty in applying quantitative methods is how to quantify affective and cognitive needs that are qualitative *per se*. In this regard, the simplest forms are counts and frequencies of qualitative constructs used for statistical analysis. For instance, counts of different proposition types (e.g., recall, inference, assumption) used in patient diagnosis are treated as a statistic measure to differentiate cognitive styles of physicians and nurses (Johnson and Turley, 2006). Kim and Han (2008) code binary factors of design elements into 0 and 1 as usability measures for consumer electronic products. Further, ratings and rankings are widely used as quantitative measures. For example, semantic differential scales (Osgood *et al.*, 1957) are often used in Kansei engineering, where participants are asked to rate design candidates against a series of bipolar adjectives (e.g., attractive – not attractive) (Delin *et al.*, 2007). Sedgwick *et al.* (2003) adopt semantic differential techniques to inform users of the surface's physical characteristics to enhance emotional engagement for product packaging. Marketing analysis techniques are also adopted to quantify affective or cognitive needs. For example, conjoint analysis is broadly used to measure preferences to different product profiles and to build market simulation models (Green and Srinivasan, 1978). Jiao *et al.* (2007) apply conjoint analysis to measure different affective product profiles of truck cabs based on ratings on a 9-point Likert scale.

On the other hand, quantitative methods are able to deal with uncertainties and fuzziness inherent in qualitative measures. For example, in order to tackle uncertainties inherent in the hierarchical structures, neural networks based on Kohonen self-organizing map are applied to consolidate the relationships between affective and cognitive needs and formal elements (Chen *et al.*, 2006). Moreover, the fuzzy set and rough set techniques are especially suitable to deal with uncertainties and vagueness inherent in affective and cognitive needs. Yan *et al.* (2006) apply a fuzzy *c*-means algorithm to integrate design alternatives for clustering design options in order to select preferred product concepts. Yan *et al.* (2008) propose a fuzzy target-oriented decision analysis method and three types of fuzzy targets are defined to represent users' affective preferences. Nevertheless, the choice of fuzzy membership functions is critical for the performance of a fuzzy system. In the applications of subjective evolutions and heuristics, the determination of fuzzy membership functions is usually based on experience and intuition (Jin, 2003). Given this disadvantage, Zhai *et al.* (2008) propose the concept of rough numbers, which do not require membership functions. Instead, the imprecise information is represented in the form of intervals with their upper and lower limits that are directly computed from raw data collected. Therefore, they convert subjective ratings of affective and cognitive needs into rough numbers, based on which the ranking of affective and cognitive needs provides more reliable management of information about user needs (Zhai *et al.*, 2009).

2.5.3 Combined Methods

While quantitative and qualitative methods are often presented as if they were in binary opposition to one another, they can also be used to complement one another. Glesne and Peshkin (1992) point out that 'they may, but such methods are supplementary, not dominant...Different approaches allow us to know and understand different things about the world'. One of the mostly used and representative methods is Petri nets (PNs). They are graph-based modeling languages for discrete distributed systems (Murata, 1989) and allow a smooth transition from the conceptual level to the implementation level of process models (Adam *et al.*, 1998). Ordinary PN models generally do not have such functions as quantitative aspects. However, extensions of PNs, such as (generalized) stochastic PNs (Bause and Kemper, 1994), colored PNs (Ha and Suh, 2008), and hybrid PNs (David and Alla, 1992) allow for qualitative and/or quantitative analyses of resource utilization, effect of failures, throughput rate, etc. Other combined methods are also proposed. For example, Inoue *et al.* (2007), on the other hand, combine the rough set method and analytic hierarchy process in usability study. Such combined methods often retain advantages of both qualitative and quantitative methods and therefore are able to give more insights into affective and cognitive analysis.

2.6 Affective and Cognitive Fulfillment

The fulfillment task is mainly concerned with the creation of a structurally concrete and precise specification of product requirements based on affective and cognitive needs of users. Fung *et al.* (1998) refer product specifications to the mapping process from the voice of customers to the voice of designers that takes the form of design requirements in terms of design features or elements.

2.6.1 Cognitive Techniques

In order to facilitate transformation of cognitive requirements to design requirements, cognitive techniques, such as CTA methods, are broadly applied to the fields of cognitive systems engineering and HFE. Unlike marketing researches that focus on users' attitudes, preferences or beliefs, these methods often identify design specifications and design guidelines by unveiling human cognitive information processes, especially decision making processes during specific tasks (Wickens and Hollands, 1999; Crandall *et al.*, 2006). For example, Hoffman *et al.* (2004) create an "audit trail" that links the eventual design back to decision requirements. Crandall *et al.* (2006) apply CTA methods to analyze (1) how users think about products and make decisions, and (2) the context that surrounds the purchase and use of products to specify critical factors for design improvement. GOMS (goals, operators, methods, and selection rules) models have been used to make predictions about human-product interaction processes, and to identify design features that cause high cognitive requirements (e.g., errors, long time), making it possible to iterate through design revisions early in the design process (John and Kieras, 1994). Salvucci *et al.* (2005) apply the ACT-R model to predict in-vehicle driving distractions by running simulations, according to which design features causing distractions are identified and possible improvement is made.

2.6.2 Quality Function Deployment

Quality function deployment (QFD) has widely been used to translate customer requirements (usually functional needs) into technical design requirements (Prasad, 1998). However, it is also applicable to the affective and cognitive mapping process. It utilizes a house of quality – a matrix providing a conceptual map for the design process – to relate various user needs with necessary design requirements that can fulfill these needs (Zhai *et al.*, 2009). For instance, Mazur (2005) makes use of QFD to translate lifestyle, image, and psychological needs into design requirements for designing the B787 Dreamliner commercial aircraft. Yun *et al.* (2005) apply QFD to transform usability and affective quality into design requirements for mobile data services.

In order to deal with ambiguous affective and cognitive needs in the QFD process, QFD extensions have been proposed to capture the elasticity of imprecise requirements, such as fuzzy QFD (Ertay and Kahraman, 2007) and rough QFD (Zhai *et al.*, 2008). Kim *et al.* (2000) propose a multi-attribute value theory combined with fuzzy regression and fuzzy optimization in QFD for designing car doors. Shen *et al.* (2001) propose a process model using linguistic variables, where fuzzy arithmetic and defuzzification techniques allow QFD users to avoid subjective and arbitrary quantification of linguistic data. Fung *et al.* (2006) apply an asymmetric fuzzy linear regression approach to estimate the relationships between customer needs and engineering characteristics in the QFD process. Zhai *et al.* (2008; 2009) propose a rough-set based QFD, where subjective crisp variables, including customer needs and design elements, are expressed by rough numbers.

In the QFD process, it is also imperative to deal with the engineering concerns (e.g., maintainability, availability) as well as multiple, conflicting objectives to minimize cost and maximize customer value (Kovach and Cho, 2008). Thus, a clear method of prioritization of design requirements is crucial (Chan and Wu, 2002; Jiao and Chen, 2006). Karsak (2004) propose a fuzzy multiple-objective programming approach to determine the level of fulfillment of design requirements in QFD. Ertay and Kahraman (2007) compare three different fuzzy multi-attribute outranking methods to evaluate design requirements. Zhai *et al.* (2009) transform subjective importance ratings into rough numbers to prioritize design requirements in the QFD process.

2.6.3 Linear and Non-linear Methods

Linear methods of multivariate analysis are frequently employed to explore the relationships between customer needs and design requirements, such as those in Kansei engineering (e.g., Kim *et al.*, 2003) and usability studies (e.g., Han *et al.*, 2000). Many researchers emphasize this problem using regression analysis. Ishihara *et al.* (2001) apply a multiple regression model for car panel affective design. Kim *et al.* (2003) propose a general linear model to link quantitative relations between design factors and emotional dimensions. Schütte *et al.* (2004) apply a linear regression model of type I quantification theory to derive the relationships between human perceptions and product design factors. Han *et al.* (2000) develop multiple linear regression techniques to identify the relationships between usability quality and design elements.

However, the methods mentioned above may not well analyze users' psychological needs because they (e.g., beautiful or not) do not always bear linear characteristics. As a matter of fact, emotional responses to products are usually fuzzy and vague in nature and thus should be nonlinear and not applicable to linear methods based on the normal distribution (Nagamachi *et* *al.*, 2006). Therefore, more advanced non-linear methods are proposed to address the vague and nonlinear relationships between affective and cognitive needs and design elements, such as fuzzy logic, genetic algorithms, neural networks, and rough set theory. Tsuchiya *et al.* (1996) propose a procedure combining genetic algorithms and fuzzy logic for designing driving comfort for automobiles. Arakawa *et al.* (1999) stress on the characteristics of fitness function and optimization of Kansei and show the possibility of genetic algorithms in affective design. Lai *et al.* (2006) use an artificial neural network to map the user emotional model to software usability appraisal coefficients. Inoue *et al.* (2007) rank the products using an analytical hierarchy process according to rough approximation, based on which cognitive requirements are associated with the components in the graphical user interfaces of the products. Zhai *et al.* (2007) propose a dominance-based rough set approach to effectively extract imprecise affective knowledge, which can be easily integrated into an expert system for customer-oriented product development.

2.6.4 Backward Mapping

As mentioned in Section 2.3, one of the tasks of affective and cognitive fulfillment is leveraging engineering concerns. This usually necessitates a reasoning process from the designer domain to the user domain (referred to as backward mapping) to accommodate engineering concerns of the producer. However, the main literature sources indicate a small interest in this aspect. Nagamachi (1995) is one of the pioneers advocating the importance of backward inference in Kansei engineering, whereby design candidates are diagnosed with respect to affective descriptors. Matsubara and Nagamachi (1997) propose a hybrid Kansei engineering system that can support both users' and designers' decisions. In the backward inference process, user preferences are mainly modeled using market analysis techniques, such as conjoint analysis (Green *et al.*, 1981; Jiao *et al.*, 2007), discrete choice experiments (Green *et al.*, 1981), and fuzzy systems (Turksen and Willson, 1992). The gist is to assign importance weights or part-worth utilities for multi-criteria decision-making. However, backward mapping can hardly contribute to affective or cognitive design without proper coordination with forward mapping. Thus, it demands decision support mechanisms that incorporate bidirectional mapping relationships between the user and designer domains.

2.7 Recent Trends and Future Directions

Upon reviewing comprehensive related work in this area, affective and cognitive design has been tackled from a broad scope of product definition involving many disciplines. Tables 2-2 and 2-3 summarize the typical literature of affective and cognitive design reviewed, respectively. Recent trends and several possible future directions are speculated for further research.

2.7.1 Expanding Macrocognition in Design

As the literature review shows, the macrocognitive perspective in design has received little attention. This calls for more efforts in this aspect. For one thing, to a great extent, macrocognitive processes are emergent phenomena – only obvious once researchers begin to investigate performance in natural contexts (Klein *et al.*, 2003). It thus can improve our understanding of the functions and processes encountered at the macrocognition level and in turn help the systems we would design in the real world. For another, microcognitive approaches to product design tend to get lost in a single person interacting with a single product, missing how people engage in broader activities for larger purposes (Woods and Roesler, 2008). Furthermore, macrocognitive approaches enable us to design strategies for users and/or computers to control complex and highly dynamic systems, especially systems operated in distributed environments (Klein *et al.*, 2003). This is particularly true when macrocognitive functions are performed in collaboration with a combination of advanced computational techniques (e.g., wireless sensor networks, AI, and virtual environment). For example, wireless sensor networks employed in activity recognition provide ubiquitous connectivity which reshapes how and when we interact with daily objects. Under this circumstance, if computers that are equipped with adequate AI might be able to make smart and proactive decisions on behave of the user. It thus augments special users, such as the cognitively impaired or disabled, with regard to ADLs in the home environment, for instance. Therefore, it is necessary to explore macrocognitive design with advanced computational techniques.

2.7.2 Exploring Theoretical Framework for Affective Design

Although the perspective of affect in the design community has been highlighted recently, only a paucity of literature proposes general explanations on how affective responses are elicited by products. Jordan (2000a) introduces a framework for pleasures in design – the four pleasures, namely, physio-pleasure (to do with the body and the senses), psycho-pleasure (to do with the mind and the emotions), socio-pleasure (to do with relationships and status), and ideo-pleasure (to do with tastes and values). Further, he illustrates how products can bring about each of these types of pleasures and how to link the pleasures to particular aspects of product design. This framework thus can be considered as a design tool. Norman (2004) proposes a framework for emotional design based on three levels of processing, i.e., visceral, behavioral, and reflective. At each level, there is a distinct type of product affect with a corresponding design focus. Desmet (2008) propose the mechanism of how products eliciting emotions based on appraisal theory (Scherer *et al.*, 2001). Appraisal is an evaluation of the significance of a stimulus for one's personal well-being and it is this personal significance of a product rather than the product itself that elicit the emotion (Scherer *et al.*, 2001; Desmet, 2008).

These frameworks provide theoretical foundation and practical guidance for affective design. However, in order to effectively take advantage of affect in product design using systematic methods, many important questions remain to deal with. For example, (1) what is the role of demographic factors, such as culture and gender (which are often not emphasized in the current literature), in the complex emotion elicitation process? (2) What are the effective methods that are capable of eliciting affective needs and translating them into concrete product design solutions? (3) How can we improve task performance and high value-added user satisfaction by leveraging affective factors in product design? And (4) what are the interactive relationships between affect and cognition in terms of their roles in product design? Therefore, it is imperative to develop theoretical frameworks or conceptual models for a more profound understanding of the relationship between affect and the targeted product.

2.7.3 Integrating Affect and Cognition

Affect and cognition have long been treated as independent entities in psychology (Zajonc, 1980). However, in the current view, we suggest that affect and cognition are, in fact, highly interdependent (Storbeck and Clore, 2007) and should be integrated, because the phenomena themselves are integrated (Parrott and Sabini, 1989). Both laboratory findings and everyday observation suggest a unity and interrelatedness of the cognitive and affective processes, and that trying to dissect them into separate faculties would neglect the richness of mental life (e.g., Adolphs and Damasio, 2001; Storbeck and Clore, 2007). Therefore, there is an increasing tendency to study the interaction between affect and cognition to understand the fundamental human needs. For example, Lisetti and Nasoz (2002) investigate how affect interacts with cognition and develop a multimodal affective user interface to simulate human intelligence. Ahn and Picard (2005) propose a computational AC framework for learning and decision making. Stephane (2007) tries to combine cognitive models with affective models to assess workload, situation awareness, and self-awareness in a coherent framework. The affective user-designer model proposed by Helander and Khalid (2006) also integrates affective and cognitive systems for pleasurable design. Citarasa engineering is a new initiative that combines cognition with affect so as to uncover user needs, measure user satisfaction, and identify the mapping relationships between user needs and design elements (Helander *et al.*, 2007).

However, our understanding of affect and cognition and their relationship, interaction mechanism, and their place in a set of mind is less obvious. Many questions are pending. For example, (1) how are the user's affective states evolving along the cognitive process during the human-product interaction process? (2) How to model this process to explore the main factors contributing to UX and informing design? (3) Are there any specific patterns in product judgment and purchase decision making with regard to affective and cognitive factors? (4) What are the engineering solutions to map affective and cognitive needs into concrete design elements? Looking at these research issues, collaboration from psychology, engineering design, HFE, and HCI presumably will reveal a deeper insight into the complex interplay between affect and cognition that supports a paradigm of AC design.

2.7.4 Ecosystem Thinking for Product Design

The term *product ecosystem* has been informally used by researchers and industry practitioners to signify the consideration of multiple related products, retail environments, and use contexts in a coherent process, compared with the conventional viewpoint of static, isolated products. The user's ambient factors is more than what can be seem directly, rather it includes social structures, shared concepts, conventions, and of course human-fashioned products and services. The active interaction process operates just as strongly when the user's experiences, observations, and actions are influenced by the ambient factors. In this sense, the product ecosystem concept echoes the notion of macrocognitive design where the user usually interacts with multiple products in broader activities, emphasizing how people actively explore in the world.

Besides the product with which the user is interacting, affective UX is usually under influences of multiple factors, including physical, socio-cultural, and interpersonal contexts (Dolan, 2002). Hence, it is useful to frame the problem of human-product interaction broadly enough so as to incorporate its ambient factors (Jiao *et al.*, 2007). In a holistic fashion, it facilitates the integration of affect and cognition and their interactions in one design paradigm. Furthermore, the consideration of the ambience where the behavior of users is contextualized is generally helpful to achieve reliable and efficient need elicitation and consequently contributes to an ecologically validated product ecosystem. For example, Jiao *et al.* (2007) adopt this term to highlight human-product-ambience interactions in their work of designing products for affective user satisfaction. It provokes the designer to shift the focus from isolated products to the ecosystem thinking of multiple products as well as their ambient factors.

2.7.5 Affective-Cognitive Design of Product Ecosystems for User Experience

UX is an important concept that connects users with product quality. Hassenzahl and Tracinsky (2006) define it as dynamic, context-dependent, internal states of users, which consist of both instrumental and emotional aspects. In the design community, these two aspects correspond to cognitive and affective factors, respectively. Therefore, the work done in terms of affective and cognitive design in this chapter lays the basis for the UX design. However, most of the work only considers either cognitive or affective aspect with regard to a single product. Moreover, based on the discussion about the recent trends and future directions, it is imperative to aggregate them into a coherent research topic, i.e., affective-cognitive design of product ecosystem for UX. As discussed in Subsection 2.7.1 and Subsection 2.7.2, cognitive design in terms of expanding macrocognition (Chapter 5) and affective design in developing theoretical frameworks are needed (Chapters3, 4, and 7). Furthermore, Subsection 2.7.3 and Subsection 2.7.4 promote integration of affect and cognition with an ecosystem thinking, endeavors towards these two trends are necessary (Chapter 6).

2.8 Summary

Owing to the flurry of various research efforts, this field of research has developed rapidly. Meanwhile, quite some problems remain not well-answered and still need to be examined both theoretically and methodologically, especially with regard to the aspects discussed in Section 2.7. It highlights the motivation to carry out an in-depth study the role of both affect and cognition for UX in a paradigm of product ecosystem design. The notion of product ecosystem introduces a few important concepts, such as the ecosystem architecture, the ambience, and UX. By integrating products, users, and business processes into a coherent model, the product ecosystem expands the scope of traditional product and service process design, thus facilitating consistent design decisions. The notion of the ambience has two implications – for the user, it enables better reflection of the causal relationship between UX and design elements; for the designer, it provokes the designer to shift the focus from isolated products to the synergy of multiple products. The explicit definition of UX allows the system performance to be evaluated in a dynamic process, thus accommodating the temporal, uncertain, and human-oriented business process. Further, with an emphasis on the UX in terms of user affective states and the cognitive task processes, the product ecosystem is expected to elicit pleasurable, consistent UX, and ultimately high user satisfaction. The endeavors towards this research will be described in details in the following chapters.

Table 2-2 Summary of typical literature on affective design

Literature	Product Studied/stimulus	Affect		Affective Need Elicitation					Affective Analysis		Affective Fulfillment		
		Positive	Negative	KE	CTA	AI	Physiological Methods	Behavioral Methods	Qualitative	Quantitative	Cognitive Techniques	QFD	Statistical Methods
Arakawa *et al*. (1999)	Human faces			x						x			
Bailenson *et al*. (2008)	Film clips	x	x				x	x		x			
Bos (2008)	Pictures & sounds	x	x				x			x			
Chen *et al*. (2006)	Mobile phones			x		x				x			x
Chen (2000)	Audios & videos	x	x				x			x			
Cohen *et al*. (2003)	Videos	x	x				x			x			
Crandall *et al*. (2006)	Brand shift	x			x				x				
Delin *et al*. (2007)	Bottle packaging	x	x	x		x				x			
Desmet (2003)	Automobiles	x	x	x						x			
Ekman (1982);	Human faces	x	x				x						
Ertay & Kahraman (2007)	PVC windows											x	
Essa & Pentland (1997)	Human faces	x	x					x					
Fragopanagos & Taylor (2005)	Human faces & voices	x	x					x		x			
Helander *et al*. (2007)	Automobiles	x		x	x				x		x		
Ishihara *et al*. (2001)	Automobiles	x		x		x			x				x
Jiao *et al*. (2007)	Truck cabs	x		x						x			x
Jiao *et al*. (2006)	Mobile phones	x		x						x			x
Kano *et al*. (1984)	General products	x	x						x				
Kasak (2004)	Jean jackets	x		x						x		x	
Kim *et al*. (2003)	Web pages	x		x						x			x
Lee & Narayanan (2005)	Audio s	x	x					x		x			
Li (2006)	Film clips	x	x				x			x			
Li & Chen (2009)	Videos	x	x				x			x			
Maffiolo & Chateau (2003)	Telecom services	x	x					x					
Mazur (2005)	B787 aircraft	x	x	x						x		x	
Nadia (2001)	Web images	x	x						x				
Nasoz *et al*. (2003)	Film clips	x	x				x			x			
Picard *et al*. (2001)	Imagery	x	x				x			x			
Scheirer *et al*. (2002)	Mouses		x				x			x			
Tsuchiya *et al*. (1996)	Automobiles	x		x						x			x
Wansink (2003)	Brands			x									
Yan *et al*. (2008)	Traditional crafts	x		x						x			
Zhai *et al*. (2007; 2009)	Automobiles/ bicycles	x								x		x	

Note: KE = knowledge elicitation; CTA = cognitive task analysis; AI = artificial intelligence-based methods; QFD = quality function deployment

Table 2-3 Summary of typical literature on cognitive design

Literature	Product studied /stimulus	Cognition		Cognitive Need Elicitation					Cognitive Analysis		Cognitive Fulfillment		
		Micro-cognition	Macro-cognition	KE	CTA	AI	Physiological Methods	Behavioral Methods	Qualitative	Quantitative	Cognitive Techniques	QFD	Statistical Methods
Carbonara &Scozzi (2006)	Sofa design development		x	x					x				
Coffey & Carnot (2003)	Rocket science knowledge	x			x				x				
Crandall *et al*. (2006)	Product purchasing	x			x				x		x		
Dekker (2002)	Firefighting		x		x			x		x			
Favela *et al*. (2007)	Hospital activities		x										
Fredericks *et al*. (2005)	Three cognitive tasks						x						
Gu *et al*. (2009)	Daily activities		x					x		x			
Ha &Suh (2008)	Product development		x						x	x			
Han *et al*. (2000)	Consumer electronics	x		x						x			x
Hoffman *et al*. (2000)	Weather forecast	x			x				x				x
Inoue *et al*. (2007)	Digital music players	x		x					x	x			x
John & Turley (2006)	Healthcare software	x		x	x				x				
Kim & Han (2008)	DVD players	x		x					x	x			
Lai *et al*. (2006)	Software	x								x			x
Liu & Satur (1999)	Geographic information system	x							x				
Parasuraman & Caggiano (2005)	General cognitive tasks	x					x						
Pentney *et al*. (2006)	Daily activities		x					x		x			
Perusich (2008)	Terrorist attack on a university		x						x				
Pfautz & Roth (2006)	Software	x			x								
Salvucci *et al*. (2005)	In-vehicle devices	x				x				x	x		
Shen *et al*. (2001)	Web pages	x		x						x		x	
Smith *et al*. (2007)	Air traffic systems		x						x				
Takeshi *et al*. (1998)	Microsoft office	x			x								
Trejo *et al*. (2007)	Arithmetic questions	x					x			x			
Ward *et al*. (2006)	Assembly tasks		x					x		x			
Woods & Roth (2006)	Performance evaluation		x		x								
Xirogiannis *et al*. (2004)	Urban design	x							x				
Yun *et al*. (2005)	Mobile data services	x		x					x			x	

Note: KE = knowledge elicitation; CTA = cognitive task analysis; AI = artificial intelligence-based methods; QFD = quality function deployment

CHAPTER 3
FUNDAMENTALS OF PRODUCT ECOSYSTEM DESIGN FOR USER EXPERIENCE

This chapter examines the fundamental issues underlying product ecosystem design for UX, including the definition of a product ecosystem, the notion of the ambience, and UX in terms of affect and cognition. A conceptual model is outlined to elucidate the underlying factors and the operational mechanism of product ecosystem design for value-added UX and satisfaction. The technical challenges and key research issues of product ecosystem design are identified within a proposed technical framework and the corresponding solution strategies are subsequently proposed.

3.1 Product Ecosystem

3.1.1 Definition

A product ecosystem is defined as a dynamic unit that consists of all interdependent products and users, functioning together with its surrounding ambient factors, as well as their interactive relations and business processes. According to the mechanism of human attention allocation (Wickens and Hollands, 1999), the user is interacting with only one product or user focally at a time (i.e., focal interaction with regard to a focal user). However, the interaction can be directly influenced by other ambient factors so that it forms a paradigm of human-product-ambience interactions. Hence, *ambience* is technically defined as ambient factors that influence UX (especially affective aspects, e.g., feelings) according to the user's temporal relationships with his/her surroundings, including other users, products, as well as environmental, social, and cultural factors. It is context-sensitive and depends on the specific perspectives of the focal user. For example, in Figure 3-1, User 1 is focally interacting with

Product 1; meanwhile User 1 is directly related to User 2 and Products 2, 3, which collectively constitute User 1's ambient factors. A third notion is the interaction sequence that the user adopts to complete a particular task. In such a way, the efficiency and productivity goal as well as UX can be better accomplished. Figure 3-1 depicts the entities and relations in the product ecosystem, where it primarily includes users, products, and ambient factors that collectively engender UX through human-product-ambience interactions.

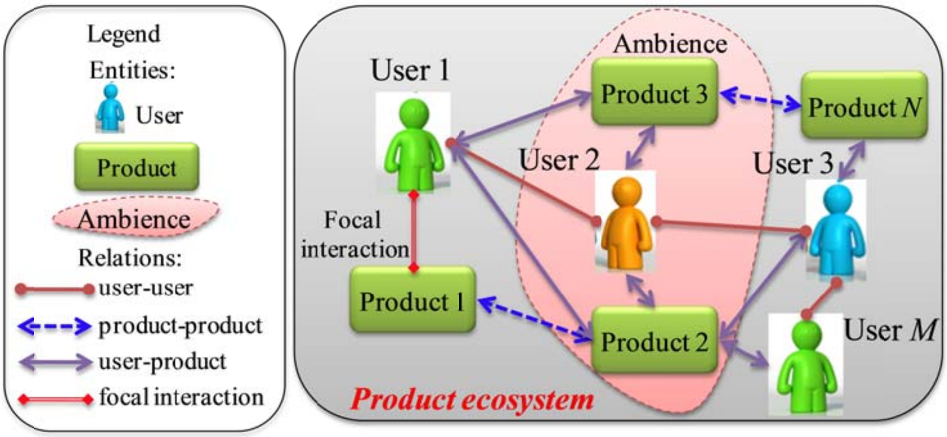


Figure 3-1 Entities and relations that form a product ecosystem

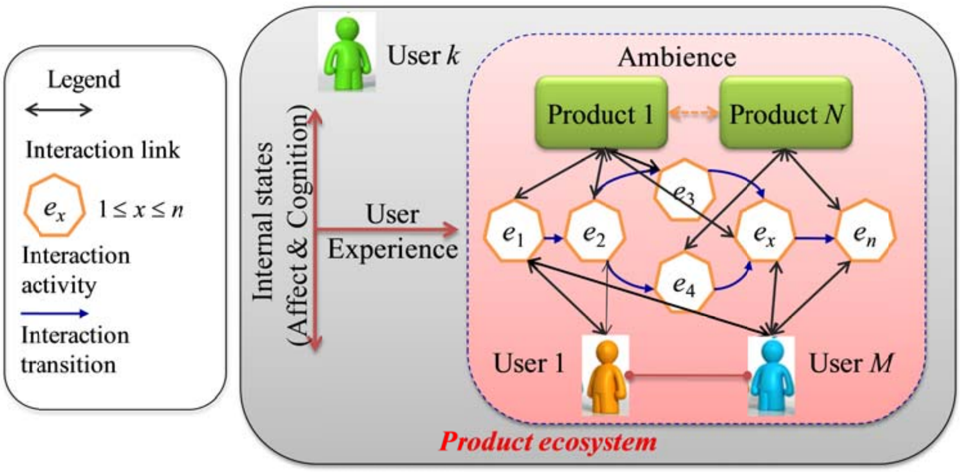


Figure 3-2 User experience in a product ecosystem

3.1.2 User Experience Modeling

Based on the product ecosystem formulation, UX is described as evolution of the user's internal states (i.e., affective states and cognitive processes) along the chain of interaction activities as a result of human-product-ambience interactions. Figure 3-2 shows the possible UX of User k evolving along the interaction activity sequence in the product ecosystem. Therefore, UX, in the context of product ecosystem, is more than the consequence of a single interaction regarding one activity, but rather of a sequence of interactions regarding all the activities needed to perform a particular task. Nevertheless, in order to effectively capture UX, the dimensions for measuring UX have to be formally defined, including users' (1) affective states and (2) cognitive processes.

(1) Affective States. Human core affect is defined as a neurophysiological state that is consciously accessible as a simple feeling, an integral blend of valence (pleasure–displeasure) and arousal (sleepy–activated) (Russell, 2003). It is primitive, universal, simple, and object-free. Nevertheless, core affect can be developed into directed affective states when it is attributed to product ecosystem elements through human-product-ambience interactions and is changeable over time. How one's core affect attributed to these elements is complicated. There are various factors leading to it, including the elements themselves and representations of the elements, either externally provided (e.g., via advertisements) or internally generated (e.g., by imagining the elements) (Cohen *et al*., 2008). For example, browsing interactive web pages with a smooth and fast speed seated in a comfortable chair can elicit a delightful experience, while surfing web pages with a slow speed alone causes frustration. In this case, affective states are now directed at (multiple) elements in the web surfing ecosystem. Moreover, affective states can shift from one to another because of the stimulus in the interaction process. As a consequence, they can be short-lived with regard to emotions in the current state, or become a long-lasting attitude as a chronic disposition, not only directional in valence, but also fluctuating in intensity (Russell, 2003).

(2) Cognitive Processes. Human cognition deals with the information processing tasks with respect to the stimulus in the interaction process. It is advocated that product ecosystems cater to human cognitive capabilities and limitations, including numerous components of cognition that are attributed to attention, action and control, memory, decision-making (Ashcraft, 2002), etc. This research adopts several widely accepted assertions that are germane to the design rationale of product ecosystems. Above all, human cognitive requirements should be well accommodated when performing a particular task. Further, systems with good usability can reduce errors, increase productivity, and enhance safety and comfort (Nielsen, 1994). Moreover, it is proposed that information is processed with a variety of parameters, such as cognitive loads, accuracy, and speeds, i.e., processing fluency. High processing fluency (e.g., low cognitive loads, high accuracy and speeds) is related to positive UX, either within the cognitive systems (the human thinks positively) or toward the stimulus (the stimulus is positively evaluated) (Reber *et al.*, 2004).

(3) Affect-Cognition Integration. To summarize, it is imperative to accommodate both affective and cognitive factors so as to improve different facets of UX. However, in this regard, there is a paucity of published work and a lack of good, well-documented case studies in terms of product ecosystem design for UX. Furthermore, UX modeling is often confined to interactions between human users and a single product. Therefore, UX might be evolved in a haphazard manner over time if there is no systematic planning and coordination among multiple products in the context of product ecosystems. The strategy of this research aims to optimize UX that incorporates two essential dimensions, namely, the affective and cognitive dimensions, when the user is interacting with multiple products in series in the product ecosystem.

3.1.3 Implications

The notion of product ecosystems resembles that of the natural ecosystem in some interesting ways. There is a dynamic balance of interest sharing among all the stakeholders, including users and the producer that runs the product ecosystem. Therefore, to design an effective product ecosystem, two aspects need to be considered (Iansiti and Levien, 2004). The first aspect involves the creation of products in the form of services, resources, tools, and/or technologies that offer solutions and create affective and cognitive value to users in the product ecosystem. It compels the producer to examine the product lifecycles and value profiles to identify key success factors. The second aspect involves the balance of benefits throughout the 'residents' in the product ecosystem. This allows them to share the surplus with each other, considering the value of products divided by the cost of creating, maintaining, and sharing them with an increasing number of ecosystem users. This makes the producer design products with efficient service delivery processes, in which multiple products collectively and consistently contribute to pleasurable UX within a certain amount of cost.

Furthermore, in order to systematically design such a product ecosystem, a conceptual model should be developed for the purpose of understanding, predicting, and reasoning about processes of UX. Specifically, it should explicitly define the entities of the product ecosystem (i.e., design elements in the product ecosystem), the relationships between different entities, and the operational factors leading to UX. The model must also be able to capture interactions among users and products, while being adaptable to the evolution of the ambience, giving rise to a paradigm of human-product-ambience interactions. Then the behavior among products and different users can be analyzed in the scope of product ecosystem design.

3.2 A Conceptual Model

Towards this end, this research elaborates product ecosystem design based on the appraisal theory (Ellsworth and Scherer, 2003). It states that human evaluates stimuli in terms of the perceived significance to the well-being of the person concerned. The major underlying factors consist of needs and goals under considerations of his/her ability to cope with consequences and the compatibility of the underlying actions with social norms and self-ideals. In the scenario of product ecosystem design for UX, user needs are mainly concerned with affective-cognitive needs (ACNs) as motivational forces. Furthermore, product affective quality, target users, ambient factors are also taken into account. Therefore, a conceptual model is proposed to elucidate the underlying operational mechanism as shown in Figure 3-3. Rather than including comprehensive factors individually, critical ones are discussed in terms of their interrelatedness and dynamics, which in turn shape UX with its two inherent dimensions: the affective and cognitive dimensions.

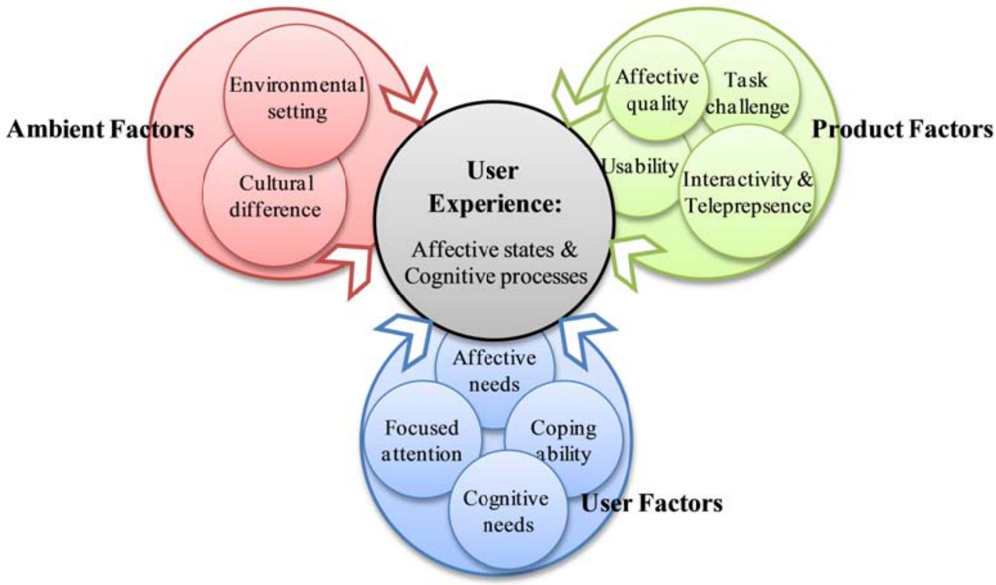


Figure 3-3 A conceptual model of product ecosystem design for user experience

3.2.1 Affective Quality

Affective quality is the ability of a product (feature) to cause changes in one's core affect (Russell, 2003). While core affect exists within the user, affective quality lies in the product. However, the user can estimate the product's affective quality by a perception process, which in turn changes the user's core affect and influences affective UX.

Affective quality has two dimensions, i.e., hedonic valence and activated arousal (Russell, 2003). Valence or intrinsic pleasantness is a basic dimension of a product feature coded in perception (Ellsworth and Scherer, 2003). Pleasant features produce likes and preferences, such as aesthetic pleasure. It determines the fundamental reaction or response of the user, i.e., likes or attraction, which encourages approach, versus dislikes or aversion, which leads to withdrawal or avoidance, independent of the momentary state of the user (Schneirla, 1959).

Arousal is a physiological and psychological state of being awake that affects sensory alertness, mobility and readiness to respond (Kubovy, 1999). It is reported that there is an inverted-U relationship between arousal and optimal performance and too little or too much arousal can adversely affect task performance (Yerkes and Dodson, 1908). Although arousal is determined by multiple factors, such as stimuli, incentives, and the task itself, product features (and ambient factors) appropriately designed have the ability to optimize arousal for task performance.

3.2.2 Affective Needs

Affective needs are high level psychological needs and focus on emotional responses and aspirations (Jiao *et al.*, 2007), yet implanted deeply in the basic needs to minimize pain and maximize pleasure, both physically and mentally. The strength of pleasure or pain depends on the dynamic relationships between users and the product, which is of critical importance for ensuing consequences (Lewin, 1951).

Most appraisal theorists believe that an interaction activity appraised as conducive to need satisfaction and goal attainment leads to positive affect (Ellsworth and Scherer, 2003). Thus, the aspects that are conducive to need satisfaction ought to be highlighted in the product creation process. With regard to affective needs, good affective quality substantially contributes to affective need satisfaction by attributing positive affect to product (features). Furthermore, users often expect positive emotions derived from interaction experiences with products in terms of appearance, performance, and utility, and so on. For example, a mobile phone is expected to be a fun social interaction tool. Nevertheless, for many more important products, users' emotional responses go much further (Phillips *et al.*, 1995). Taking iPhone for example, most users might expect it to be exciting, fun, and cool before purchasing, and find it fulfilled, proud, and even surprised during the usage stage. One good reason for this is that it is a well-designed smartphone ecosystem, a combination of a revolutionary mobile phone, a widescreen iPod, and a breakthrough Internet device, as well as so many software applications. On the other hand, products and systems can be designed to aid irritated users, manage their frustrations or prevent other negative emotions (Picard, 1997; Picard *et al.*, 2001). For example, when the gaming system detects that the user is in a frustrated state due to the difficulty of the game, it can adapt its difficulty level automatically to stimulate the user. In this sense, products that elicit positive affective responses and deal with negative ones are more likely to meet users' affective needs and thus improve affective UX.

3.2.3 Cognitive Needs

Cognitive needs are the requirements of how products and systems designed to accommodate human cognitive capabilities and limitations. They are non-functional requirements and define how products and systems are supposed to be in terms of human information processing. Therefore, they are critical to user acceptance, accessibility, and usability of products and systems (Johnson and Turley, 2006).

In order to adequately address cognitive needs, Patel and Kushniruk (1998) argue that additional basic research is needed to understand users, their work activities, and their reasoning processes. Johnson and Turley (2006) propose that users and their tasks in a particular product ecosystem are two interacting components to understand cognitive needs of users and human-product interactions. In cognitive ergonomics, HCI, and software engineering, system interfaces should be designed to be simple but engaging. One of the best examples is Angry Birds (http://en.wikipedia.org/wiki/Angry_Birds), a puzzle video game developed by Rovio Mobile for smart phones and tablet PCs. It is simple because it allows the user to quickly build a mental model of the game's interaction methodology, core strategy and scoring process; it is engaging because of the carefully scripted expansion of the user's mental model of the strategy component and incremental increases in problem/solution methodology. Additionally, perceived affective quality has a positive effect on both perceived usefulness and perceived ease of use (Zhang *et al.*, 2006a). In this sense, perceived affective quality reduces cognitive burdens imposed by the task and thus serves as the instrumental ends for users (Davis, 1989). Another important factor fulfilling cognitive needs is usability, denoting the extent to which a user can make use of a product to achieve a goal (Nielsen, 1994). For instance, iPhone's compass can sense the user's environment and change the picture orientation from portrait to landscape as needed.

3.2.4 Coping Ability and Task Challenge

Based on the appraise theory, UX also depends on the assessment of one's ability to cope with the task by reaching, modifying, postponing, or giving up goals or needs (Ellsworth and Scherer, 2003). Given one's coping ability at a certain challenge level, it is plausible that UX not only has a direction (displeasure–pleasure), but also varies in strength or intensity. The concept of flow is the one that involves the intensity of UX, in which one is so intensely absorbed and immersed in the task that it results in positive emotions, exploratory behavior, and behavioral perceived control (Csikszentmihalyi, 1990).

To design products that can elicit flow experiences, one needs to consider the dynamics among multiple factors. Above all, the elicitation of flow depends on the dynamic relations between user skills and task challenges. The product should facilitate the learning process for novice users in a short period of time. As the user's skill increases over time, the level of task challenge coded in the product should also increase proportionally. Other factors, including focused attention, arousal, interactivity, and telepresence, have also been identified (Hoffman and Novak, 1996). Take web-based e-learning as an example. First, one of the crucial factors for focused attention is the motivational forces. A significant positive correlation is also found between intrinsic interest/curiosity and focused attention (Webster *et al.*, 1993). Second, it is necessary to remove distractions within and around the system whenever possible. Third, an inverted-U relationship between arousal and flow experience is identified (Hoffman and Novak, 1996), though the optimal arousal level is task-specific. Fourth, to improve interactivity and telepresence, one point is to use edutaining methods such as games, puzzles, simulation tools, presentation tools for learning and to provide timely visual and auditory feedback in appropriate forms.

3.2.5 Moderating Ambient Factors

Although there are multiple ambient factors influencing UX in the interaction process, two typical ones, i.e., environmental settings and cultural differences, are of particular interest in this research. Note that the ambient factors influence the (causal) relationships between user factors and product factors and are considered as moderator variables rather than mediator variables (see Baron and Kenny, 1986). As they can either enhance or weaken the relationships between user factors and product factors (i.e., moderator variables) but not explain why there are relationships between them (i.e., mediator variables).

(1) Environmental Setting. Prudent design must consider environmental factors (e.g., its surrounding products, the presence of a scent or music, lighting, temperatures). Empirical evidence has shown that these factors influence users' perception of product value and evaluations. The sequence effect states that a design can be positively appraised in isolation, yet be ultimately disliked and avoided due to its poor fit with previously possessed products, such as kitchen appliances, computer kits, and furniture (Bloch, 1995). For example, the upward- and downward-compatibility problem of the Vista operating system causes negative UX. Another factor received much attention in consumer and marketing psychology is the background music. For example, Baker *et al*. (2002) report that favorable music alleviates consumers' perceived amount of shopping time/effort as well as their mental/emotional labor during shopping experience. As more products are increasingly knitted into a larger ecosystem, designers should try to consider the interrelated environmental factors to deliver 'the whole thing' right.

(2) Cultural Difference. As humans are socially living species, to a great extent, cultural backgrounds affect the way how people experience. For example, aesthetic stereotypes, such as the national shape or color, often elicit cultural-specific emotions (Lee, 2004). Therefore, it is important to take into account the reactions of organizational members when designing products. Furthermore, social organizations are built on shared rules, concerning status hierarchies, prerogatives, and acceptable and unacceptable values (Ellsworth and Scherer, 2003). For example, Zhang *et al*. (2006b) report that people who are individualistically cultured (from U.S., U.K., Canada, and Germany) prefer angular patterns while people who

are collectively cultured (from Hong Kong, South Korea, and Japan) prefer rounded patterns. Hence, it is also important to consider these factors for product ecosystem design.

3.3 Technical Challenges

To drive the development of rigorous research methodologies of product ecosystem design for UX, a technical framework is presented in Figure 3-4. In essence, the technical framework must account for the multiple factors that contribute to desirable UX as elaborated in the conceptual model. Furthermore, it must take into account the interactive relations among multiple factors in favor of decision support for UX.

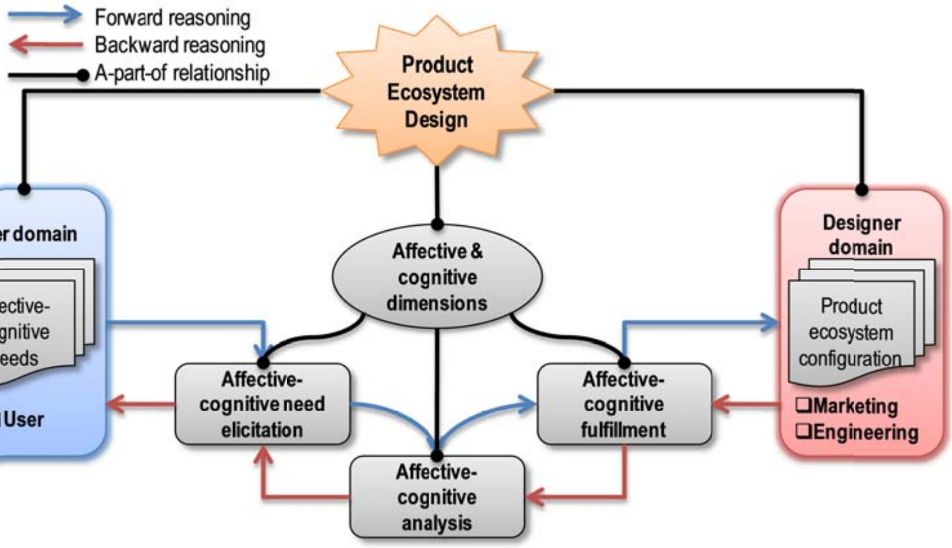


Figure 3-4 A technical framework for product ecosystem design

From the perspective of engineering design, it must deal with three issues, namely, (1) identify the key design elements of the product ecosystem, including the ecosystem structure, user characteristics, and major products, (2) develop effective measures of UX, and (3) construct UX from the derived elements, their interactive relations, and business processes. From the information processing perspective, such issues can be addressed by studying the mapping relationships between user information and design information. User ACNs are the primary target to acquire (coping abilities can be reflected by cognitive needs) for user information while design information is to determine an optimal ecosystem configuration based on the user information. Figure 3-4 shows the technical framework, emphasizing how to convey ACNs from the user domain to the designer domain. It entails three sequential and iterative steps, i.e., AC need acquisition, AC analysis, and AC fulfillment.

3.3.1 Affective-Cognitive Need Acquisition

Understanding ACNs accurately during the elicitation and analysis of requirement information has significant implications on the design of the product ecosystem in terms of its quality, lead time, and cost (Jiao and Chen, 2006). However, two major challenges about ACN elicitation are identified as follows:

(1) The nature of affect and cognition. In psychology, affect is considered to be complex, multi-componential, dynamic processes that require sophisticated measurement of changes in the different components (e.g., cognition, motivation, physiological reactions, motor expressions, and feeling) (Grandjean *et al.*, 2008). Furthermore, affective needs are often under the influence of physical, socio-cultural, and interpersonal context (Dolan, 2002). Cognition is used to refer to the mental processes, including comprehension, inference, decision-making, planning and learning (Lycan, 1999). The cognitive requirements of a task are both the macrocognitive challenges that the task poses (e.g., decision making, replanning, problem detection) and the requirement to address these challenges (e.g., building mental models, managing uncertainty and attention) (Crandall *et al.*, 2006). Thus, multiple measures that describe different aspects of cognitive performance should be included. Traditional measures are often hard, if not impossible, to take all aspects of ACNs, leading to an incomplete acquisition of them.

(2) Non-structured ACNs. There hardly exists any definitive structure of affective or cognitive needs, although there are multiple models of affect and cognition in psychology and

AI. For example, there are basic (Ekman, 1999) and dimensional (Russell, 2003) models of affect while two frequently used cognition models are ACT-R (Salvucci *et al.*, 2005) and SOAR (Marinier *et al.*, 2008). However, ACNs are usually expressed verbally. While traditional criteria for functional needs are often considered as tangible and relatively easy to be quantified by numerical variables, ACNs are of a qualitative nature and subjective *per se*. Hence, ACNs are hard to express in a measurable and testable form (Nuseibeh and Easterbrook, 2000).

3.3.2 Affective-Cognitive Analysis

AC analysis for product ecosystems is to model UX, emphasizing how users' affective states and cognitive processes evolve in the interaction process within the product ecosystem. In particular, the following issues needs to be tackled:

(1) Formulating product ecosystem. A formal model should be developed that denotes multiple interdependent products, whose functionalities overlap, complement, or conflict with each other, and multiple users whose objectives and behaviors are diverse. Moreover, the model must be able to capture interactions among users and products, while being adaptable to the evolution of the ambience (Melan, 1999).

(2) Modeling affective states and cognitive processes. Focusing on UX, the users' affective states and cognitive task processes have to be examined. In particular, it is crucial to develop a model that incorporates the multiple dimensions of affect and cognition, and their interplays in the context of product ecosystems (Forgas, 1995; Picard *et al.*, 2004).

(3) Constructing UX. The product ecosystem entails a scenario of the entire system design for UX. It emphasizes human-product-ambience interactions to create the real product usage context and genuine UX. Therefore, it is useful to frame the design problem in the related

ambience under different interaction activities, thus avoiding the classic pitfall of design divorced from the problem context (Giboin, 1999).

(4) Analyzing product ecosystem behavior. Analyzing the behavior of the product ecosystem is a pressing task for designers to justify the actual value of the system. However, the traditional "build-test-evaluate-redesign" cycle is both costly and time-consuming due to the capital-intensive, human-centered nature of product ecosystems (Fitzsimmons and Fitzsimmons, 2006). Hence, a cost-effective model that simulates the behavior of the ecosystems must be developed.

3.3.3 Affective-Cognitive Fulfillment

This stage is to explicitly and systematically translate ACNs into design elements using engineering methods accommodating both UX and engineering concerns, i.e., AC mapping (ACM). Therefore, the following research issues are identified:

(1) No explicit mapping relationships. At early stages of product ecosystem design, explicit ACM relationships between ACNs and design requirements may not be in existence. This is due to the high degree of subjectivity of affective and cognitive judgments, in which individual judgments may vary significantly compared with clear technical ones. Besides, ACM decisions are intricate and can hardly be consolidated with a structured mapping mechanism.

(2) Leveraging engineering concerns. User need fulfillment is traditionally addressed through mapping ACNs to design requirements, referred to as *forward ACM* (FACM). The fulfillment of ACNs should accommodate two key stakeholders: users and the producer. While meeting users' affective needs, the producer must seek for economy of scale in product realization (Jiao *et al.*, 2006). The producer must also assess ACNs with consideration of a number of potential couplings and interrelationships among various design requirements,

along with cost, scheduling, and quality constraints (Jiao and Zhang, 2005). Such engineering concerns at the backend of product design require feedback from designers with regard to ACNs, whereby users may have to compromise or negotiate the 'price' of their affective preferences and cognitive tendencies. This entails a reasoning process from the designer domain to the user domain, which is referred to as *backward ACM* (BACM). In a holistic view, the mapping process requires to address tradeoffs between UX and engineering concerns while maximizing profits/sales and choice varieties (Urban and Hauser, 1993).

(3) Assessment and refinement of affective-cognitive mapping. Traditionally, the assessment of ACM of a given product has been carried out by experts, based on their experience and rules of thumb where a number of heuristics are assumed *a priori* (Thurston and Locascio, 1994). Furthermore, noises and variances related to different contexts in interviews, surveys, and questionnaires (Barone *et al.*, 2007) often weaken model fitting and estimation. Especially for affective appraisal, it is also associated with a so-called halo effect – a cognitive bias occurring in psychological rating (Beckwith and Lehmann, 1975). For example, one may overrate other Apple products, if s/he likes the iPhone very much. It is imperative to develop *objective measures* to deal with the subjectivity and vagueness of ACNs for FACM. It is equally important to formulate decision models that incorporate *correction methods* to filter out noise factors for BACM.

3.4 Strategy for Solution

Based on the literature review in Chapter 2 and the technical challenges proposed above, the corresponding strategy for solutions is proposed as follows:

3.4.1 Ambient Intelligence for Affective-Cognitive Need Acquisition

Information communication technology is transforming the way people interact among themselves and with objects around them. In particular, technology's focus is gradually shifting away from the computer to the human user (Riva, 2005). Among many others, Ambient Intelligence (AmI) (Augusto, 2007), which leverages pervasive computing, wireless sensor networks, HCI, and AI, has emerged as a promising platform to offer great potential for affective and cognitive design. A key feature of AmI is context awareness, which enables the system to understand user needs as well as the situational context so as to provide personalized services by tailoring its reaction upon the environment and user needs anticipatorily (Aarts, 2004).

For one thing, ACN elicitation and measuring can be facilitated in AmI-enabled environments. As discussed in Subsections 2.4.4 and 2.4.5 of Chapter 2, multiple sources of sensor data can provide a comprehensive picture of different affective and cognitive states in a continuous way, such as physiological and behavioral data as well as objects involved in the human-product-ambience interaction process. It thus allows human affective and cognitive states to be evaluated in real time. Compared with the subjective methods (e.g., retrospective self-reports, and focus groups), the real-time feature is particularly desirable for products that seek to respond to users' affective and cognitive states in different ways to improve the interaction (Bailenson *et al.*, 2008). It is also reported that physiological signals are less likely to be affected by contextual influence than the subjective measures when reflecting affective and cognitive states (Picard *et al.*, 2001). If these data are combined with subjective linguistic data, it would be highly possible to acquire a relatively full spectrum of ACNs.

For another, with AI, AmI-enabled systems have the capability of basic reasoning for day-to-day functioning; even emotions or affective ability can be incorporated into models of intelligence, and particularly, into computers and their interactions with humans (Picard, 1997; Augusto, 2007). Such models could be embedded in intelligent systems to monitor, quantify and predict users' affective and cognitive states in real time in a continuous manner

(Fairclough, 2009). As a result, the relationships between ACNs and design elements in product ecosystems might be identified.

Given the advantages of AmI, AmI-based methods for ACN acquisition with objective measures are proposed in details in Chapter 4 and Chapter 5, respectively.

3.4.2 Graph-based Modeling for Affective-Cognitive Analysis

Given the technical challenges mentioned in Subsection 3.3.2, a powerful modeling technique is needed that is able to (1) model multiple entities and relationships in the product ecosystem, (2) model the interaction and dynamics between affect and cognition, and (3) identify fuzzy causes and effects between UX and product ecosystem entities to improve efficiency and reduce cost. In Subsections 2.5.3 of Chapter 2, graph-based methods that can accommodate both qualitative and quantitative data suggest themselves to be powerful tools for AC analysis.

Among many others, PNs have an exact mathematical definition of their execution semantics, with a well-developed mathematical theory for process analysis (Murata, 1989). The dynamic and non-deterministic nature is well suited to model the product ecosystem behavior. The qualitative nature of PNs is expected to foster the development of systematic methods for the representation of product ecosystems, based on which fulfillment of the user's ACNs can be analyzed in a quantitative manner with simulation methods, for example. In such a way, it is also possible to carry out 'what-if' analysis for constructing UX and simulating the business processes. The outcome of the analysis can thus provide designers with decision support to optimize UX, and enhance the operational efficiency of the product ecosystem. Towards this end, this research develops a technique named FRPNs for AC modeling and analysis in Chapter 6.

3.4.3 Hybrid Data Mining for Affective-Cognitive Fulfillment

ACM entails a typical 'data rich yet knowledge sparse' decision-making scenario. Reusing historical product and sales data appears to be a natural technique to explore AC decision-making patterns. Data mining techniques lend themselves to be powerful tools for sifting through layers of seemingly unrelated data for meaningful relationships (Larose, 2005). These techniques can anticipate, rather than simply react to, user needs, and create intelligent and proactive pathways back to users. For example, Jiao *et al.* (2006) apply data mining techniques to identify affective mapping patterns as association rules. Despite the fact that a large number of association rules can be generated in the first place, semantics and logics regarding these rules must be further scrutinized and refined before any useful knowledge pattern can be deployed for decision making. It, thus, inspires us to integrate association mining with rule refinement as an iterative process to accommodate both FACM and BACM. Such a hybrid association mining and refinement system can leverage both ACM and engineering concerns within a coherent framework that encompasses both the user and designer domains.

As a case example, affective mapping and refinement for affective fulfillment is presented in details in Chapter 7. As for the *forward affective mapping* (FAM) process, an improved association rule mining technique, i.e., *K*-optimal rule discovery method, is adopted, due to its effectiveness in dealing with semantics of association mining (Webb and Zhang, 2005). As for *backward affective mapping* (BAM), Likert-style dependent variables are introduced in order to model customer preferences as a natural order of possible outcome values. For categorical response data, ordinal logistic regression (OLR) lends itself to be an advantageous model for BAM refinement, owing to its assumption-free property about distributions of independent variables, including normality, linearity and homogeneity of variance. Thus, OLR is applied for BAM.

In addition, refinement techniques for FAM and BAM are also proposed. For one thing, as a systematic knowledge discovery tool with analytical power in dealing with rough, uncertain and ambiguous data (Li and Cercone, 2006; Nagamachi *et al.*, 2006), the rough set theory bears potential for FAM refinement. A rough set-based rule importance measure is proposed to select the most important rules for refinement. For another, controlling variances among design elements is the main purpose of refining BAM relationships. A relative importance measure is introduced in order to discern different roles of design elements in backward mapping. It is reported that inclusion of weights in a design matrix can effectively filter the effect of noise factors to the extent that parameter significance can be changed and model fitting can be improved up to a better case (Barone *et al.*, 2007). Hence, a weighted OLR model is developed, incorporating conjoint analysis of affective needs (Green *et al.*, 1981).

3.5 Summary

Product ecosystem design aims to provide a full spectrum of UX based on the affective dimension and the cognitive dimension inherent in the human-product-ambience interaction process. In order to support for product ecosystem design for UX, a conceptual model is proposed, in which factors that engender UX and their possible underlying interaction mechanisms between affect and cognition are discussed. These fundamental theories of the model provide a more profound understanding of product ecosystem design for UX. Subsequently, a three-stage technical framework is proposed, namely, ACN acquisition, AC analysis, and AC fulfillment. Along with the technical framework, the main challenges and possible solutions of each stage are identified. The detailed problem formulation, methodology, and experimental and case studies related to these three stages are presented in Chapters 4, 5, 6, and 7, respectively.

CHAPTER 4
AFFECTIVE NEED ELICITATION AND PREDICTION BASED ON WEARABLE SENSOR NETWORK

This chapter aims to elicit and predict affective needs using physiological measures with consideration of gender and culture (ambient factors). Specifically, standardized affective pictures as visual stimuli are used to elicit affect. Each stimulus is presented for six seconds and multiple physiological signals are measured, including facial EMG, respiration rate, EEG, and SCR. Three data mining methods (i.e., decision rules, *k*-nearest neighbors, and decomposition tree) based on the rough set technique are applied to construct prediction models from the extracted physiological features. Furthermore, we create three types of models, i.e., gender-specific (male vs. female), culture-specific (Chinese vs. Indian vs. Western), and general models with different sample size and direct comparisons are made among these models. The best average prediction accuracies in terms of the F_1 measures are 60.2%, 64.9%, 63.5% for the general models with 14, 21, and 42 samples, 78.0% for the female models, 75.1% for the male models, 72.0% for the Chinese models, 73.0% for the Indian models, and 76.5% for the Western models, respectively. The results from this study further suggest that the specific models perform better than do the general models in terms of predicting affective states. Factors like gender and culture play an important part in eliciting affect.

4.1 Introduction

As discussed in Chapter 2, in order to have optimal performance and enjoyable UX, such as tutoring and training, driving, and video gaming, it is often necessary to maintain or prevent particular affective states (e.g., nervous and vigilant). Therefore, it needs to elicit and predict users' affective needs effectively. It involves two fundamental questions: (1) How can we effectively record users' affective states without interference in real time? (2) How can we measure and predict users' affective states in the interaction process? Traditional solutions to these questions are typically subjective methods as introduced in Chapter 2, such as user interviews, focus groups, self-reports about one's affective states, and subjective ratings or rankings. These methods either are subject to linguistic ambiguity (Grandjean *et al.*, 2008) or suffer from recall and selective reporting biases (Stone and Shiffman, 1994). On some occasions, affect information can be collected concurrently (e.g., the think-aloud protocol (Ericsson and Simon, 1993)). However, concurrent data collection often interferes with users' normal activities (Detenber, 2001).

Evidence has shown that objective measures can be acquired in a continuous manner which is consistent with the way people perceive emotions (Schiano *et al.*, 2004) and thus allows users' affective states to be evaluated in real time. Unlike models constructed from subjective measures that require conscious evaluations of products or systems at hand, objective measures can be automatically acquired via wearable sensors attached on the user's body and fed into the models as input in real time with little interference with the current activities. This feature is essential to improve interactions by responding to the user's affective state timely, for example cars which seek to avoid accidents for drowsy drivers or video games which seek to match their difficulty level to the affective states of players (Bailenson *et al.*, 2008). Earlier studies have also suggested that objective data collected in real time can help optimize user pleasure and efficiency (Fairclough, 2009), and detect unnecessary irritation or frustration caused by products, without having to interrupt the user (Mandryk and Atkins, 2007), thereby helping designers target areas for redesign and improvement.

4.1.1 Related Work

Physiological specificity refers to the notion that affective states can be distinguished in terms of their associated patterns of physiological signals (Levenson, 2003). Although researchers have extensively studied the capability of physiological specificity (e.g., Fridlund and Izard, 1983; Ekman, 1992), not many results have been generated. Cacioppo and Tassinary (1990) pointed out that it is in part due to the shortcomings in the quantification of physiological data and more importantly to the way in which how the researchers contemplate the relation between physiological signals and psychological operations. Another reason for this may lie in the misconceptions about affect, such as whether affect is categorically distinguished (Ekman, 1992) or dimensional in a continuum (Lang *et al*., 1993). Appraisal theory, on the other hand, hypothesizes that an affective state is the result of our appraisals of the circumstances with a number of evaluation dimensions (Grandjean *et al*., 2008). In a cross-cultural study, Fontaine *et al*. (2007) pointed out that affect is not just two-dimensional, but that it needs four dimensions to satisfactorily represent it, including evaluation-pleasantness, potency-control, activation-arousal, and unpredictability in the order of importance. Although, it seems that appraisal theory bridges the dimensional and categorical conceptions in a reasonable good fashion, not many studies have applied it to affective HCI. With the development of wearable sensors that can effectively capture physiological data as well as the establishment of the valence-arousal model of affect, Lang *et al.* (1993) found significant covariation between facial EMG and affective valence ratings and between SCR and arousal ratings by viewing affective pictures. These findings were further confirmed by Bradley *et al.* (2001a) and expanded when the participants listened to affective sound-clips (Bradley and Lang, 2000). These studies provide empirical evidence with statistical tests (e.g., ANOVA) that physiological signals are able to distinguish different affective states.

However, not until this century, did a few studies employ machine learning techniques to predict affective states from physiological features. For example, Picard *et al.* (2001) acquired physiological data of a single subject over multiple days, including SCR, EMG of the jaw, blood volume pulse (BVP), and respiration of a single subject over multiple days. A combination of sequential floating forward search and fisher projection methods was used to classify eight affective states with 81% accuracy. Comparable results were also reported for multi-user classifiers. For example, Katsis *et al.* (2008) collected facial EMG, EDA, ECG, and respiration data in constructing and predicting four different affective states with almost 80% accuracy using an adaptive neuro-fuzzy inference system. Similarly, Nasoz *et al.* (2003) examined six affective states using physiological signals from 29 undergraduate students, including SCR, heart rate, and temperature. They obtained classification accuracies of 71%, 74%, and 83% using *k*-nearest neighbor (*k*-NN) algorithm, discriminant function analysis, and Marquardt back propagation, respectively. Later Lisetti and Nasoz (2004) reported an even higher accuracy score (84.1%) in classifying six affective states using similar methods. More recently, Frantzidis *et al.* (2010) proposed a combination of a C4.5 decision tree algorithm and a Mahalanobis distance classifier to differentiate four different affective states with multiple physiological recordings, including EEG and SCR; they gained an average recognition rate around 78% among 28 participants. Chanel *et al.* (2009) assessed three human affective states defined in the valence-arousal space, using peripheral and EEG physiological signals on short-time periods among ten subjects. The accuracies presented ranged from 63% to 80% applying different feature sets. Gu *et al.* (2010) proposed a Gaussian mixture model in two stages for multi-subject affective state recognition using physiological responses, such as ECG, BVP, SCR, respiration data, and facial EMG. The classification accuracies ranged from 80.7% to 90.3% for four affective states.

4.1.2 Research Objective

This chapter aims to investigate to what extent multiple physiological measures acquired from wearable sensors can be used to predict users' affective states in real time, considering the factors of gender and culture.

Toward this end, an experiment is first designed to elicit a wide range of affective states using standardized visual affective stimuli, during which multiple physiological measures were recorded using wearable sensors. Visual information is the most frequently used stimuli presented in products and systems, and the results from standardized affective stimuli are comparable across different studies.

Then, 42 potentially relevant features are extracted based on previous studies for model construction using data mining methods. Data mining techniques are powerful tools for sifting through layers of seemingly unrelated data for meaningful relationships. These advanced techniques can anticipate affective states using predictive models from a combination of features extracted from physiological measures rather than simply differentiation among physiological measures concerning particular affective states. Evidenced by many previous studies in the last decade (e.g., Picard et al., 2001; Mandryk and Atkins, 2007; Liu et al., 2008; Frantzidis et al., 2010), these techniques are envisioned to result in more cost-effective, efficient and usable HCI systems, which would, to a large extent, address the problems of traditional methods of affect elicitation and prediction. Among many others, rough-set based data mining methods were chosen due to their good capability of dealing with imprecision, vagueness and uncertainty by rough approximations (Pawlak, 1991).

Finally, given that we have collected a large amount of data from participants of different genders and cultures, we are able to create three types of models and provide direct comparisons between each type of models to investigate the influence of ambient factors (i.e., gender and culture) on affect elicitation and prediction. The first type is a general model, in which both training and testing data are collected from participants regardless of their gender or culture with three different sample sizes. This type of models can be used for affective design in which various people interact with the same products or systems, such as bank automated teller machines. The second one is a gender-specific model, whose training and testing data are gender-specific while the third one is a culture-specific model, whose training and testing data are culture-specific. Specific models are useful both practically and theoretically. For example, gender-specific models are useful for affect prediction when users are interacting with products, such as jewellery targeted at female customers and video games for male players, while culture-specific models are insightful for human-product-ambience interaction applications in which products are culture-specific. Moreover, more valuable information can be obtained on how factors of gender and culture influence affective responses in terms of physiological measures quantitatively.

4.2 Experiment Design for Affect Elicitation

4.2.1 Participants

Forty-six college students (23 males and 23 females), including 16 Chinese, 15 Indians, and 15 Westerners (all Caucasians: five from Germany, one from France, two from the UK, and the remainder from the USA), take part in the experiment. In order to increase homogeneity within cultural groups, Chinese and Indian students are required to be born and raised in mainland China and India, respectively, and to have lived in Singapore for less than 2 years; while the Westerners are exchange students at Nanyang Technological University, Singapore, for less than six months. All the participants are aged between 20 and 30 (mean = 24.4; standard deviation = 2.3). Each participant was interviewed by the experimenter to screen out mental disorder or drug and alcohol abuse. Due to technical difficulties, only data collected from 14 participants in each cultural group (i.e., N = 42 in the final) with gender balance were kept. Informed consent was obtained from each participant.

4.2.2 Affective Stimuli

In this study, affective stimuli are selected from the International Affective Picture System (IAPS) (Lang *et al.*, 2008). The IAPS is a set of 1194 normative affective coloured pictures that depict a variety of semantic categories and affective tones distributed evenly in a two-dimensional space (autonomic arousal vs. hedonic valence). One important question when estimating human affective response is how to operationalize the affective state (Liu *et al.*, 2008). Although numerous studies have generally shown that this two-dimensional space can well represent emotional space (e.g. Lang *et al.*, 1993; Russell, 2003), other emotion theorists subscribe to discrete emotional models where emotions can be distinguished from one another by specific attributes, such as prototypical facial expressions, physiological reactions, and action tendencies (Plutchik, 1980; Ekman, 1992). Researchers often focus on basic emotions, such as anger, disgust, fear, happiness, sadness, surprise, though theorists differ on the number and nature of basic emotions. More recently, other emotions have also been regarded as basic emotions, including contentment, amusement, and excitement (Ekman, 1999). Nevertheless, in this research, we are not trying to find a comprehensive set of basic emotions, but rather are considering emotions that might be predicted as accurately as possible, given the available affective stimuli and their relevance to possible scenarios of human-product-ambience interactions.

Twenty eight pictures are chosen (Table 4-1) based on their affective semantics, and thus they are categorized into seven groups, corresponding to seven discrete affective states: excited, amused, content, neutral, sad, fearful, and disgusted. Semantically, these pictures are selected in an effort to elicit one discrete emotion more than another or blended emotions; they are also selected for the reason that they are located in the valence-arousal 2-dimensional space based on the ratings in the IAPS such that they can be potentially separated (see Figure 4-1). The selected affective states are considered to be most relevant to affective design applications. The study by Mikels *et al.* (2005) has pointed out that in the IAPS the top four negative emotional labels are fear, disgust, sadness, and anger whereas the top five positive emotional labels are awe, amusement, contentment, excitement, and happiness. In this study, anger is excluded because anger induction generally involves a demeaning offense against the self (Lazarus, 1991), and such a precondition is often hard to achieve just by viewing static images in IAPS. Awe and happiness are also excluded since awe is a blend of fear and surprise (Plutchik, 1980), whereas happiness is also a complicated construct with a multiplicity of meanings, such as pleasure, life satisfaction, positive emotions, and so on (Diener *et al*., 2003). Finally, neutral is included as a special state with no particular emotions.

Table 4-1 Selected visual affective stimuli from the IAPS

Affective States	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted
IAPS Picture #	4645 4677 4687 4694	1340 1811 2341 2352.1	2340 2360 2550 2530	7233 7045 7010 7003	2276 2800 2900 9220	6260 6350 1120 1050	3080 3130 3170 3000

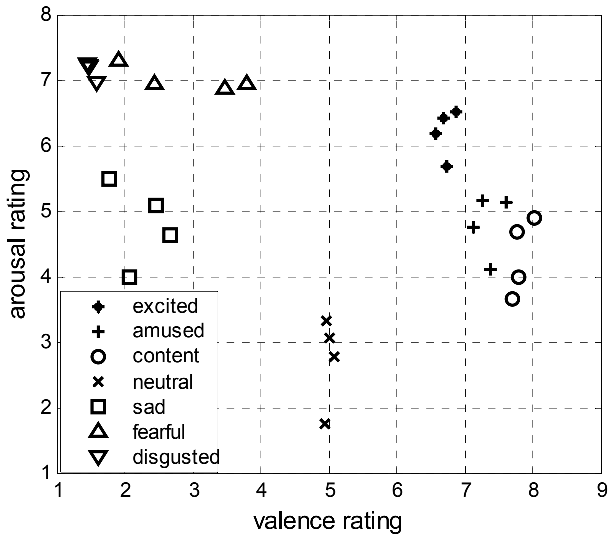


Figure 4-1 The position of selected pictures in the valence-arousal space

4.2.3 Emotion Labelling

Emotion labelling is one of the prime challenges in this research. According to previous research, emotion labelling is either conducted by subjective reports by professionals, such as trained experts (Bailenson *et al*., 2008), therapists (Liu *et al.*, 2008), or by the participants themselves (Nasoz *et al*., 2003). In this research, the emotional labels are obtained according to the participants' self-report. Participants are instructed to select one affective adjective that best corresponds to the affective state they felt when viewing the picture; these affective adjectives include excited, amused, content, neutral, sad, fearful, and disgusted. However, it might be possible that what the participants reported are different from the semantics of the affective pictures selected from the IAPS. Hence, the self-report process generated the following confusion matrix (see Table 4-2). Nevertheless, based on the majority rule (see recall in Table 4-2), the labelling process generated the same results as the selected IAPS labels. Note that in all our experiments, the precision, the recall and the F_1 measure are calculated (Eqns. (4-1)-(4-3)). For a multi-class classification problem, assume there are C different classes, and the i-th class has a total number of N_i instances in the dataset. If the model predicts correctly C_i for the i-th class and predicts C_i^* instances to be in the i-th class where those actually belong to other classes, then the previous measures are defined below (Bailenson et al. 2008):

$$\text{Precision}=\frac{C_i}{C_i+C_i^*}, \tag{4-1}$$

$$\text{Recall}=\frac{C_i}{N_i}, \tag{4-2}$$

$$F_1=\frac{2\times\text{Precision}\times\text{Recall}}{\text{Precision+Recall}}, \tag{4-3}$$

Hence, precision accounts for how well the model predicts (i.e., a measure of exactness) and recall accounts for how well the model does not miss the target (i.e., a measure of completeness). The F_1 measure combines the precision and the recall and is the harmonic mean of them. It thus gives the optimal accuracy. Based on the precision and the recall in Table 4-2, the F_1 measures for the seven affective states are 0.815, 0.634, 0.700, 0.803, 0.843, 0.789, and 0.778, respectively. Note that the F_1 measures demonstrate that the agreement among the participants is substantial (larger than 0.75) for the categories of excited, neutral, sad, fearful, and disgusted, but moderate (between 0.50 and 0.75) for the categories of amused and content. Such results might mainly stem from the affective stimuli. A lack of agreement does not necessarily mean that the self-reported data is not reliable. However, since the subjective report from the participants acts as the reference point connecting the objective physiological data to their affective states, we expect that it might also be hard to distinguish between amused and content when models based on physiological signals are used to predict affective states.

Table 4-2 Confusion matrix of emotion labelling by the participants' self-report

		Self-reported by participants								
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Instance of Pictures	Recall
Actual semantics of the affective stimuli	Excited	132	14	3	7	1	11	0	168	0.786
	Amused	9	103	38	14	0	3	1	168	0.613
	Content	9	30	119	10	0	0	0	168	0.708
	Neutral	1	5	9	149	4	0	0	168	0.887
	Sad	0	1	2	12	145	4	4	168	0.863
	Fearful	4	4	1	11	2	140	6	168	0.833
	Disgusted	1	0	0	0	24	29	114	168	0.679
	Tested Pictures	156	157	172	203	176	187	125	1176	0.767
	Precision	0.846	0.656	0.692	0.734	0.824	0.749	0.912	0.773	0.766

Note '0.767' and '0.773' are the mean recall and precision, respectively, and '0.766' is the mean F_1 measure of all the affective states

4.2.4 Apparatus

A physiological sensing system and the E-Prime software (Psychology Software Tools, Pittsburgh, USA) are used for data collection. The physiological sensing system includes an eight-channel Biofeedback & Neurofeedback System v5.0, i.e., the ProComp Infiniti system (Thought Technology, Montreal, Canada) and a Myomonitor Wireless EMG System (Delsys, Boston, USA). The former is used to collect SCR, respiration, and EEG data. The latter is applied to collect facial EMG signals.

4.2.5 Procedure

First, after the participants have signed the consent forms, they are briefed that there would be affective pictures that might prompt different affective states and that they should attend to the entire stimulus presentation for six seconds. Before formal data collection, a practice trial with six pictures differed from those in the formal experiment is conducted by the participant. This enables the participant to familiarize with the experiment protocol. After all the sensors are installed on the participant, a two-minute rest is followed before the first stimulus is presented on a 17-inch desktop around one meter away. During this time, the sensors are expected to collect the baseline levels of the participant's physiological signals. The experiment takes place in a project room with dim lighting and controlled temperature around 25 Celsius degrees. The passive viewing methodology is employed when the participant is seated comfortably in an armchair. The order of stimulus presentation is random, but the stimuli are not repeatedly generated for each participant so as to minimize order effects and habituation effects. In order to label the affective state of each picture, after viewing each, the participant is asked to choose one affective adjective that best corresponds to the affective response s/he feels to the stimulus from the given terms on the screen just after the stimulus presentation, including excited, amused, content, neutral, sad, fearful, and disgusted. To minimize carry-over effects, there is a 10-second interval between two consecutive affective stimuli, during which a blank white picture is presented. In order to reduce within-group variability, the physiological measures, including facial EMG, respiration rate, and SCR, are the change scores where baseline levels are subtracted from task levels.

4.2.6 Measures and Preprocessing

SCR, also known as electrodermal response, is a measure of the skin's ability to conduct electricity and represents changes in the sympathetic nervous system (Bernstein, 1969). It has been proved to be linearly related to affective arousal and independent from affective valence (Lang *et al.*, 1993). SCR (in μS) is measured by fastening the electrode straps around the second and the fourth fingers of the participant's left hand. Then, SCR is smoothed and log transformed [log(SCR+1)] to normalize the distribution of the response (Lang *et al.*, 1993).

Respiration measures the rate or volume of air exchange in human lungs by its rate or amplitude. It is observed that high arousal generally increases respiration rate while low arousal decreases respiration rate (Stern *et al.*, 2001). In this study, the respiration sensor is sensitive to stretch and is strapped around each participant's abdomen. The respiration rate data are automatically computed and collected by the ProComp Infiniti system. Empirically, the baseline is defined as the mean rate of three seconds before stimulus onset. Then, the change score for respiration rate (in cycle/min) is calculated by subtracting the baseline from the mean rate at each half-second after stimulus onset for the following six seconds (i.e., 12 samples are collected).

EEG is the recording of electrical activity along the scalp produced by the firing of neurons within the brain and reflects correlated synaptic activity caused by post-synaptic potentials of cortical neurons (Creutzfeldt *et al.*, 1966). It is the summation of oscillations with a frequency range from 1 to 80 Hz, with amplitudes of 0.01 to 0.1 V (Kandel *et al.*, 2000). In this research, the alpha (8-12 Hz) and beta (12-30 Hz) frequencies are extracted to reflect different affect related activities (Niemic, 2002). Alpha waves are typical for an alert but relaxed mental state, visible over the parietal and occipital lobes, while beta waves are related to an active state of mind (busy, alert, anxious thinking, and/or active concentration), most evident in the frontal cortex (Kandel *et al.*, 2000). In this research, the only sensing electrode is placed at the Fpz which is defined by the international 10-20 system (Niedermeyer and Lopes da Silva, 2004). The two reference electrodes are located at the left and right ear lobes. In order to minimize artefacts introduced in the EEG signals, participants are instructed not to blink during the six-second stimulus presentation as they could, and electrooculogram artefacts are corrected by an adaptive filter based on the least mean squares regression (Haykin, 1996) using EEGLab software based on Matlab R2008b (Natick, MA, USA). The EEG data are then bandpass filtered into alpha and beta waves using an elliptic, short IIR filter.

Facial EMG measures muscle activity by detecting and amplifying the tiny electrical impulses that are generated by muscle fibres when they contract (Shelley and Shelley, 2001). Facial EMG measures from the zygomaticus major (ZM) and corrugators supercilii (CS) are widely used for recognition of affective states (Laparra-Hernández *et al.*, 2008). In this research, EMG electrodes are placed over ZM and CS on the left side of the face. EMG signals (in μV) are bandpass filtered from 100 to 1,000 Hz using an elliptic, short infinite impulse response (IIR) filter, amplified (× 5,000) and rectified (Lang *et al.*, 1993). The baselines for ZM and CS are defined as the mean activity in the one second before stimulus onset (Lang *et al.*, 1993). Then, the change scores for both ZM and CS are computed by subtracting their respective baselines from the mean responses sampled at each half-second time interval after stimulus onset for the following six seconds (i.e., 12 samples were collected).

4.3 Affect Prediction Based on Data Mining

In order to effectively predict affective states, feature-based data mining methods are promising. Consequently, before model construction, a variety of features are proposed and adapted based on the previous psychophysiology and emotion literature before model construction (e.g., Lang *et al*., 1993; Picard *et al*., 2001).

4.3.1 Feature Extraction

A collection of 42 features is proposed. In Table 4-3, 33 features are obtained from the statistic features of ZM, CS, the difference score between CS and ZM change scores, i.e., CZ = CS – ZM, integrated ZM and CS change scores, CS – ZM over the presentation time, and respiration. Taking ZM for example, the change scores of ZM are denoted by Y and let Y_i represent the *i*-th sample within one emotion segment ($i = 1,...,12$). The definitions of the statistic measures are defined as follows:

(1) The means of raw change scores

$$\mu_Y = \frac{1}{12}\sum_{i=1}^{12} Y_i \,, \tag{4-4}$$

(2) The standard deviations of the raw change scores

$$\sigma_Y = \sqrt{\frac{1}{11}\sum_{i=1}^{12}\left(Y_i - \mu_Y\right)^2} \,, \tag{4-5}$$

(3) The means of the absolute values of the first differences of the raw change scores

$$\delta_Y = \frac{1}{11}\sum_{i=1}^{11}\left|Y_{i+1} - Y_i\right| . \tag{4-6}$$

Let $\overline{Y_i}$ refer to the normalized signal, i.e., $\overline{Y_i} = \left(Y_i - \mu_Y\right)/\sigma_Y$.

(4) The normalized means of the absolute values of the first differences of the raw change scores

$$\overline{\delta_Y} = \frac{1}{11}\sum_{i=1}^{11}\left|\overline{Y_{i+1}} - \overline{Y_i}\right| = \frac{\delta_Y}{\sigma_Y}, \tag{4-7}$$

(5) The means of the absolute values of the second differences of the raw change scores

$$\gamma_Y = \frac{1}{10}\sum_{i=1}^{10}\left|Y_{i+2} - Y_i\right|, \tag{4-8}$$

(6) The means of the absolute values of the second differences of the normalized raw change scores

$$\overline{\gamma_Y} = \frac{1}{10}\sum_{i=1}^{10}\left|\overline{Y}_{i+2} - \overline{Y_i}\right| = \frac{\gamma_Y}{\sigma_Y}, \tag{4-9}$$

(7) The average acceleration of ZM change scores

$$a_Y = \frac{1}{11}\sum_{i=1}^{11}\left(Y_{i+1} - Y_i\right) = \frac{1}{11}\left(Y_{12} - Y_1\right). \tag{4-10}$$

Table 4-3 Features of facial EMG and respiration data

Statistic measure	ZM	CS	CZ	Integrated ZM	Integrated CS	Integrated CZ	Respiration
Mean	√	√		√	√	√	√
Standard deviation	√	√	√	√	√	√	√
MAFF	√	√	√	√	√	√	
NMAFF	√	√	√				
MASF	√	√		√	√	√	
NMASF	√	√					
Acc				√	√	√	√

Note '√' shows that the corresponding statistic measure is calculated for the physiological signal. The means of the absolute values of the first differences (MAFF), the normalized means of the absolute values of the first differences (NMAFF), the means of the absolute values of the second differences (MASF), the normalized means of the absolute values of the second differences (NMASF), the average acceleration (Acc)

Alpha wave and beta wave are obtained by preprocessing the EEG data using EEGLab. Then the following energy features are calculated:

(1) The power of alpha (E_α),

(2) The power of beta (E_β),

(3) The power of alpha and beta ($E_{\alpha+\beta}$),

(4) The power of beta to alpha ratio ($E_{\beta/\alpha}$),

(5) The ratio of beta power to alpha power (E_β/E_α) during the stimulus presentation.

The power spectral density (PSD) function of DelSys EMGworks analysis software (Delsys, Boston, USA) determines the PSD using the Welch method (Welch, 1967). Then, the corresponding energy features are obtained within the specified (i.e., alpha, beta, and alpha + beta frequency) frequency band by integrating PSD within them. These features tell at which frequency ranges variations are strong and at which frequency ranges variations are week.

Last, four temporal features of SCR were illustrated in Figure 4-2 and were computed using Matlab R2008b (Natick, MA, USA) as follows:

(1) The SCR amplitude, regarded as the conductivity difference among the peak point and the initiation point,

(2) Latency, which is the amount of time between the stimulus and the rise of the wave,

(3) The rise time, corresponding to the temporal interval between the peak and the start point,

(4) The half recovery time, i.e., the amount of time it takes for the wave to fall back to half of its amplitude.

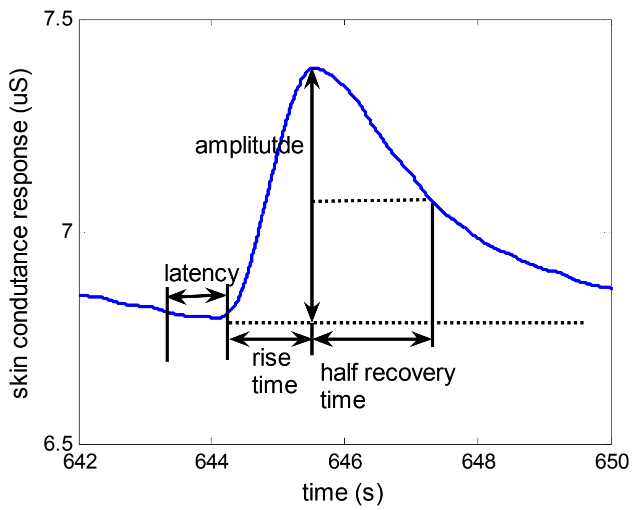


Figure 4-2 Illustration of SCR features

4.3.2 Feature Transformation

It is important to synthesize diverse physiological features and identify the most relevant ones for building a robust prediction model. This usually involves a process of reducing the number of features as much as possible that the constructed model is more computationally efficient and accurate (Fodor, 2002). Among many others, linear discriminant analysis (LDA) and principal component analysis (PCA) are frequently used for feature transformation. However, unlike PCA which only draws on between-class information, LDA explicitly makes use of both between-class and within-class difference information for better performance (Martinez and Kak, 2001). Therefore, LDA is first used to reduce the dimensionality of the original feature space by finding a linear combination. Then, the rough set theory excels in classifying approximations of concepts from multiple features (Pawlak, 1991). Three data mining methods based on the rough set technique were then used separately to predict affective states.

The original feature space is represented by a matrix, $\mathbf{X} = \left\{x_{ij}\right\}_{N\times M}$, where x_{ij} is the j-th sample of the i-th feature vector, $\boldsymbol{x}_{i*}$, N is the total number of features involved, and M is the total number of samples. Hence, each column of $\mathbf{X}$ (i.e., $\boldsymbol{x}_{*j}$) across all the features describes one particular affective state. In order to search for those feature vectors in the underlying space that best discriminate among all the affective states, LDA creates a linear transformation

$$\mathbf{Y}_{L\times M} = \left(\mathbf{W}^{T}\right)_{L\times N} \mathbf{X}_{N\times M}, \tag{4-11}$$

where $\mathbf{W}$ is the projection matrix that maps the original N-dimensional feature space onto an L-dimensional feature subspace (L is the dimensionality of the new feature subspace and usually $L << N$) when maximizing the following objective (Martinez and Kak, 2001):

$$J(\mathbf{W}) = \frac{\mathbf{W}^T \mathbf{S}_B \mathbf{W}}{\mathbf{W}^T \mathbf{S}_W \mathbf{W}} , \tag{4-12}$$

where $\mathbf{S}_B$ and $\mathbf{S}_W$ are the between-class and within-class scatter matrices defined below:

$$\mathbf{S}_W = \sum_{c=1}^{C} \sum_{j=1}^{N_c} \left(\boldsymbol{x}_{*j}^c - \boldsymbol{u}_c \right) \left(\boldsymbol{x}_{*j}^c - \boldsymbol{u}_c \right)^T , \tag{4-13}$$

$$\mathbf{S}_B = \sum_{c=1}^{C} \left(\boldsymbol{u}_c - \boldsymbol{u} \right) \left(\boldsymbol{u}_c - \boldsymbol{u} \right)^T , \tag{4-14}$$

where C is the total number of affective states, $\boldsymbol{x}_{*j}^c$ is the j-th column of the c-th affective states in $\mathbf{X}$, $\boldsymbol{u}_c$ is the mean vector of class c, N_c is the total number of samples in class c, and $\boldsymbol{u}$ is the grand mean across C classes. It has been proved that the column vectors of the projection matrix $\mathbf{W}$ are the eigenvectors of $\mathbf{S}_W^{-1}\mathbf{S}_B$ (Fisher, 1938). Nevertheless, it should be noted that the upper bound of L is $\min\left(C, N\right) - 1$.

In this research, there are seven (C = 7) classes of affective states, 42 (N_c = 42) samples in each class, and 42 features (N = 42). According to Eqns. (4-13)-(4-14), we obtain the between-class and within-class scatter matrices $\mathbf{S}_B$ and $\mathbf{S}_W$, from which the projection matrix $\mathbf{W}$ is derived. The final six-dimensional (L = 6) feature subspace is determined according to Eqns. (4-11)-(4-12).

4.3.3 Model Construction

Three data mining methods based on the rough set technique are adopted to construct the models based on the extracted features, including decision rules (DR), k-NN, and decomposition trees (DT) (Bazan *et al.*, 2000). These methods all take a decision table as the input. The transposed subspace, $\mathbf{Y}_{M \times L}$, with the corresponding labels of different affective states is first tabulated as a decision table $T = \left(F \cup D, I\right)$, where F is a non-empty feature set such that for any feature vector $\boldsymbol{f} = \left\{f_l\right\}_L \in F$. For example, for the six-dimensional feature subspace, $\boldsymbol{f} = \{f_1, ..., f_6\}$ describes one particular affective state. D is a non-empty decision set such that for any decision vector $\boldsymbol{d} = \{d_h\}_H \in D$, where H is the total number of the decision variables (only one decision variable involved, i.e., affective state, in this study). $F \cup D$ is the universe of inference I ; $\boldsymbol{i} = \{I_m^*\}_M \in I$, where M denotes the total number of the training samples in the decision table. A specific training sample of T , $I_m^* - (F_m^* \Rightarrow D_c^*)$, embodies the inference relationship from the features F_m^* to the corresponding affective state D_c^*. $F_m^* = \{f_{ml}^*\}_L$ is the value set of the feature vector $\boldsymbol{f}$; $D_c^* = \{d_c^*\}_C$ is the value set of $\boldsymbol{d}$, and in this study $D_c^* = \{excited,\ amused,\ content,\ neutral,\ sad,\ fearful,\ \ disgusted\}$. An example of the decision table used in data mining methods was given in Table 4-4.

Table 4-4 An example of the decision table used in data mining methods

# Entry	Feature 1	Feature 2	Feature 3	Feature 4	Feature 5	Feature 6	Decision
1	-2.23	-2.60	-2.67	0.11	-0.52	-0.77	excited
2	3.34	-1.03	-1.28	-1.84	-3.14	-2.43	excited
…	…	…	…	…	…	…	…
293	-3.71	-3.23	-4.63	-2.94	-0.63	1.35	disgusted
294	-3.66	-4.09	-3.93	-2.94	1.81	0.70	disgusted

Decision Rules: This method uses IF-THEN rules to predict the affective states (see Eqn. 4-15). Rule generation is based on the concept of reduct that is a subset of attributes in a decision table that can fully characterize the knowledge contained in the decision table (Pawlak, 1991). Assuming an information system, $I^S = (U, F)$, where U is a non-empty finite set called the universe such that $\forall \boldsymbol{f} \in F,\ \boldsymbol{f} : U \to F^*$ and F^* is the value set of F . A reduct is defined as a subset of features in I^S , such that $\Phi = \{\phi_n\}_N \subset T$, where $\phi_n = (f_n^\phi, d_n^\phi)$ is subject to an indiscernibility relation, in which, for objects $x \in U$ and $y \in U$, a pair $(x, y) \in U \times U$ belongs to Φ. Therefore, for any object $z \in U$, a decision rule can be generated, such that

$\forall q \in [1, Q]$, where Q denotes the total number of features instantiated by this rule, the predecessor of the rule takes the conjunction of certain feature instances, $f_q^{\phi}(z)$, and the successor takes on specific values of decision variables, $d^{\phi}(z)$. The general form of a decision rule constructed for reduct Φ and object z is thus given as the following:

$$IF\left(f_1^{\phi} = f_1^{\phi}(z)\right) \wedge \left(f_2^{\phi} = f_2^{\phi}(z)\right) \ldots \wedge \left(f_Q^{\phi} = f_Q^{\phi}(z)\right) THEN\left(d^{\phi} = d^{\phi}(z)\right). \tag{4-15}$$

To further get better prediction results, the features are discretized into different intervals using cuts that are produced with the global strategy based on the maximal discernibility heuristics (Pawlak, 1991). The extent to which a rule is applicable to (i.e., matches) the training sample is determined by the degree of support, which is equal to the number of training samples from the decision table for which this rule applies correctly. For example, one rule was *'IF (f_1="(-Inf,-2.57)") ∧ (f_2="(-2.67,-1.03)") ∧ (f_6="(-Inf,-1.49)") THEN (affective_state=neutral)(8)*'. It means that if the values of Feature 1, Feature 2, and Feature 6 belong to the intervals (-Inf,-2.57), (-2.67,-1.03), and (-Inf,-1.49), respectively, then the corresponding affective state is neutral with a support of eight. For a given test sample, *tst*, the subset of rules matched by *tst* is selected. If *tst* matches only rules with the same affective state, then the affective state predicted by those rules is assigned to *tst*. However, if *tst* matches rules with different affective states, a commonly used measure in Eqn. (4-16) for conflict resolving is to be made so that the affective state with the highest measure value is chosen (Gora and Wojna 2002).

$$Strength(tst, c) = \left| \bigcup_{r \in MatchRules(tst, c)} SupportSet(r) \right|, \tag{4-16}$$

where c denotes the c-th affective state, *SupportSet*(r) is a set of training examples matching the rule, r, *MatchRules*(*tst*, c) is a subset of minimal rules that are applicable to *tst* and the affective state is c, and $|*|$ in Eqn. (4-16) denotes the cardinality of a set.

k-nearest neighbour: This is a method for classifying one affective state by a majority vote of its neighbours, with the affective state being assigned to the class most common amongst its k nearest neighbours. Here the k-NN (k = 5, 10, 20, 30, 40 in this research) method does not compute the whole support set of the minimal rules covering *tst*, but is restricted to its neighbourhood $S(tst, k)$ as the set of k training examples defined by a similarity measure (Gora and Wojna, 2002):

$$\delta_f(x, y) = \left| (f(x) - f(y)) / (\max(f) - \min(f)) \right|, \tag{4-17}$$

where $x = (f_1(x), f_2(x), ..., f_6(x), d(x))$ and $y = (f_1(y), f_2(y), ..., f_6(y), d(y))$ are two training samples; max(f) and min(f) are the maximum and minimum values for feature f among the training examples (Note the features here are not discretized as the measure, δ_f, in Eqn. (4-17) is numeric). For one training sample, *trn*, within $S(tst, k)$, the algorithm constructs a local rule $r_{tst}(trn)$ for *tst*. Then it checks whether it is consistent with the remaining training examples in $S(tst, k)$, If so, $r_{tst}(trn)$ is added to the support set for predicting affective states. Finally, the algorithm selects the affective state with the support set of the highest cardinality.

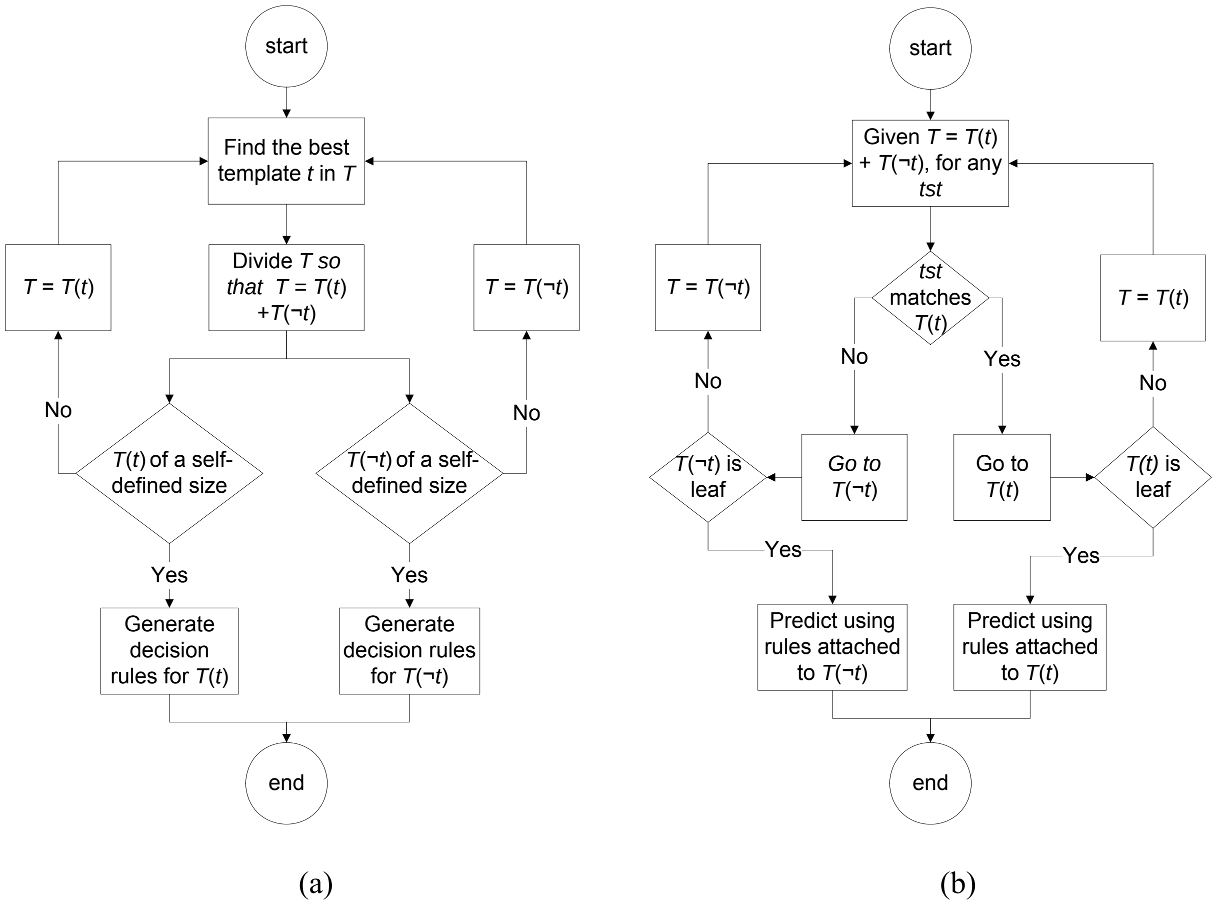


Figure 4-3 (a) Flow chart of generating a decomposition tree; (b) Flow chart of predicting a testing sample using the generated decomposition tree

Decomposition tree: This is similar to a binary decision tree in which each route from the root to the leaf leads to the final class of affective state. However, at the leaf stage, the final class is predicted by the decision rules attached. The tree's every internal node is labelled by some template (any non-leaf vertex of the tree) and every external node (leaf) is associated with a set of training samples matching all the templates in a path from the root to a given leaf (Nguyen, 2000). For a decision table $T = T(t) + T(\neg t)$, where $T(t)$ and $T(\neg t)$ are sub-tables (or sub-trees) containing all training samples matching and not matching template *t*, respectively. The generation of a decomposition tree is depicted as in Figure 4-3(a) and the prediction process for a testing sample, *tst*, is depicted in Figure 4-3(b) (Bazan and Szczuka, 2000; Nguyen, 2000).

4.4 Results

In this research, seven models based on the rough set technique are constructed to predict affective states, including DR, DT, 5-NN, 10-NN, 20-NN, 30-NN, and 40-NN. In order to validate these predictive models, a 10-fold cross-validation method is adopted. Level of significance (α) is set at 0.05 for all the statistical tests in this study.

4.4.1 Prediction Results by General Models

In order to make the general model comparable to gender-specific models (constructed with 21 participants) in terms of the sample size, data collected from 42 participants are randomly divided into two groups with equal size. Specific selections are made to balance across gender and culture in each group. These two groups of datasets are then used to construct two general models. This procedure is run three times so that 6 general models that are comparable with gender-specific models are constructed. Similarly, in order that the general model is comparable with culture-specific models (constructed with 14 participants), we randomly divide the data collected from 42 participants into three groups with equal sizes. Specific selections are also made to balance across gender and culture in each group. This procedure is run twice so that another 6 general models that are comparable with culture-specific models are constructed. Besides, the general model with all the participants is also constructed.

Table 4-5 Prediction results (F_1 measures) for general models with 14 participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.713	**0.544**	0.394	0.807	**0.692**	0.439	0.623	**0.602**
DT	0.745	0.434	0.381	0.760	0.509	0.457	0.611	0.557
5-NN	0.697	0.477	**0.411**	0.834	0.639	0.473	0.653	0.598
10-NN	0.723	0.403	0.374	0.837	0.652	**0.541**	0.655	0.598
20-NN	0.684	0.444	0.396	0.809	0.645	0.499	**0.728**	0.601
30-NN	**0.716**	0.416	0.395	0.810	0.634	0.523	0.694	0.598
40-NN	0.690	0.451	0.334	**0.849**	0.631	0.473	0.681	0.587
Mean	0.710	0.453	0.384	**0.815**	0.629	0.486	0.664	0.592

Table 4-6 Prediction results (F_1 measures) for general models with 21 participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.722	**0.554**	0.466	0.772	0.721	0.549	0.689	0.639
DT	0.684	0.520	0.551	0.742	0.580	0.558	0.607	0.606
5-NN	0.701	0.524	**0.555**	0.776	0.671	0.502	0.723	0.636
10-NN	**0.787**	0.484	0.464	0.830	0.636	**0.588**	0.753	**0.649**
20-NN	0.721	0.547	0.522	0.822	0.636	0.528	0.746	0.646
30-NN	0.643	0.543	0.518	**0.831**	**0.726**	0.498	**0.760**	0.646
40-NN	0.719	0.531	0.517	0.806	0.658	0.548	0.710	0.641
Mean	0.711	0.529	0.513	**0.797**	0.661	0.539	0.713	0.638

Table 4-7 Prediction results (F_1 measures) for general models with all the participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.681	0.546	0.533	0.740	0.626	**0.640**	**0.633**	0.629
DT	0.651	**0.602**	**0.587**	0.752	0.575	0.427	0.540	0.591
5-NN	0.585	0.527	0.493	0.674	0.600	0.400	0.533	0.545
10-NN	0.659	0.556	0.545	0.767	**0.643**	0.537	0.575	0.612
20-NN	0.667	0.533	0.525	0.750	0.598	0.506	0.587	0.595
30-NN	0.644	0.578	0.539	0.734	0.585	0.513	0.605	0.600
40-NN	**0.706**	0.572	0.579	**0.809**	0.612	0.571	0.600	**0.635**
Mean	0.656	0.559	0.543	**0.747**	0.606	0.513	0.582	0.601

The average F_1 measures of these three types of general models across all the data mining methods are presented in Table 4-5, Table 4-6, and Table 4-7, respectively. For individual affective states, the best results are indicated in bold font; and it seems that neutral is predicted most accurately both for the three types of general models (81.5% in Table 4-5, 79.7% in Table 4-6, and 74.7% in Table 4-7) and content least accurately in Table 4-5 (38.4%) and Table 4-6 (51.3%), and fearful in Table 4-7 (51.3%).

As seen from Tables 4-5, 4-6, and 4-7, the mean F_1 measures range from 55.7% to 60.2%, from 60.6% to 64.9%, and from 54.5% to 63.5% among different methods for the general models built with 14, 21, and 42 samples, respectively. Their best results are obtained by DR (60.2%) in Table 4-5, 10-NN (64.9%) in Table 4-6, and 40-NN (63.5%) in Table 4-7. The respective confusion matrices of the best results are given in Tables 4-8, 4-9, and 4-10. According to the precision, one sees that the greatest false predictions lie in the categories of content, content, and amused for the general models with 14, 21, and 42 samples, respectively; according to the recall, one finds that the greatest misses also lie in the categories of content for all the types of general models. When the best results in Table 4-5 (60.2%), Table 4-6 (64.9%), and Table 4-7 (63.5%) are compared with the affective word selection result (76.6%), it decreases by 16.3%, 11.7%, and 14.1%, respectively.

Table 4-8 Confusion matrix of best general model with 14 participants by DR

		Predicted								
Actual		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instance	Recall
	Excited	57	6	7	1	1	1	0	73	0.781
	Amused	6	40	25	7	0	0	0	78	0.515
	Content	19	22	27	9	0	0	0	77	**0.351**
	Neutral	5	1	1	65	0	0	0	72	0.903
	Sad	0	0	0	2	56	13	8	79	0.709
	Fearful	0	0	0	3	19	32	29	83	0.386
	Disgusted	0	0	0	2	7	17	52	78	0.667
	Tested instance	87	69	60	89	83	63	89	540	0.619
	Precision	0.655	0.580	**0.450**	0.730	0.675	0.508	0.584	0.597	0.602

Table 4-9 Confusion matrix of best general model with 21 participants by 10-NN

		Predicted								
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instance	Recall
Actual	Excited	96	13	4	6	1	0	0	120	0.800
	Amused	16	59	47	0	0	0	0	122	0.484
	Content	6	48	54	9	1	0	0	118	**0.458**
	Neutral	6	2	8	105	0	0	0	121	0.868
	Sad	0	0	2	6	78	27	6	119	0.655
	Fearful	0	0	0	6	31	70	16	123	0.569
	Disgusted	0	0	0	0	15	18	84	117	0.718
	Tested instance	124	122	115	132	126	115	106	840	0.654
	Precision	0.774	0.484	**0.470**	0.795	0.619	0.609	0.792	0.645	0.649

Table 4-10 Confusion matrix of best general model with all the participants by 40-NN

		Predicted								
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instances	Recall
Actual	Excited	30	6	0	1	1	1	3	42	0.714
	Amused	2	26	11	2	0	1	0	42	0.619
	Content	1	13	22	3	1	1	0	41	**0.537**
	Neutral	0	1	1	36	3	0	1	42	0.857
	Sad	2	0	0	3	26	9	2	42	0.619
	Fearful	1	1	1	1	10	24	4	42	0.571
	Disgusted	7	2	0	1	2	6	21	39	0.538
	Tested instance	43	49	35	47	43	42	31	290	0.637
	Precision	0.698	**0.531**	0.629	0.766	0.605	0.571	0.677	0.639	0.635

4.4.2 Prediction Results by Gender-Specific Models

Similar analysis is performed by building individual prediction models for both male (N = 21) and female (N = 21) participants. It is achieved by dividing the whole dataset into two parts with one only containing male participants and the other female participants. Tables 4-11 and 4-12 summarize F_1 measures of female models and male models, respectively; Further, by comparing the mean F_1 measures of different data mining methods in Tables 4-11 and 4-12, the female models significantly outperform the male models ($t(12) = 4.511$, $p < 0.01$); upon close observation, it is found that the female models successfully perform better than the male models for *fearful* ($t(7.913) = 6.578$, $p < 0.001$, Levene's test for equality of variances is significant) and *disgusted* ($t(12) = 5.767$, $p < 0.001$). Neutral is predicted most accurately both for the male and female models (87.7% in Table 4-11 and 86.3% in Table 4-12) and content least accurately for the female models in Table 4-11 (57.6%) and fearful for the male models in Table 4-12 (53.5%).

When the mean F_1 measures of different methods are compared to those of the general models with 21 samples (Table 4-6), the male and female models significantly outperform the general ones (male vs. general: $t(12) = 5.095$, $p < 0.001$; female vs. general: $t(12) = 12.018$, $p < 0.001$).

Tables 4-13 and 4-14 present the confusion matrix of the best results of the female (78.1% by 30-NN) and male (75.1% by DT) models, respectively. Based on the precision and the recall, the greatest false predictions and the greatest misses occur to content and amused for the female model and to fearful and fearful for the male model, respectively.

Table 4-11 Prediction results (F_1 measures) for female models

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.820	0.541	0.513	0.894	**0.849**	**0.818**	0.927	0.766
DT	0.824	0.588	0.500	0.867	0.769	0.778	0.895	0.746
5-NN	0.842	0.579	0.585	0.889	0.778	0.780	0.927	0.769
10-NN	0.750	0.531	0.511	**0.913**	0.718	0.722	0.900	0.721
20-NN	0.789	**0.722**	**0.698**	0.872	0.757	0.735	0.895	0.780
30-NN	**0.842**	0.631	0.651	0.837	0.789	0.773	**0.945**	**0.781**
40-NN	**0.842**	0.552	0.572	0.864	0.718	0.732	0.930	0.744
Mean	0.816	0.592	0.576	**0.877**	0.768	0.763	0.917	0.758

Table 4-12 Prediction results (F_1 measures) for male models

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.727	0.513	0.540	0.878	0.762	**0.611**	0.830	0.694
DT	0.833	**0.621**	**0.692**	0.872	0.789	0.583	**0.867**	**0.751**
5-NN	0.762	0.556	0.632	0.844	0.791	0.555	0.750	0.699
10-NN	0.800	0.564	0.556	**0.927**	**0.820**	0.564	0.683	0.702
20-NN	0.791	0.526	0.611	0.809	0.757	0.600	0.769	0.695
30-NN	0.800	0.556	0.632	0.900	0.696	0.444	0.773	0.686
40-NN	**0.857**	0.515	0.611	0.809	0.727	0.389	0.700	0.658
Mean	0.796	0.550	0.611	**0.863**	0.763	0.535	0.767	0.698

Table 4-13 Confusion matrix of best female model by 30-NN

	Predicted									
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instance	Recall
Actual	Excited	16	1	0	1	0	1	0	19	0.842
	Amused	1	12	7	1	0	0	0	21	**0.571**
	Content	1	4	14	2	0	0	0	21	0.667
	Neutral	0	0	1	18	1	0	0	20	0.900
	Sad	0	0	0	1	15	4	0	20	0.750
	Fearful	1	0	0	0	2	17	0	20	0.850
	Disgusted	0	0	0	0	0	2	17	19	0.895
	Tested instance	19	17	22	23	18	24	17	140	0.782
	Precision	0.842	0.706	**0.636**	0.783	0.833	0.708	1.000	0.787	0.781

Table 4-14 Confusion matrix of best male model by DT (Total coverage: 111/140=0.79)

	Predicted									
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instance	Recall
Actual	Excited	15	1	1	0	0	0	0	17	0.882
	Amused	3	9	2	1	0	1	0	16	0.563
	Content	1	3	9	1	0	0	0	14	0.643
	Neutral	0	0	0	17	0	1	0	18	0.944
	Sad	0	0	0	2	15	1	0	18	0.833
	Fearful	0	0	0	0	4	7	2	13	**0.538**
	Disgusted	0	0	0	0	1	1	13	15	0.867
	Tested instance	19	13	12	21	20	11	15	111	0.753
	Precision	0.789	0.692	0.750	0.810	0.750	**0.636**	0.867	0.756	0.751

4.4.3 Prediction Results by Culture-Specific Models

Separate data mining models for each cultural group are also created. Similarly, the F_1 measures of the Chinese models (N = 14), Indian models (N = 14), and Western models (N = 14) are presented in Tables 4-15, 4-16, and 4-17, respectively. Neutral is again predicted most accurately for all the culture-specific models (80.6 in Table 4-15, 83.2% in Table 4-16, and 91.7% in Table 4-17) and amused least accurately for the Chinese models in Table 4-15 (46.5%), fearful for the Indian models in Table 4-16 (52.6%), and content for the Western models in Table 4-17 (47.8%).

Table 4-15 Prediction results (F_1 measures) for Chinese participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.714	0.435	0.486	0.727	**0.889**	**0.762**	**0.904**	0.702
DT	0.720	0.423	0.538	0.769	0.785	0.720	0.833	0.684
5-NN	0.750	0.455	0.480	0.828	0.710	0.455	0.800	0.640
10-NN	**0.846**	**0.518**	0.615	**0.846**	0.733	0.506	0.815	0.697
20-NN	0.667	0.444	0.578	0.828	0.714	0.643	0.769	0.663
30-NN	0.762	0.483	0.486	0.800	0.615	0.522	0.815	0.640
40-NN	**0.846**	0.500	**0.640**	**0.846**	0.733	0.640	0.833	**0.720**
Mean	**0.758**	**0.465**	**0.546**	**0.806**	**0.740**	**0.607**	**0.824**	**0.678**

Table 4-16 Prediction results (F_1 measures) for Indian participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.759	0.462	0.471	0.800	**0.785**	0.477	**0.815**	0.653
DT	**0.897**	0.462	0.522	0.812	0.741	0.500	0.786	0.674
5-NN	0.815	0.615	0.600	**0.880**	0.740	**0.643**	**0.815**	**0.730**
10-NN	0.608	0.563	0.581	0.815	0.714	0.408	0.692	0.626
20-NN	0.833	0.583	0.500	0.833	0.600	0.370	0.690	0.630
30-NN	0.695	0.444	**0.608**	0.828	0.692	0.640	**0.815**	0.675
40-NN	0.786	**0.667**	0.600	0.857	0.714	**0.643**	0.762	0.718
Mean	**0.770**	**0.542**	**0.555**	**0.832**	**0.712**	**0.526**	**0.768**	**0.672**

Table 4-17 Prediction results (F_1 measures) for Western participants

Method	Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	Mean
DR	0.800	0.571	0.435	0.867	0.839	**0.909**	0.857	0.754
DT	0.857	0.538	0.476	0.815	0.923	0.769	0.769	0.735
5-NN	**0.889**	0.500	**0.541**	0.889	0.889	0.750	0.783	0.749
10-NN	0.800	0.538	0.438	0.960	**0.929**	0.720	0.846	0.747
20-NN	0.800	0.518	0.500	0.960	0.880	0.720	**0.880**	0.751
30-NN	0.857	**0.643**	0.435	**0.965**	0.857	0.720	0.846	0.761
40-NN	0.818	**0.643**	0.522	0.960	0.815	0.740	0.857	**0.765**
Mean	**0.832**	**0.564**	**0.478**	**0.917**	**0.876**	**0.761**	**0.834**	**0.752**

By comparing the mean F_1 measures of different methods of the three culture-specific models as well as those of the general models constructed from 14 samples using one-way ANOVA, significant difference is found ($F(3, 24) = 40.640$, $p < 0.001$). Further, post-hoc analysis by the Tukey HSD (honestly significant difference) test shows that Western models perform significantly better than the other two types (Chinese vs. Western: $p < 0.01$; Indian vs. Western: $p < 0.001$). A closer look at the culture-specific models, post-hoc analysis by the Turkey HSD test shows that the Western models perform significantly better in the categories of neutral (Chinese vs. Western: $p < 0.01$; Indian vs. Western: $p < 0.01$), sad (Chinese vs. Western: $p < 0.01$; Indian vs. Western: $p < 0.001$), and fearful (Chinese vs. Western: $p < 0.05$; Indian vs. Western: $p < 0.01$) than the Chinese and Indian models. Further, culture-specific models perform significantly better than the general models with 14 samples (Chinese, Indian, or Western vs. general: $p < 0.001$).

With regard to the best prediction results, 40-NN (72.0%) performs best among the Chinese models, 5-NN (73.0%) among the Indian models, and 40-NN (76.5%) among the Western models; their confusion matrices are also shown in Tables 4-18, 4-19, and 4-20, respectively. According to the precision of each confusion matrix, one sees that the greatest false predictions lie in the categories of amused for the Chinese and Indian models, and of content for the Western models; according to the recall of each confusion matrix, one finds that the greatest misses lie in the categories of amused for the Chinese models and of content for the Indian and Western models.

Table 4-18 Confusion matrix of best Chinese model by 40-NN

	Predicted									
Actual		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of instance	Recall
	Excited	11	1	1	1	0	0	0	14	0.786
	Amused	1	6	5	1	0	0	0	13	**0.462**
	Content	0	3	8	0	0	0	0	11	0.727
	Neutral	0	1	0	11	0	1	0	13	0.846
	Sad	0	0	0	0	11	1	1	13	0.846
	Fearful	0	0	0	0	5	8	1	14	0.571
	Disgusted	0	0	0	0	1	1	10	12	0.833
	Tested instance	12	11	14	13	17	11	12	90	0.725
	Precision	0.917	**0.545**	0.571	0.846	0.647	0.727	0.833	0.727	0.720

Table 4-19 Confusion matrix of best Indian model by 5-NN

		Predicted								
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of instance	Recall
Actual	Excited	11	1	1	0	0	0	0	13	0.846
	Amused	1	8	1	1	2	0	0	13	0.615
	Content	1	4	6	1	0	0	0	12	**0.500**
	Neutral	1	0	0	11	0	0	0	12	0.917
	Sad	0	0	0	0	10	3	0	13	0.769
	Fearful	0	0	0	0	2	9	2	13	0.692
	Disgusted	0	0	0	0	0	3	11	14	0.786
	Tested instance	14	13	8	13	14	15	13	90	0.732
	Precision	0.786	**0.615**	0.750	0.846	0.714	0.600	0.846	0.737	0.730

Table 4-20 Confusion matrix of best Western model by 40-NN

		Predicted								
		Excited	Amused	Content	Neutral	Sad	Fearful	Disgusted	No. of Instance	Recall
Actual	Excited	9	1	1	0	0	0	0	11	0.818
	Amused	0	9	4	0	0	0	0	13	0.692
	Content	2	4	6	0	0	0	0	12	**0.500**
	Neutral	0	1	0	12	0	0	0	13	0.923
	Sad	0	0	0	0	11	2	0	13	0.846
	Fearful	0	0	0	0	2	10	2	14	0.714
	Disgusted	0	0	0	0	1	1	12	14	0.857
	Tested instance	11	15	11	12	14	13	14	90	0.764
	Precision	0.818	0.600	**0.545**	1.000	0.786	0.769	0.857	0.768	0.765

4.5 Discussions

(1) Objective Measures. This study proposes mathematical models based on three data mining methods to predict affective states that are elicited by viewing static colour pictures from the IAPS. These models use physiological and behavioural signals acquired with wearable sensors as inputs and discrete affective states as outputs. As indicated by previous studies, our results again highlight the advantages of physiological computing in the affective HCI field. From a technological perspective, the wearable sensors and computing system provide one means of monitoring, quantifying and representing users' affective states in real

time. Based on the mechanisms presumed to underlie the elicitation and differentiation of affect, affect is a multi-componential phenomenon, including efferent physiological, behavioral, and subjective manifestations, unfolding over time with possibly highly organized response profiles (Grandjean *et al*., 2008), multiple measures from different modalities can be used to predict users' affective states more accurately. Using wearable sensors, during the human-product interaction process, users' affect transitions can be uncovered without interfering with users or retrospective bias recalls that self-reports often have.

(2) Prediction Accuracy. Given the prediction accuracy, the results obtained from the proposed models are comparable to previous studies in terms of the best average F_1 measures (general with 14 vs. 21 vs. 42 samples: 60.2% vs. 64.9% vs. 63.5%; female: 78.1%; male: 75.1%; Chinese: 72.0%, Indian: 73.0%; Western: 76.5%). Nevertheless, much higher accuracies have also been reported, such as Picard *et al*. (2001) with 8 emotions at 81%, Lisetti and Nasoz (2004) with 6 at 84%, and Gu *et al*. (2010) with 4 at 90%. While acknowledging their achievement, it is cautious to do direct comparisons. First, Picard *et al*. (2001) only employ one healthy subject with 2 years of acting experience. It is possible that the specific features and prediction results achieved from one single subject may not be applicable to other subjects well. In other words, the results from Picard *et al*. (2001) may not be well generalized to the overall population. Second, Gu *et al*. (2010) use a smaller sample size and a smaller number of emotions to be recognized compared to the present study. This is also recognized by Gu *et al*. (2010) who points out that their subject pool should be expanded for further study. Third, the prediction accuracy is also influenced by the affective stimuli used for emotion elicitation. Lisetti and Nasoz (2004), for example, utilize movie scenes for eliciting emotions, and the duration of the presentation of these movie scenes is from 70 to 231 seconds. This duration is much longer than that in our picture viewing strategy.

Nevertheless, it is also difficult to have such movie scenes that have a strong capability of eliciting emotions in real human-product interaction scenarios.

Unlike previous work, our study further focuses on the sample variety in terms of gender and culture. First, it is interesting to find that when the sample size is 21, it has the best result by one-way ANOVA (21 samples vs. 14 samples, $p < 0.01$; 21 samples vs. 42 samples, $p < 0.01$) in terms of the average F_1 measures across different data mining methods (see Tables 4-5, 4-6, and 4-7 for comparisons). This may be explained that when the sample size is too small, there is not enough data for model construction and that when the sample size is too large, the models constructed cannot account for huge individual differences.

(3) Influence of Gender and Culture. The main contribution of the present study is that the specific-models generally perform better than the general models in terms of the best average F_1 measures for different models and different affective states. This generally supports the notion that the objective specificity in the same gender group or in the same cultural group is higher than that in the general group. In terms of gender differences, consistent with previous research studies (e.g., Bradley *et al*., 2001b), females seem to be more reactive to aversive pictures (i.e., fearful and disgusting stimuli) than males. As for cultural differences, Western participants seem to show a higher specificity than the other two groups, especially for the categories of neutral, sad, and fearful. Therefore, it is likely that culture factors plays a role in the affective responses and people in the same cultural group generally show higher homogeneity than those in diverse cultural groups. This finding is consistent with previous studies that reported affective responses are culturally shaped (e.g., Mesquita, 2003). However, the current method cannot identify which specific physiological signals play important roles in making these differences. Nevertheless, it is both theoretically and practically meaningful to compare culture-specific, gender-specific, and general models. Theoretically, by comparing

between gender-specific models and between culture-specific models, we are able to identify to what extent objective measures account for different cultural and/or gender effects (e.g., sensitivity) on specific affective states. It thus provides practical guidelines when designing products and HCI applications that males and females might respond to rather differently, such as jewellery, video games (indicating gender differences), culturally specific clothing and accessories, and so on. Several HCI applications have been successfully developed to assess and utilize the affective information of typical users in order to permit more meaningful and natural HCI (e.g., Mandryk and Atkins, 2007; Liu *et al*., 2008).

(4) Emotion Labelling. Furthermore, the performance of these models depends on many factors, such as the quality of the collected data, the participants involved, the stimuli applied, the data mining methods used, and so on. One prime problem is how to label emotion reliably. In this study, this is done by the participants' verbal reports. As one's verbal reports move further away, the variability of objective measures might increase, and their sensitivity might decrease. This, to some extent, influences the performance of the models. This is demonstrated by the low F_1 measures of amused and content in most of the models. Another important issue, we hypothesize, is the possible unresponsiveness in terms of some participants' *some* physiological reactions to the selected affective stimuli. It potentially introduces a real danger that group averages only reflect blunted emotion effects. In order to compensate for such adverse effects, it would be desirable to have a screening procedure to exclude the unresponsive participants to the target affective states for further research. For example, this can be done by measuring intensity of elicited emotions by the participant's self-report or by excluding the objective measures that are below certain limit. However, this is still an open question since individuals might be quite diverse in terms of their physiological and/or behavioural unresponsiveness. Finally, another limitation is that we are not able to

differentiate contagious emotion and mimicry by the visual stimuli from the real evoked emotion by the semantics of the visual stimuli. Therefore, further research that can differentiate the differences among them using physiological measures is desirable.

(5) Emotion Elicitation Context. Another difficulty is how to elicit reliable affective data that links to real affective states of users in day-to-day scenarios. In this research, the data are collected using wearable sensors via passive viewing static affective pictures. For one thing, although the IAPS provides standardized affective stimuli and facilitates comparisons among different research groups, the way in which emotions are elicited in the strictly controlled laboratory environment limits the social-cultural interactions. It thus is deviated from real applications, where emotions are often not only biologically constituted facts, but also social and cultural products. In the future, we plan to use real human-product interaction applications as ways to elicit users' affective experience, for example, assessing how affective states influence driving safety, video gaming, as well as online social networking. Further, it is also important to consider the nature of these social-cultural interactions. Using the example of video gaming, players might plausibly exhibit very different physiological profiles depending on whether the scenario is single-player or multi-player and cooperative or competitive. For another, the data are collected from 42 participants with different demographic backgrounds. It not only allows us to build three different types of person-independent affective models, but also these demographics as well as other contextual information, such as the activity the user is doing, time, location, and so on, can even be combined with appropriate features for modelling future affective HCI applications.

(6) Data Mining Methods. The obtained results are also tied to the specific data mining methods as well as to the ways in which we divided the data. Hence, in this research, as many as three advanced data mining techniques with seven different methods are applied and their

modeling produced different patterns of results. Other methods reported in the previous literature, such as support vector machine (Liu *et al*., 2008), Marquardt back propagation (Lisetti and Nasoz, 2004), and a combination of different techniques is also promising (Frantzidis *et al*., 2010).

4.6 Summary

In this chapter, multiple affective responses are measured using facial EMG (ZM and CS), respiration rate, EEG (alpha wave and beta wave), and SCR with wearable sensors when participants are exposed to a wide range of visual affective stimuli. Three types of models are constructed that provide more insight in how gender and culture shape users' affective responses. Results demonstrate that objective signals are capable of predicting categorical affective states in real time.

These findings indicate that along with mathematical models, measuring objective signals using wearable sensor networks in real time might be an effective way to determine the affective states, and further to improve affective design. As affective design suggests, we try to maximize pleasure and minimize pain during the human-product interaction process. Therefore, if we can predict uses' affective states during the interaction process with systems, we can try to adjust the system based on the user's affective states. In some instances, optimal performance requires an appropriate arousal level and vice versa (Yerkes and Dodson, 1908). For example, in aviation safety and repetitive work, a state of boredom and low vigilance with high levels of automation may increase risks of accidents. If we detect such boredom and low vigilance, we can remind the user to be more alert. In other areas, such as tutoring and training, driving, and video gaming, it is often necessary to maintain or prevent particular affective states (e.g., nervousness) to have optimal performance and enjoyable user experiences. The core element that makes these applications successful is to embed emotional intelligence, or at least the capability of eliciting, measuring, and predicting affective states into systems.

CHAPTER 5
COGNITIVE NEED ACQUISITION AND ANALYSIS WITH CASE-DRIVEN AMBIENT INTELLIGENCE

This chapter focuses on acquisition and analysis of cognitive needs with case-driven ambient intelligence (C-AmI). A case of macrocognitive design for elderly in-home assistance (EHA) is presented in a smart home ecosystem. Specifically, a C-AmI system is proposed that aims to sense, predict, reason, and act in response to the elderly's ADLs at home. The C-AmI system architecture is developed by synthesizing various sensors, activity recognition, case-based reasoning (CBR), along with EHA customized knowledge, within a coherent framework. An EHA information model is formulated through the activity recognition, case comprehension and assistive action layers. The rough set theory is applied to model activities of daily life (ADLs) based on the sensor platform embedded in the smart home ecosystem. Assistive actions are fulfilled with reference to *a priori* case solutions and implemented within the AmI system through human-product-ambience interactions. Initial findings indicate the potential of C-AmI for cognitive need acquisition and analysis in terms of enhancing context awareness of EHA applications.

5.1 Introduction

Healthcare systems, in particular for the elderly, have attracted enormous attention worldwide (Cortés *et al.*, 2007). The National Association of State Units on Aging has reported an urgent need for EHA, whereby the elderly suffering from various cognitive impairments are equipped with homecare assistance in their daily living. Due to high cost of institutional living, it is imperative for social security and healthcare systems to take advantage of the prevailing assistive technologies (Blake and Bodine, 2002), such as wireless sensor networks (WSNs), HCI, and AI. The potential of assistive technologies for EHA applications manifests itself through a smart system design that is capable of detecting those undesirable situations that are building up, like a hazard or security threat (Aarts, 2004).

As discussed in Chapter 2, high eventual satisfaction of a cognitive need can be predicted from the low level operations and actions that form the activity (Leont'ev, 1977). When individuals engage and interact with their environment, productions of interactions are resulted. These interactions are “exteriorized” forms of mental processes, and as these mental processes are manifested in tools, they become more readily accessible and communicable to other people, thereafter becoming useful for social interaction: you are what you do (Fjeld *et al.*, 2002). Hence, through activities that people perform, it is likely to tell their plans, goals, intentions, and cognitive needs.

Therefore, an important aspect of EHA is to monitor the behavior of the elderly regarding their ADLs when they are not accompanied by caregivers. Such activities include self-care, work, homemaking, and leisure (ADLs, 1998). It is likely that elderly people tend to exhibit certain symptoms like memory loss, and as a result may forget to turn off power after cooking, for example. It is desirable for the system to act upon the ongoing EHA situation based on activity recognition to remind users to turn off power if the system has detected any anomaly as compared with the normal user activity patterns. However, successful operations of such systems rely not only on hardware and software infrastructures, but also on soft computing techniques, as well as integration of sensing, predicting, reasoning, and acting in a coherent and systematic fashion (Cortés *et al.*, 2003).

In this regard, AmI, which leverages pervasive computing, WSNs, HCI, and AI, has emerged as a promising platform and attracted much attention (Remagnino and Foresti, 2005; Augusto, 2007). The key feature of AmI is context awareness, that is, to enable systems to understand users' cognitive needs and situational contexts so as to provide personalized services by tailoring its reaction upon the environment and users' cognitive needs proactively (Aarts, 2004). To make the user-system interaction more natural, the system is embedded in the environment and adaptive to user feedback. AmI lends itself to be a new paradigm of information and communication technologies, taking the integration provided by pervasive computing one step further to realize context awareness (Ducatel *et al.*, 2001).

While AmI provides a powerful technological platform to meet users' cognitive needs, the EHA solutions must be embedded into the unique decision making scenarios of specific EHA applications. Moreover, a system model for coherent integration of various AmI components is imperative (Chen *et al.*, 2009). Towards this end, this chapter proposes a C-AmI model to sense, predict, reason, and act in response to the elderly's ADLs in a smart home ecosystem. A C-AmI system architecture is developed by synthesizing various sensors, activity recognition, CBR, along with EHA customized knowledge, within a coherent framework.

5.2 Information Model for Elderly in-Home Assistance

EHA has been envisioned to shift from the traditional emphasis on providing physical assistance by caregivers to health promotion and quality of life conservation through a context-aware AmI system embedded in a home environment (Cook, 2006). To achieve AmI context awareness, enormous EHA information needs to be organized systematically in accordance with the EHA decision making process. As shown in Figure 5-1, EHA decisions imply a sophisticated information model, which entails a pyramid of abstraction from data to knowledge, involving four levels of decision making.

The *activity level* is a physical layer that comprises all the hardware (including sensors) and interactions between users and the environment. A context space exists corresponding to various activities that take place in relation to each particular EHA scenario, yet explicit contexts can hardly be inferred at this level.

Based on these raw data, a specific EHA context can be identified at the *context level*. Activity recognition is fulfilled through diverse sensors embedded in the environment. The AmI system aggregates and interprets the collected activity-related sensor data into important contextual labels (e.g., John, aged 68, arthritis, etc.), based on which an EHA context model can be constructed.

Then the AmI decision-making process further goes up to the *case comprehension level*, whereby concrete stories of an EHA scenario, namely, an EHA case, are articulated by a reasoning engine. Structured descriptions of each individual EHA case are stored in the knowledge base. The AmI system analyzes potential problems that the elderly are facing in the EHA case, by matching them with previous stored EHA patterns. These EHA cases must be knowledge-intensive and capable of explaining the ongoing activities in the situation.

At the *assistive action level*, the system suggests appropriate assistive actions based on similar cases retrieved from the case base. Each assistive action (e.g., a reminder through a PDA) is transited down to the activity level for acting upon the user and the environment. It is important that the entire process constitutes a closed-loop system such that it can be adaptive and sensitive to user feedback.

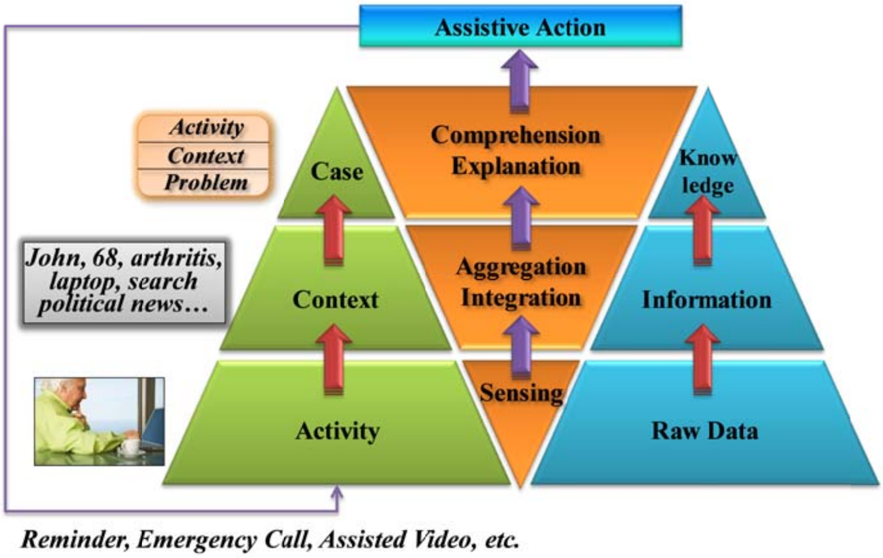


Figure 5-1 Levels of abstraction in EHA

5.3 Case-Driven Ambient Intelligence

The complexity of EHA decision making manifests itself through such key technical challenges for achieving EHA context awareness as:

(1) Context identification – how to identify users' cognitive needs through ADLs and other relevant contexts embodied in their activities;

(2) Context modeling – how to acquire activity-related data and describe, interpret and organize such data as structured information;

(3) Case comprehension – how to reason adequately about the contextual information and articulate users' cognitive needs and behavior;

(4) Assistive action – how to act appropriately to provide homecare assistance corresponding to the ongoing EHA situation.

To deal with these challenges, we propose a C-AmI system, which performs as an intelligent system to sense, predict, reason, and act in response to the elderly's ADLs. As a well-established AI paradigm, CBR lends itself to many advantages towards modeling and implementation of EHA context awareness. Cases are composed and represented from multiple sources of contextual information, and thus benefit from prior experience and make comprehensive knowledge easy to understand. In addition, each prior case implies an actual problem solving episode of experience. Representative cases chosen after validation are conducive to producing clarification of causes and consequences of problems. Moreover, a C-AmI system can solve new problems based on solutions of similar past cases with a presumably extensive, multi-relational model of customized domain knowledge (Prentzas and Hatzilygeroudis, 2007).

As illustrated in Figure 5-2, a C-AmI system exemplifies a layered architecture comprising four steps, including context identification, context modeling, case comprehension, and assistive actions (Joëlle *et al.*, 2005; Becker *et al.*, 2006). While the context space represents the physical environment where ADLs of users take place, the mediation of the C-AmI system starts from context identification, encompassing sensing, perception, context middleware, and recognizing layers. The *sensing layer* is to capture the raw contextual data using various sensors in the AmI environment (e.g., RFID tags and readers, motion and environmental sensors). The *perception layer* is to transform a continuous sensor stream into discrete percepts of data in a multimodal form, e.g., a hexadecimal ID representing a tagged object. Percepts can be further processed by cognitive subsystems and constructed as a conceptual network of knowledge by the upper layers of the C-AmI system. The *context middleware layer* describes the hardware and software on the server, and converts the physical space, where heterogeneous contexts are acquired, into a semantic space. It facilitates the contexts to be easily accessed by context-aware services, including a context interpreter and aggregator (Gu *et al.*, 2005). The interpreter maps contextual information from a lower to a higher abstraction level. The aggregator gathers logic-related information and makes it available within a single component for the next layer (Dey *et al.*, 2001). The *recognizing* *layer* formulates activity models to predict key contextual information of ADLs by processing location, time, personal profiles, environmental, and other relevant information obtained from the context interpreter and aggregator.

The next step is context modeling. It constitutes a *representation layer,* where context models are built for a rigorous description and management of diverse contextual information. Following this step is case comprehension, which aims to understand specific EHA cases through the CBR engine at the *reasoning layer*. CBR entails a mapping mechanism from the problem space (new cases) to the solution space (the case base). The last step comprises three layers that perform as a problem solver to provide homecare assistance services. The *assisting layer* finds solutions of assistance actions for a specific EHA case. The *controlling layer* then executes commands by decomposing these solutions into single actions (Becker *et al.*, 2006). The *acting layer* performs physical actions upon the user and/or the environment, for example, turning off the power switch of a coffee maker, or sending a message reminder via a mobile phone. It is noteworthy that the C-AmI architecture is structured as a closed-loop system, which is adaptive to the dynamic context, responsive to users, and consequently conducive to natural human-product-ambience interactions.

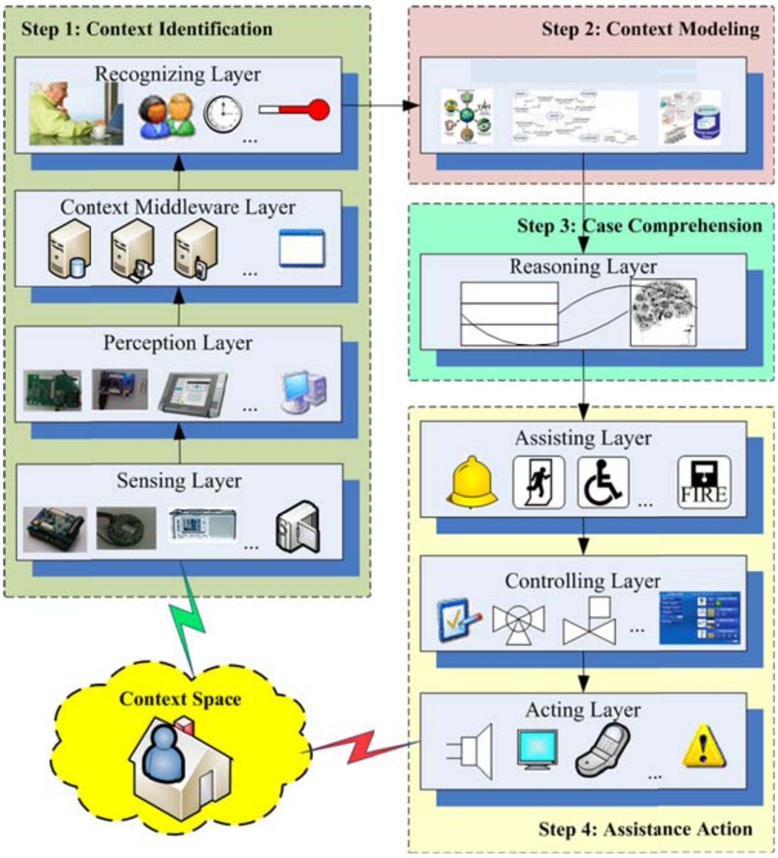


Figure 5-2 Case-driven AmI system architecture

5.4 Testing Cases

Four EHA cases have been composed to test the C-AmI system in a smart home ecosystem, called STARhome (www.starhome.i2r.a-star.edu.sg). Figure 5-3 shows the layout of the STARhome along with testing cases. These cases involve five different types of contexts: personal, task, social, spatiotemporal, and environmental contexts. Case 1 (see Figure 5-4(a)) is assumed to be a new EHA case that seeks smart solutions, whilst the other three cases, depicted in Figure 5-4(b)-(d), are solved cases stored in the case base.

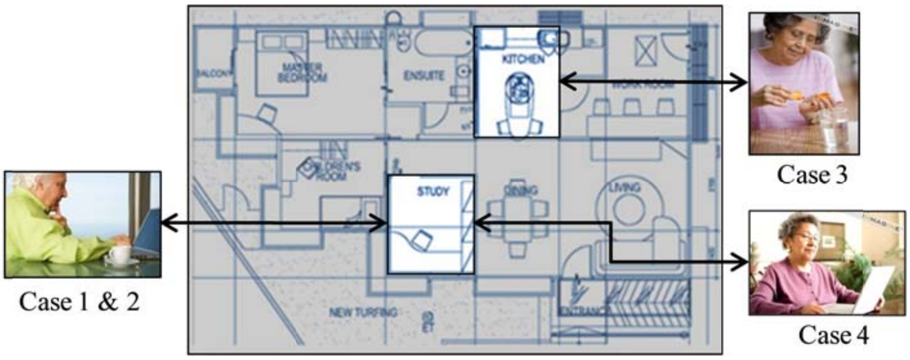


Figure 5-3 Layout of the STARhome with each testing case.

An EHA Scenario: Using Computer
Personal: John, Male, 68, likes political news, has high blood pressure & arthritis; Task: download political news video; Social: suburb, grandpa with limited IT knowledge; Spatiotemporal: 10am, 29-OCT-2008, Study room; Environment: 25 ˚C, 50% humidity, with moderate lighting, quiet;
Problem: how to download political news video?

(a) Testing case 1

Case 2: Using Computer
Personal: John, Male, 68, likes political news, has high blood pressure & arthritis; Task: search info about high blood pressure; Social: suburb, grandpa with limited IT knowledge; Spatiotemporal: 10:30am, 19-Sept-2008, Study room; Environment: 26 ˚C, 56% humidity, with moderate lighting, quiet.
Solution: remind to use Google for searching high blood pressure.

(b) Testing case 2

Case 3:Taking Medication
Personal: Mary, Female, 67, likes Peking opera, has heart disease; Task: Take medication 3 times per day after meal Social: suburb, grandma; Spatiotemporal:11:30am, 19-Sept-2008, Kitchen; Environment: 22 ˚C, 46% humidity, bright, quiet.
Solution: If the user takes pills 30min later than usual, remind him/her with moderate voice.

(c) Testing case 3

Case 4: Using Computer
Personal: Mary, Female, 67, likes Peking opera, has heart disease; Task: watch Peking opera on YouTube; Social: suburb, grandma; Spatiotemporal: 1130am, 19-Sept-2008, study room; Environment: 22 ˚C, 46% humidity, bright, quiet.
Solution: YouTube website, typing key words to find relevant opera for watching.

(d) Testing case 4

Figure 5-4 EHA testing cases

To solve a new case, it is important to decide precise feedback for triggering the assistive action. In the case of taking medication or downloading videos, the system needs to know if the medicine has really been taken or the video has been successfully downloaded. This means that, even though CBR can make high-level decisions, the exact decision still needs to be fine-tuned. Hence, a rule-based customized knowledge model is adopted for solution adaptation within the CBR framework.

5.5 Context Identification

5.5.1 Sensor Platform for Data Acquisition

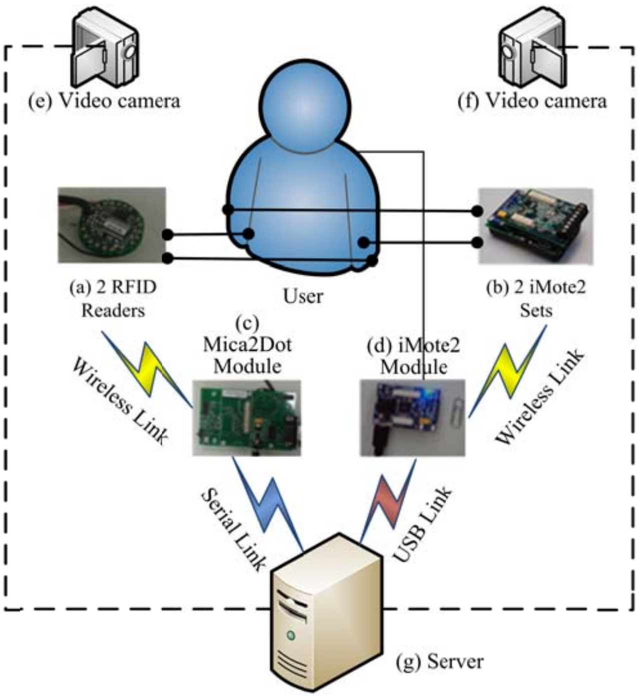


Figure 5-5 Sensor platform

Figure 5-5 shows the configuration of a sensor platform for raw data collection, involving a user's hand motion, locations, user ID, temperature, humidity, and lighting. Wearable sensors include three Crossbow iMote2 sets and two RFID readers. Ambient sensors consist of multiple video cameras installed on the ceilings of the testing area and 77 RFID tags attached to the daily objects involved in the testing process (See Appendix A). All the RFID tags are installed by a small team of researchers in the smart home for about 3 hours while the video cameras have already been installed in the smart home. Then all the RFID readers are installed and debugged successfully in 2 days.

The user wears a RFID wristband reader and a Crossbow iMote2 set on each of his/her wrist and hand, and a third Crossbow iMote2set on the waist. The RFID reader is used to detect tagged objects involved in an activity within a distance from 6 cm to 8 cm sampled at a rate of 2 Hz. The iMote2 set is for detecting hand and body motion (i.e., 3-axis accelerometer), surrounding temperature, lighting, and humidity with a sampling rate of 128 Hz. The tag ID detected will be transmitted wirelessly to a Mica2Dot Module linked to the server through a serial port. The raw data sensed by the iMote2 set will be transmitted wirelessly to iMote2 module linked to the server via a USB port. The server runs on a Tiny OS-based laptop with a MIB510CA serial interface board. A UHF RFID reader is embedded in each room to identify the user ID and his/her location using two different UHF tags. The cameras record the overall situation of an activity. These ambient sensors are useful to construct the ground truth for activity recognition testing.

5.5.2 Rough Sets for Activity Model Construction

The rough set theory is applied to synthesize diverse sources of ADLs to construct activity models as rule-based classification problems. A rough set software system, RSES 2.2.2, is adopted for data analysis (Bazan and Szczuka, 2005). The rough set model excels in tackling vagueness and uncertainty using rough approximations (Pawlak, 1991). There exist inevitably noise and missing data during data acquisition. RFID readers might collect ‘Null’ values, when outside the sensing area from the tagged objects. Unlike those probabilistic activity recognition methods, rough-set data analysis is self-contained and does not require *a priori* assumptions of probabilistic distributions (Duntsch and Gediga, 1998). A rough-set model produces a complete set of consistent and minimal decision rules using an objective knowledge induction process for reference (Pawlak, 1991). It also facilitates data fusion from various sensors without considering their distributions. Moreover, it can handle both symbolic and numeric data (Bazan *et al.*, 2000), thus valuable for dealing with qualitative and quantitative reasoning that is always involved in EHA applications. Similar to that elaborated in Chapter 4, the basic reasoning process is according to the rough set theory below.

The raw data from multiple sensor readings are preprocessed and organized as feature vectors. In general, a data set of sensor readings (i.e., observations) can be represented as an information system, $S = (U, V)$, such that $\forall \mathbf{v} \in V$, $\mathbf{v}: U \rightarrow V^*$, where U is a nonempty finite set called the universe, V is a nonempty finite set of sensor variables, and V^* is the value set of an observation vector $\mathbf{v}$. An observation vector of symbolic and numeric sensor readings depicts an EHA state, including user motion, environmental information, and the IDs of tagged objects in the form of $\mathbf{v} = \mathbf{v}^{\mathrm{s}} \cup \mathbf{v}^{\mathrm{n}}$, where $\mathbf{v}^{\mathrm{s}} = \{v^s{}_s\}_S$ and $\mathbf{v}^{\mathrm{n}} = \{v^n{}_n\}_N$, denoting the symbolic and numerical vectors with S and N variables, respectively. Accordingly, $V^* = V^{s*} \cup V^{n*}$, where V^{s*}, V^{n*} are the respective value sets of $\mathbf{v}^{\mathrm{s}}$ and $\mathbf{v}^{\mathrm{n}}$.

For the testing cases at STARhome, an observation vector is defined with 16 sensor variables, i.e., $\mathbf{v}$ = {*accel_body_x*, *accel_body_y*, *accel_body_z*, *accel_right_x*, *accel_right_y*, *accel_right_z*, *accel_left_x*, *accel_left_y*, *accel_left_z*, *temperature*, *humidity*, *lighting*, *location*, *left_object*, *right_object, user_ID*}. These variables describe the contextual information in a particular EHA case. The first 12 variables are numeric measures and the last four are symbolic. The data are collected at a fixed frequency (i.e., once per second) such that the numeric ones take average values of the raw data whereas the symbolic ones might be 'Null', indicating no tagged objects are involved during that sampling interval. All the data are then tabulated into a standard vector form. For example, a specific instance of the observation vector could be V_{10}^*= [*164, 9513, 1894, 36501, 5457, -54704, -3420, -122147, -28837, 26, 49, 12, 01E00401000231D269, Null, 0BE00401001876A8E2, 01E00401000231D4B0*]. The first

12 numerical values indicate the user's body and hand motion and the environment status. The last four tag ID numbers suggest the 'location' of the activity, the 'objects' that interacted with the left hand and right hand, and the 'user' involved in the activity, respectively. To facilitate rule generation, numeric measures are discretized using cuts that are produced with the global strategy based on the maximal discernibility heuristics (Bazan *et al.*, 2000).

Corresponding to sensor data collected at the activity level, a set of EHA decision variables are defined to characterize the context labels at the context level (see Figure 5-1). Let $\mathbf{d} = \{d_k\}_K \in D$ denote a decision vector with K decision variables. Accordingly, $D_h^* = \{d_{1h}^*, ..., d_{Kh}^*\}_H$ is the value set of **d**, where H is the total number of decision scenarios. For the testing cases, training data are composed as a decision table, $\Omega = (V \cup D, C)$ .Two types (K=2) of decision variables exist for the testing cases: *'activity_name'* and *'user_role'*. The former refers to the context of an activity among 20 ADLs in Table 5-1. The latter indicates who is carrying out the activity, either *'John'* or *'Mary'*. For example, an instance of the context vector would be D_{10}^* = [*'taking medication', 'Mary'*], corresponding to observation vector V_{10}^*.

For any object $z \in U$, we can generate a decision rule based on the rough set theory, such that $\forall q \in [1, Q]$, the predecessor of the rule takes the conjunction of certain sensor variable instances, $v_q^\phi(z)$, and the successor takes on specific values of decision variables, $d^\phi(z)$, where Q denotes the total number of sensor variables instantiated by this rule. The general form of a decision rule constructed for reduct Φ and object z is thus given as the following:

$$\left(v_1^\phi = v_1^\phi(z)\right) \wedge \left(v_2^\phi = v_2^\phi(z)\right) \wedge ... \wedge \left(v_Q^\phi = v_Q^\phi(z)\right) \Rightarrow d^\phi = d^\phi(z). \quad (5\text{-}1)$$

We set up a five-fold cross-validation experiment for the testing EHA cases. Accordingly, there are 810, 923, 893, 927 and 839 rules generated by five iterations, respectively. Among five reducts, the maximal support is 16 and the minimum is one. For example, one identified rule reads as: *'((left_object=water) ∧ (right_object=Null) ∧ (location=kitchen) ∧ (user_ID= 01E00401000231 D4B0) ⇒ (activity_name =taking _medication, user_role=Mary(4)).'* It means that if left hand interacts with 'water', right hand touches 'nothing', location is 'kitchen', and user ID is '01E00401000231D4B0', then we can infer that 'Mary' is 'taking medication', for which the support level is four. Such mined rules provide the basis to classify various ADLs associated with particular EHA cases.

5.5.3 Experimental Results

The experiment in the STARhome involves 20 common ADLs (see Table 5-1). Four participants are involved on an alternate basis in two weeks to collect the data. For each ADL, two persons are tested. One carries out the ADLs sequentially, while the other annotates each activity and controls the time. Each participant is asked to repeat all 20 ADLs for 5 times. All sensor data for ADLs are recorded and manually labeled with corresponding decision variables. Along with particular ADL context, each observation is tabulated into the decision table, from which a large number of entries can be obtained for the training data. For the illustrative simplicity, this study selects 330 most representative activity data for analysis.

Table 5-2 shows the experiment results. 'True positive (TP)' indicates that an activity is correctly classified as the right class, whereas 'false positive (FP)' means that an activity is labeled as a wrong class. 'False negative (FN)' corresponds to activities not reported when they occur. The column 'precision', defined as 'TP/(TP + FP)', is the measure of the probability that a given classification is correctly identified, and 'recall' is defined as 'TP/(TP + FN)', indicating the probability of correctly inferring a true activity. For all testing cases, the precision and recall for 'take medication' are 91% and 71%, respectively (Case 3), whilst 88% and 100% for 'using a computer' (Cases 2 & 4). The average precision and recall across all activities are both 92%, indicating an acceptable activity model recognized for 20 common ADLs.

Table 5-1 ADLs involved in the experiment

1	Washing face	11	Ironing
2	Making up	12	Listening to radio
3	Cleaning a dining table	13	Making tea
4	Taking medication	14	Vacuuming the room
5	Brushing teeth	15	Using a phone
6	Combing hair	16	Making orange juice
7	Cooking an oatmeal	17	Using a computer
8	Dinning	18	Toileting
9	Watching movies/DVD	19	Watching TV
10	Washing clothes	20	Making coffee

Table 5-2 Experiment results of 20 ADLs

ADL#	TP	FP	FN	Precision	Recall
1	11	1	3	0.92	0.79
2	16	0	0	1.00	1.00
3	15	3	2	0.83	0.88
4	10	1	4	0.91	0.71
5	12	2	2	0.86	0.86
6	10	2	0	0.83	1.00
7	19	1	0	0.95	1.00
8	17	0	0	1.00	1.00
9	18	2	1	0.90	0.95
10	18	1	2	0.95	0.90
11	18	1	0	0.95	1.00
12	15	2	3	0.88	0.83
13	16	1	4	0.94	0.80
14	18	0	0	1.00	1.00
15	18	0	1	1.00	0.95
16	16	3	3	0.84	0.84
17	15	2	0	0.88	1.00
18	17	1	0	0.94	1.00
19	11	0	0	1.00	1.00
20	13	3	2	0.81	0.87
Total	303	26	27	0.92	0.92

5.6 Context Modeling

In order to deal with imperfect and ambiguous information, the context space is described as five components, namely, personal (ct_1), task (ct_2), social (ct_3), spatiotemporal (ct_4), and environmental (ct_5), based on the activity theory (Kofod-Petersen and Cassens, 2005). Figure 5-6 shows the taxonomy of EHA context representation for Case 1. Each component is characterized by one of the three properties: profiled, sensed, or predicted. Each property further assumes a confidence level (independent from each other), regarding the truth of each piece of contextual information. Profiled contexts are mainly descriptive and relatively unchanged in most situations. Hence, we assume its confidence level as $P_{profiled}$ = 98%. Sensed contexts are those directly acquired from the sensors. The confidence level is determined by the sensor itself, which is set at P_{sensed} = 95%. Predicted contexts correspond to the information derived from the activity recognition module. The confidence level is the overall accuracy (recall), i.e., $P_{predicted}$ = 92%. Each context has several feature variables to describe detailed contextual information. For example, the feature variables in spatiotemporal context are time, activity sequence and location, whereas user location is at the granularity of rooms. Time is sensed using the iMote2 set, and activity sequence is based on the time. Consistent with a bottom-up approach, pieces of contextual information are first specified in great details and then organized into different contexts associated with different properties to form upper levels, which in turn are synthesized to form a complete context space at the top level, as shown in Figure 5-6.

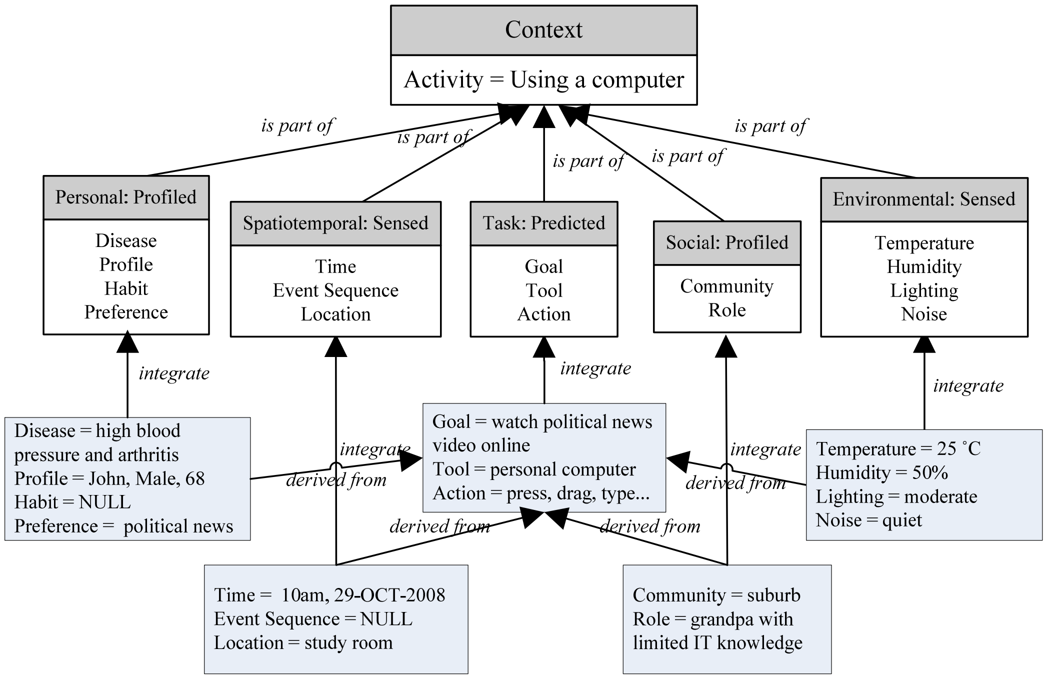


Figure 5-6 An example of context model for Case 1

5.7 Case Comprehension

The C-AmI system employs a hybrid method combining CBR and rule-based reasoning for case comprehension. High-level decisions are first derived based on CBR, and then an EHA customized knowledge model compatible with rule-based reasoning is deployed to fine-tune the decisions for particular EHA cases.

5.7.1 Case Base Organization

The case base is denoted as $C^b = \langle C_1, ..., C_{20}, I, C^k \rangle$, where $C_1, ..., C_{20}$ are 20 classes of cases, $I = \langle A, L \rangle$ is a case indexing model, and C^k is the EHA customized knowledge model for case adaptation (see an example in Figure 5-7). An ADL in a case is denoted as A, performing as the major index, whilst L depicts the location where the ADL takes place, acting as the sub-index. All cases are organized hierarchically according to the case indexing model. They are first grouped into 20 classes based on the major index, i.e., ADLs, and within each case class, cases are further categorized into sub-classes according to their locations, i.e., the sub-index. Unlike the context model, each case is represented in a top-down fashion, where contexts with different properties are described with multiple feature-value pairs, as shown in Table 5-3.

It is not uncommon in EHA applications that the same activity recognized from the sensor platform may imply different stories (i.e., context), when taking place at different locations. It is hence necessary to customize general case knowledge further according to locations of the activities. Figure 5-7 illustrates an EHA customized knowledge model developed for case adaption. It is constructed based on personal habits of the elderly and modifiable for individuals based on adaption knowledge derived through expert interviews. Corresponding to the cases at different locations, this model cohesively links major tagged objects (e.g., personal computers) that related to typical tasks (e.g., online searching). Based on the customized knowledge model, EHA solutions (e.g., Google) are fine-tuned through a downward-branching hierarchical reasoning process. Such knowledge can be articulated using IF-THEN rules. For example, the rule recommending 'Google and/or Yahoo' is expressed as '*IF (use PC for online searching in the study room), THEN (try Google and/or Yahoo)*'.

Table 5-3 Case representation of Case 3

Problem Context	Feature	Value
ct_1: Personal (profiled)	Profile	Mary, female, 67
	Preference	Peking opera
	Disease	Heart disease
ct_2: Task (predicted)	Goal	Take medication regularly
	Tool	Water and cup
	Action	Pour, rise…
ct_3: Social (profiled)	Community	Suburb
	Role	Grandma
ct_4: Spatiotemporal (sensed)	Time	11:30am, 19-SEPT-2008
	Activity sequence	After meal
	Location	Kitchen
ct_5: Environmental (sensed)	Temperature	22˚C
	Humidity	46%
	Lighting	Bright
	Noise	Quiet
Solution	Remind to take pills after meal	

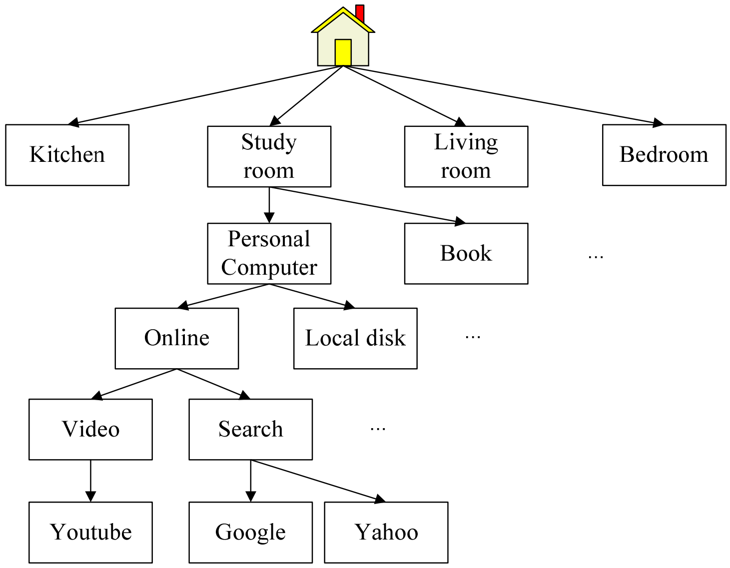


Figure 5-7 The EHA customized knowledge model

5.7.2 Case Retrieval

Case retrieval is the process of finding prior solved cases that are closest to the current case. The retrieval process starts with Case 1 and proceeds with the following steps:

(1) Identify case class k that equals to the class of Case 1;

(2) Set j = 1; select Case j from class k;

(3) Compare the location of Case 1 with that of Case j;

(4) If their locations are identical, then go to Step (5); else $j = j + 1$, go to Step (3);

(5) Calculate the similarity between Cases 1 & j;

(6) Set $j = j + 1$; if $j \le K_c$ (the total number of cases in class k), then go to Step (3); else go to Step (7);

(7) Rank the retrieved cases by a similarity measure and choose those with similarity larger than the predefined threshold.

The cosine coefficient between two cases is adopted as the similarity measure, which is calculated based on latent semantic analysis (LSA) (Martin and Berry, 2007). A semantic space for the case base must be constructed before LSA can be applied. One case base composed of n cases and m key terms (extracted from those cases, usually $m >> n$) can be represented as a term-by-case matrix, $\mathbf{A}_{m\times n}$, where element a_{ij} is the frequency of the i-th key term that appears in the j-th case. Then, $\mathbf{A}_{m\times n}$ is weighted using a log-entropy transformation to improve retrieval performance. The weighted matrix, $\mathbf{A}^{w}_{m\times n}$, is further decomposed into orthogonal components with singular value decomposition. That is, $\mathbf{A}^{w}_{m\times n} = \mathbf{U}_{m\times r}\Sigma_{r\times r}(\mathbf{V}_{n\times r})^{T}$, where the rows of $\mathbf{U}_{m\times r}$ describe the key-term vectors, and the rows of $\mathbf{V}_{n\times r}$ describe the case vectors. Matrix $\Sigma_{r\times r}$ is a diagonal one with descending-ordered scaling values. In order to remove noise, $\mathbf{A}^{w}_{m\times n}$ is reconstructed with a reduced dimension by keeping the first k largest scaling values while setting the others to zero values in $\Sigma_{r\times r}$, such that, $\tilde{\mathbf{A}}^{w}_{m\times n} = \mathbf{U}_{m\times k}\tilde{\Sigma}_{k\times k}(\mathbf{V}_{n\times k})^{T}$. Hence, case vectors can be derived by back multiplying:

$$\mathbf{V}_{n\times k} = (\tilde{\mathbf{A}}^{w}_{m\times n})^{T}\,\mathbf{U}_{m\times k}\tilde{\Sigma}^{-1}_{k\times k}. \tag{5-2}$$

In order to obtain a fine-grained similarity, the similarity between two corresponding case contexts (e.g., an identical task occurs in two different cases) are computed first. Such measure is then aggregated using a weighted function. Any context can be projected into the case semantic space. Based on Eqn. (5-2), the p-th contexts of Cases c_x and c_y are represented as $\mathbf{ct}^{x}_{p} = (\mathbf{ct}^{xw}_{p})^{T}\,\mathbf{U}_{m\times k}\tilde{\Sigma}^{-1}_{k\times k}$ and $\mathbf{ct}^{y}_{p} = (\mathbf{ct}^{yw}_{p})^{T}\,\mathbf{U}_{m\times k}\tilde{\Sigma}^{-1}_{k\times k}$ in the case semantic space, respectively. The respective values of vectors $\mathbf{ct}^{xw}_{p} = (\alpha_1, \alpha_2, ..., \alpha_m)^{T}$ and $\mathbf{ct}^{yw}_{p} = (\beta_1, \beta_2, ..., \beta_m)^{T}$ are zeros and weighted frequencies (i.e., $\alpha_1 ... \alpha_m, \beta_1 ... \beta_m$) of the key terms specified for the p-th contexts. If the angle between $\mathbf{ct}^{x}_{p}$ and $\mathbf{ct}^{y}_{p}$ is θ_p, then similarity between two corresponding contexts is computed as follows:

$$\cos\left(\theta_p\right) = \left(\mathbf{ct}_p^x \bullet \mathbf{ct}_p^y\right) \Big/ \left(\left\|\mathbf{ct}_p^x\right\| * \left\|\mathbf{ct}_p^y\right\|\right). \tag{5-3}$$

The more similar semantically, the more close to one (i.e., the maximum of a cosine value). Accordingly, similarity between Cases c_x and c_y is defined by taking weights into account, i.e.,

$$\mathrm{sim}\left(c_x, c_y\right) = \sum\nolimits_{p=1}^{5} w_p \cos\left(\theta_p\right) \Big/ \sum\nolimits_{p=1}^{5} w_p \,, \tag{5-4}$$

where w_p is the weight of the p-th contexts of ct_p^x and ct_p^y. For our context model (see Figure 5-6), the weights of context properties can be determined as: $w_1 = w_3 = P_{profiled} = 0.98$, $w_4 = w_5 = P_{sensed} = 0.95$, and $w_2 = P_{predicted}$ 0.92, by assessing the truth value associated with every context property.

For the testing cases, the cosine coefficients of the similarity measure are calculated using online LSA software (www.lsa.colorado.edu). The demo version provides one-to-many and document-to-document comparisons, whereby '*general reading up to 1^st^ year college*' is used as the LSA space, containing 200 dimensions, corresponding to k = 200 in Eqn. (5-2). First, Cases 2 and 4 are obtained as a result of the retrieval process. Then, according to Eqn. (5-3), the similarity values between the corresponding contexts in Case 1 and Case 2 from ct_1 to ct_5 are calculated as 1.00, 0.28, 1.00, 0.93 and 0.75, respectively. Similarity between the corresponding contexts in Case 1 and Case 4 is measured as 0.36, 0.59, 0.73, 0.93 and 0.54, respectively. The fine-grained similarity values are calculated using Eqn. (5-4), that is, $\mathrm{sim}\left(c_1, c_2\right) = 0.80$ and $\mathrm{sim}\left(c_1, c_4\right) = 0.59$. Finally, Case 2 is returned as the result of case retrieval, if the threshold is set at 0.70.

5.7.3 Case Adaptation

The EHA customized knowledge model constitutes the basis of case adaption, including case revision, reuse, and retain. The adaptation techniques is implemented by integrating the substitution and rule-based approaches into a soft reasoning mechanism (Pal and Shiu, 2004), involving the following steps:

(1) Substitution: It replaces invalid parts of the old solution with new content, according to key differences of a new case from the old one;

(2) Rule-based adaptation: The system further refines the solution according to the EHA customized knowledge model;

(3) Evaluation: The user performs evaluation and feedback to the system for improvement;

(4) Storage: If the adaptation is successful, the new case, along with adaptation knowledge, is stored for future use; and the customized knowledge model is also updated if necessary.

This procedure can be illustrated with the testing cases. Assume the most similar case is retrieved as Case 2. It is first analyzed that the main difference is the task context (similarity = 0.28), which is critical for the solution. Therefore, the solution is adapted as '*remind John to use Google for searching political news video*', by substituting the main task context in Case 2 with the new task. Then the EHA customized knowledge model is deployed to refine the solution by applying the rule *'IF (use PC for watching video online in the study room, THEN (try YouTube)'*. The refined solution becomes '*remind the user to try YouTube for searching videos of political news'*. At Step 3, a user, '*John*', should evaluate the refined solution. If he is satisfied, the new case and knowledge about the adaptation are stored in the case base. Otherwise the proposed adaption needs to be revised based on the feedback.

5.8 Case-Driven Assistive Actions

There are generally three categories of EHA assistive services, including emergency treatment (e.g., sudden fall, stroke), autonomy enhancement (e.g., a cooking assistance system), and comfort services (e.g., infotainment assistance) (Nehmer and Karshmer, 2006). The system should be adaptive to different categories of EHA services in order to improve UX.

For emergency treatment, it is desirable for the system to be able to predict any emergency situation proactively. Taking ‘arthritis’ in Case 1 as an example, it has been reported that arthritis has a certain relation with the environment (e.g., temperature and humidity). In order to prevent the aggravation of any symptom, the system should give an early warning. In this sense, the system should be sensitive to those ADLs related to the symptom. For autonomy enhancement, the key issue is to what extent a user is willing to be controlled by the C-AmI system. One decisive factor is whether the usefulness of a C-AmI service outweighs the cost and inconvenience of the control. Therefore, the system should be reliable and trustable with an appropriate degree of autonomy for different user profiles.

Figure 5-8 shows the procedure of case-driven assistance decision making. The assisting layer announces a call for the type of services as recommended by the CBR engine. The controlling layer then triggers action conditions to check whether it should change the control state. If ‘yes’, the acting layer executes the recommended actions upon the user and/or the environment; otherwise it returns to the assisting layer for the next round. Whenever an action is performed, the context state will be changed; otherwise it goes back to execute the input action again. If the problem is solved, the process terminates; otherwise the assisting layer issues another command based on the user feedback.

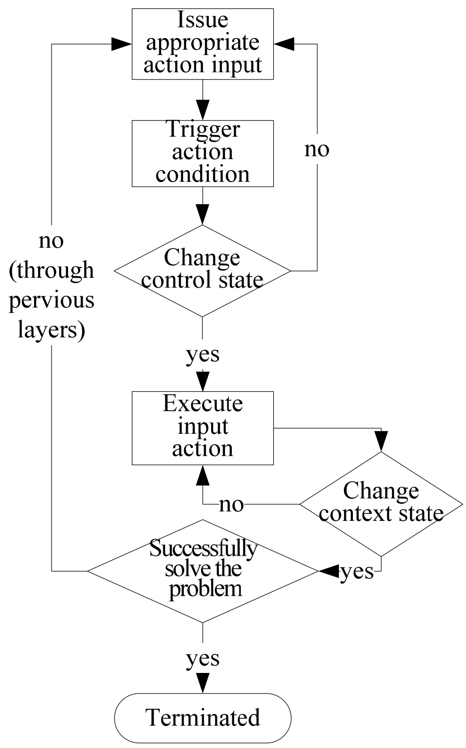


Figure 5-8 The process flow of assistive actions

Regardless of various types of services, usability is an important issue of EHA. The C-AmI system entails a paradigm of implicit HCI (Schmidt, 2005) and facilitates human-product-ambience interactions. The system first takes the user's behavior and other ambient factors as input implicitly; then recognizes, interprets, and understands users' cognitive needs; and finally provides proactive assistance. Nevertheless, such proactive behavior of the system could puzzle the users if explanations of the behavior are provided inadequately. Fortunately, CBR is helpful, to some extent, by showing the tracks of decision making. Another issue is the interface between users and the system. It is desirable that users have certain dialogues rather than monologues with the system. Current implementation of the system takes advantage of existing interfaces. For instance, the reminder can be sent to the user's mobile phone or PDA. Considering the fact that certain impairments, such as hearing or visual loss, are not uncommon among the elderly, assistive actions may be executed via the same sensor platform that is employed for activity recognition. For example, the lighting and noise sensors can also be used to draw attention from the users for taking action.

5.9 Discussions

The proposed C-AmI system takes advantage of wearable and ambient sensors to provide distributed and pervasive sensing capabilities. One example is the tagged objects that the user interacts with using the RFID technique, which offers a natural way to predict the ongoing activity. The limitation is that these prototype sensors are obtrusive for a long time of wearing. Further work lies in consideration of unobtrusive off-the-shelf sensors that are available in the market now.

The rough set-based model achieves a reasonably good performance of activity recognition in terms of the averaged recall and precision. However, it might still be inadequate for some activities. The recall of ‘taking medication’, for example, is 78%, implying that the system might remind the user to take medication even though the user has already done so. Upon examining the rules, unlike other activities that all take place in one location only, this particular activity may occur in three locations (i.e., kitchen, living room, or bedroom), corresponding to three times of taking medication per day. Although the EHA customized knowledge model deliberately incorporates location information into activity patterns, a limited set of training data used in the testing cases leads to such a low recall. Usually, the target dataset must be large enough to contain the patterns while remaining concise enough to be mined in an acceptable timeframe. Therefore, with regard to the low recall of taking medication, more training data in different locations should be included for a better accuracy. Another question worth discussing is how many ADLs should be included so that we can address as many cognitive needs of the user as possible. With only very specific ones in the smart home, we can predict user’s activity and then assist the user as needed in a satisfactory fashion. In this research, 20 ADLs are considered and the results for most of the activities are acceptable. When the number of activities increases, the patterns between two similar activities might be hard to detect and wrong decisions would be made by the system. However, here the key point is if the patterns of individual ADLs can be unique and sufficient training data is available, we expect the accuracy is acceptable.

The LSA method can capture indirect information contained in myriads of contextual information. The example presented in this study shows the potential of CBR. Case adaptation capitalizes on customized knowledge, contributing to relatively high quality of solutions. However, adaptation knowledge is obtained by a tedious process of interviews by domain experts. Usually a causal model between the problem space and the solution space is needed. In addition, complex activity patterns (e.g., interleaved and concurrent activities) are not taken into consideration in the experiment, which may restrict applicability of the system in the real world. Several soft computing techniques can be introduced to case adaption, such as fuzzy decision trees and neural networks, for supervised or unsupervised learning of adaption knowledge from prior cases (Pal and Shiu, 2004).

The C-AmI system can enhance safety by tuning emergency response. It could enhance security while preserving privacy by confining the information only to family members. By understanding more of the local context, and the habits of the users, it might be possible to build systems that better match the expectations of the people in the home. Although the study has been conducted within a home environment using experiments, the C-AmI system can be leveraged to a community or even city level with different configurations of hardware and software infrastructures. For example, within the community, the elderly can walk around, and interact with other people with reminders of taking medication via wireless communication at the same time. Therefore, design EHA applications can be considered as social-technical systems.

5.10 Summary

Cognitive needs of the elderly are acquired and analyzed with AmI that is able to develop smart and cost-effective solutions for EHA applications. It excels in revealing the context-awareness of ongoing EHA situations through human-product-ambience interactions in the smart home ecosystem. A C-AmI system integrates WSNs, activity recognition, CBR, and EHA customized knowledge within a coherent framework. It supports the sensing, predicting, and reasoning of assistive actions by taking advantage of a priori knowledge about solved cases to meet the elderly’s cognitive needs. It entails a multilayered architecture that coincides with the EHA information model that encompasses the activity, context, case comprehension and assistive action levels.

CHAPTER 6
USER EXPERIENCE MODELING AND SIMULATION WITH FUZZY REASONING PETRI NETS

Product ecosystem design involves sophisticated interactions among human users, multiple products, and the ambience, and thus entails the need for systematic modeling of UX with regard to its two dimensions: ambiguous affective states in conjunction with the cognitive process. This chapter presents UX modeling in the context of product ecosystem design, which provides different contexts of users, products, and ambient factors to examine their influence on UX. In order to deal with the uncertainty, complexity, and dynamics associated with UX modeling in the product ecosystem, a fuzzy reasoning Petri net (FRPN) is proposed. Reasoning of diverse constructs of UX is embedded in the fuzzy production rules that are derived from self-reported UX data based on rough set mining. A fuzzy reasoning algorithm is implemented to perform parallel inference by multi-criterion rules and to simulate most likely UX under different ambient factors. A case example of subway station is presented to illustrate the rationale of product ecosystem design for UX. Initial findings and simulation results indicate that the product ecosystem perspective is an innovative step toward AC engineering and the FRPN formulism excels in incorporating UX into product ecosystem analysis.

6.1 Introduction

To design a product ecosystem, it is crucial for the designers to uncover user mindsets and need states, i.e., they need to communicate with the marketing folks and/or the users to get a good grip of user expectations and achieve a shared understanding of critical success factors. However, current practices in product ecosystem development are more ad hoc than systematic, relying on designer's intuition and trial-and-error processes. Little work has been reported in developing theoretical frameworks for product ecosystem design, and providing decision support at the design stage. This, to a large extent, is attributed to a lack of a proper problem formulation of product ecosystems and effective modeling mechanisms for the affective and cognitive aspects of users.

This research presents a new formulation of product ecosystems, which embraces a formal representation of system entities and their interactions. As the pivotal idea of the ecosystem, the ambience is introduced with UX constructed as a series of interaction events. Moreover, the affective and cognitive factors are explicitly defined for UX. Also reckoned are the sources and characteristics of uncertainties for modeling affect, cognition, and their interactions. A FRPN model is proposed as both an elementary AC knowledge module and a reasoning mechanism for system behavior analysis.

The formulation of product ecosystems is expected to foster the development of systematic methods for elicitation, representation, and fulfillment of users' ACNs. Based on the proposed methods, simulation models of the product ecosystem can be built to accommodate digital human users, making it possible to carry out 'what-if' analysis for constructing UX and simulating the business processes. The outcome of the analysis can thus provide designers with decision support to improve UX in terms of user affect and cognition, and enhance the operational efficiency of the product ecosystem.

Before introducing the formal representation of product ecosystems, a subway station is exemplified for subsequent discussions as shown in Figure 6-1. Typical entities involved in the subway station are ticketing machines (TMs), gates that control entry and exit, lifts, staircases, escalators, information boards, shops, restaurants, trains, service persons, users, and their luggage, as well as the environmental settings, such as lighting conditions and noise levels. In this example, the subway station provides services to transport users from one station to another via interactions with multiple interrelated products. It thus involves a series of interaction events in the service process, including “buying a ticket”, “entering the gate”, “going to the platform”, “boarding the train”, “going to the toilet”, “shopping”, “dining”, etc. The first four events are necessary while the remaining ones are optional based on personal needs. The user interacts with the system through a series of interaction events during which UX evolves.

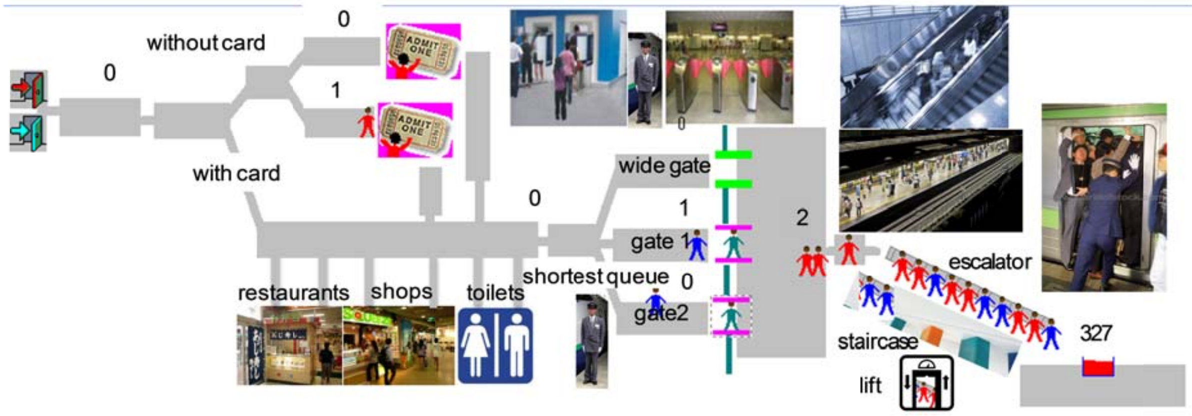


Figure 6-1 Example of a subway station in SIMUL8

The subway station ecosystem implies two aspects of the design problem. On the one hand, the ecosystem profile and the created environment of the subway station determine UX. On the other hand, the business process and the infrastructures of the subway station co-determine the capital investment and operational cost of the service provider. Therefore, the design of the subway station ecosystem must accommodate both UX and cost concerns of the service provider.

6.2 Product Ecosystem Formulation

In the example of the subway ecosystem (see Figure 6-2), User 1 is queuing in order to go to the platform via gate 1; we call User 1 is focally interacting with gate 1 when s/he is entering. However, this process is directly influenced by other products, such as TMs (whether

User 1 needs a ticket), the wide gate, his or her luggage (using wide gate or not), gate 2 (length of its queue), User 2 (who is just in front of User 1), as well as surrounding lighting and noise, and so on. These entities are called ambient factors with regard to User 1 and they collectively constitute User 1's ambient factors. A third notion is the interaction sequence the user adopts to board the train. For example, whether the user looks up at an information board before boarding if s/he is not familiar. If so, whether the information board is easily accessible and readable. In this sense, the interaction sequence also influences the efficiency and UX in the whole process. Only in a way that interdependent products and services are well designed and coordinated, can the efficiency and productivity goal as well as UX be better accomplished.

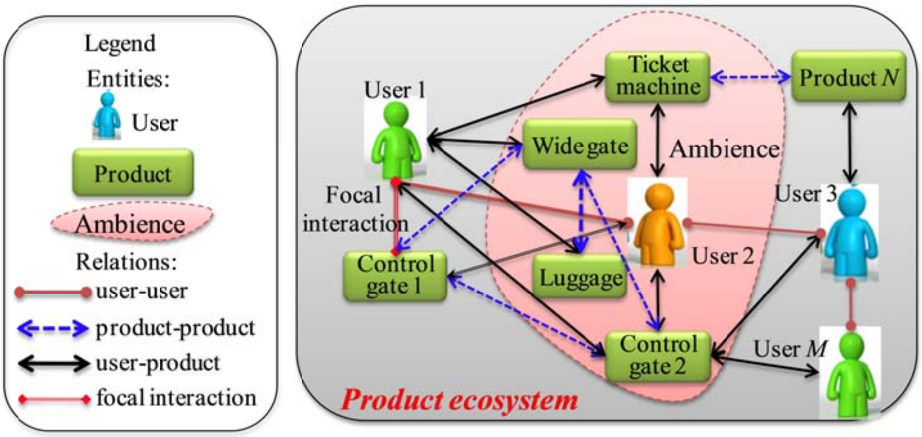


Figure 6-2 Typical entities and relations in the subway station ecosystem

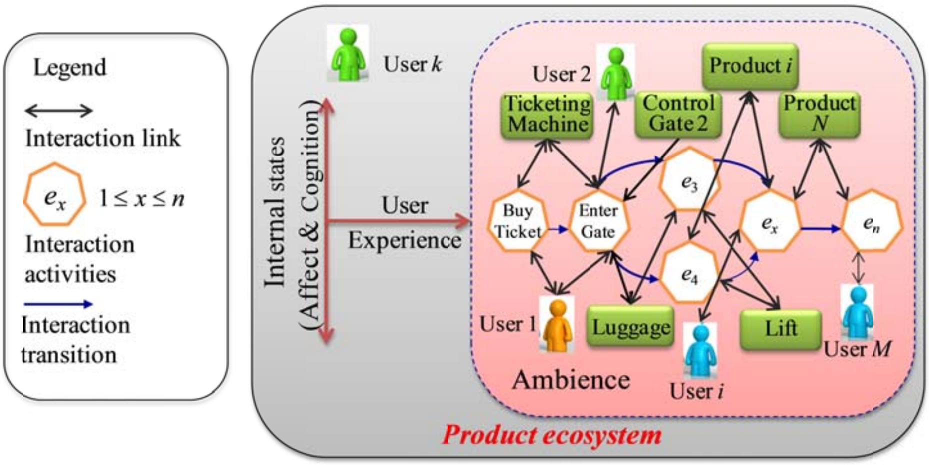


Figure 6-3 User experience evolves in the subway station ecosystem

According to the product ecosystem definition, UX is described as an evolution of the user's internal states along the chain of interaction activities. Figure 6-3 shows the possible UX of User *k* evolving along the activity sequence in the subway station ecosystem. Therefore, UX, in the context of product ecosystem, stems from a sequence of interactions regarding all the events needed to perform a particular task.

Based on the above discussions, the product ecosystem can be formally represented as a 3-tuple $P^e = (E, \Psi, SE)$, where $E = (E^U, E^P, E^A)$ is the entities of users, products, and ambient factors, where $E^U = \{u_1, u_2, ..., u_M\}$ is a set of M users, $E^P = \{p_1, p_2, ..., p_N\}$ is a set of N products, and $E^A = \{a_1, a_2, ..., a_K\}$ is a set of K ambient factors in the product ecosystem. $\Psi = \langle \Psi_1, \Psi_2, \Psi_3, \Psi_4 \rangle$ is the user-user, user-product, product-product, and user-ambient factor relationships, respectively, and $SE = \{e_1, e_2, ..., e_n\}$ is a finite set of interaction events involved in the product ecosystem. Concerning any activity $e_k \in SE$, $\Psi_1 : E^U \times E^U \big|_{e_k} \to \mu$, $\Psi_2 : E^U \times E^P \big|_{e_k} \to \mu$, $\Psi_3 : E^P \times E^P \big|_{e_k} \to \mu$, and $\Psi_4 : E^U \times E^A \big|_{e_k} \to \mu$ denotes the interactive relationships between the involved products, users, and ambient factors with regard to the focal user. Note that $\mu \in [0,1]$, where '1' indicates that the focal user is interacting with another entity, '0', otherwise, and $\mu \in (0,1)$ implies that the involved entities forming the focal user's ambient factors.

Then, the ambience can be defined according to the focal user's interaction with his/her surroundings, and depends on a specific perspective of the focal user. Actually, the ambience, $Am(u_i)$, for u_i is a sub-space of the ecosystem, which consists of all the users, products, and other factors that related to u_i. Hence, the ambience for u_i is defined as

$Am(u_i) = \langle E^U(i), E^P(i), E^A(i) \rangle$, where $E^U(i) = \{u_j \mid \Psi_1(u_i, u_j) = \mu,\ u_j \in E^U,\ i \neq j\}$, $E^P(i) = \{p_s \mid \Psi_2(u_i, p_s) = \mu,\ p_s \in E^P\}$, $E^A(i) = \{a_t \mid \Psi_4(u_i, a_t) = \mu,\ a_t \in E^A\}$, where $\mu \in (0,1)$ for all the interaction relationships.

6.3 User Experience Sampling

Experience sampling has been employed for decades to collect assessments of users' intentions, needs, and affective states (Kapoor and Horvitz, 2008). In order to build an effective UX model that can predict UX in different contexts of the product ecosystem, UX measures need to be collected over time. In order to effectively measure UX, two major dimensions of UX are formally defined in this research, including (1) users' affective states, and (2) cognitive processes. In this chapter, self-reports about users' affective states and cognitive decisions are recorded based on users' navigation through one real subway station in Tokyo, Japan. Fifteen users (nine males and six females) were recruited to navigate through a local subway station. Among them, five were new exchange students and others were local students at Tokyo Institute of Technology. They are required to identify the major interaction events and product ecosystem entities, and get familiar with possible contexts with regard to the subway station ecosystem entities. For example, after navigating through the subway station, they can make decisions and elicit specific affective states with regard to a specific context associated with a specific interaction event. Thus, various contexts about the interaction events are created, leveraging various entities in the product ecosystem as listed in Table 6-1. In addition to the products in Table 6-1, environmental setting, including lighting conditions (low vs. not low) and noise levels (high vs. not high) are also employed as context variables. The resultant cognitive decisions are dependent on the specific interaction events while affective states consist of three general ones, i.e., pleasant, neutral, and unpleasant. For example, with regard to the interaction activity, “buying a ticket,” queues of three TMs, the operation, the ticket price, and surrounding lighting and noise are employed to create the corresponding contexts. Based on the possible combinations of the ecosystem entities, a huge number of possible contexts can be produced, which is formidable for the users to self-report their UX. Therefore, ninety contexts (i.e., product profiles) are formulated through design of optimal experiment (Nair *et al.*, 1995) using SPSS 15.0 (SPSS, Chicago, USA), based on which users’ affective states and cognitive decisions were reported, as listed in Table 6-2. Similar procedure was also applied to other interaction events to collect UX self-reported data.

Table 6-1 Design elements in the subway station ecosystem for UX data collection

Product	Variable	Value Set
Ticketing machine	Queue	{long, not long}
	Status	{working, not working}
	Operation	{easy, not easy}
	Price	{high, not high}
	Number	3
Gate	Queue	{long, not long}
	Status	{working, not working}
	Number	2
Wide gate	Queue	{long, not long}
	Status	{working, not working}
	Number	1
Lift	People	{crowded, not crowded}
	Number	1
Escalator	People	{crowded, not crowded}
	Number	1
Staircase	People	{crowded, not crowded}
	Number	1
Train	Arrival interval	[60, 100]
	Seat	{available, not available}
	Stop information	{clear, not clear}
Suitcase	Size	{large, not large, no suitcase}
Information board	Number	4
	People	{crowded, not crowded}
Shop	Number	3
	People	{crowded, not crowded}
Restaurant	Number	3
	People	{crowded, not crowded}
Toilet	Number	1
	People	{crowded, not crowded}

Table 6-2 Contexts of "buying a ticket" and users' affective states and cognitive decisions

Context #	$Queue_1$	$Queue_2$	$Queue_3$	Operation	Noise	Lighting	Price	Affect	Decision
1	not long	long	not long	not easy	high	not low	not high	neutral	TM1
2	not long	long	not long	easy	high	not low	not high	pleasant	TM1
3	long	long	not long	not easy	high	low	not high	unpleasant	TM3
…	…	…	…	…	…	…	…	…	…
90	long	not long	not long	not easy	not high	low	high	unpleasant	TM2

6.4 Fuzzy Production Rules Based on Rough Set

The prediction of users' affective states and cognitive decisions involves immense uncertainties and dynamics. This necessitates an effective inference engine to be designed. As indicated in Table 6-1, some variables are fuzzy, using terms like *long, low,* and *high*. The classical means to tackle this issue is to employ fuzzy production rules. According to fuzzy logic theories, fuzzy production rules are used to represent uncertain knowledge and fuzzy reasoning process (Negoita, 1985), which take the form of

$$r_j : P_1(\theta_1)\,\&\,P_2(\theta_2)\,\&\cdots P_k(\theta_k) \Rightarrow P_l(\theta_l),\ c_j, \tag{6-1}$$

where $\theta_l \in [0,1]$, $\theta_l = \min\{\theta_1, \theta_2, ..., \theta_k\} \times c_j, \theta_i \in [0,1]$, $i = 1,...,k,l$ denotes the truth degree of proposition P_i (i.e., fuzzy variable) in rule r_j, and $c_j \in [0,1]$ denotes the confidence degree of applying rule r_j. In the context of affective and cognitive modeling, the fuzzy production rules are developed with respect to the events along the chain of UX. For a specific activity, let *P* denote a set of propositions, some of which are fuzzy. These propositions are assertions about the status and attributes of entities in the product ecosystem. Further, these fuzzy rules provide a knowledge base about the system, which can be codified as a fuzzy rule set.

As an example, consider a scenario of one user buying a ticket in the subway station. Provided that the products, ambient factors, and users involved in this interaction activity are three TMs, the operation of buying a ticket, the noise level, the light condition, the price of the ticket to the destination, the resultant UX is concerned with the user's cognitive decision over which TM to choose and the user's affective states, that is, pleasant, neutral, and unpleasant. The above mentioned entities can be represented by 13 propositions, i.e., $P = \{P_1, P_2, \ldots, P_{13}\}$ (see Table 6-3 for their detailed definitions). Then one possible rule is $(\neg P_1(0.8))\&(P_2(0.7))\&(P_3(0.9))\Rightarrow(P_8(0.7))$ with a confidence degree of 1, where $\theta_8 = \min\{\theta_1, \theta_2, \theta_3\} \times c = 0.7$. This rule means that if the queue of TM_1 is *not* (see the negation sign '¬' before P_1) long with a truth degree of 0.8, the queues of TM_2 and TM_3 are long with truth degrees of 0.7 and 0.9, respectively, the user will use TM_1 with a truth degree of 0.7.

However, the challenge is how to obtain typical fuzzy production rules that can be regarded as the inference engine with a high degree of confidence. In this regard, the rough set theory excels in tackling vagueness and uncertainty using rough approximations (Pawlak, 1991). It can produce a complete set of consistent and minimal decision rules using an objective knowledge induction process. Further, it provides criteria for selecting and refining mined patterns, such as *support* and *confidence*. Therefore, the rough set theory is applied to mine the fuzzy production rules in this research (Pawlak, 1991). The general reasoning process is described in the following:

The self-reported data are first organized as a set of feature vectors that depict different contexts of interaction events. Generally, these feature vectors can be seen as an information system, $S = (U, V)$, such that $\forall \mathbf{v} \in V$, $\mathbf{v}: U \rightarrow V^*$, where U is a nonempty finite set called the universe, V is a nonempty finite set of context feature variables, and V^* is the value set of a feature vector $\mathbf{v}$. For example, in the contexts of buying a ticket, the feature vector is defined with the first seven context variables in Table 6-2, i.e., $\mathbf{v}$ = {Queue_1, Queue_2, Queue_3, Operation, Noise, Lighting, Price}, describing the contexts of buying a ticket. Corresponding to context variables, the last two decision variables in Table 6-2, i.e., affect and cognition, are defined to characterize UX. Let $\mathbf{d} = \{d_1, d_2\} \in D$ denote a decision vector where d_1 is the user's resulting affective state and d_2 is the user's resulting cognitive decision. Accordingly, $D_h^* = \{d_{1h}^*, d_{2h}^*\}_H$ is the value set of **d**, where H is the total number of decision scenarios. In the example of buying a ticket, the resulting UX can be $D_h^* = \{\text{pleasant}, \text{TM}_1\}$, and the total number of decision scenarios H is 3×3 = 9.

For all the data with regard to one interaction activity, training data are composed as a decision table (see Table 6-2 for example), $\Omega = (V \cup D, C)$. For the first entry in Table 6-2, the potential inference relationship is V_1^* = {not long, long, not long, not easy, high, not low, not expansive} => D_1^* = {neutral, TM_1}, for example. And there are L = 90 entries for training.

Mining fuzzy production rules is based on the concept of reduction (Pawlak, 1991). For any object $P \in U$, we can generate a rule, such that $\forall i \in [1, K]$, the antecedent of the rule takes the conjunction of certain variable instances, $v_i^\phi(P)$, and the consequent takes on specific values of decision variables, $d^\phi(P)$, where K denotes the total number of variables instantiated by this rule. The general form of a decision rule constructed for reduct Φ and object P is thus given as the following:

$$\left(v_1^\phi = v_1^\phi(P)\right) \& \ldots \& \left(v_k^\phi = v_k^\phi(P)\right) \Rightarrow d^\phi = d^\phi(P). \tag{6-2}$$

For example, for the previously mentioned rule ($\neg P_1$(0.8))&(P_2(0.7))&(P_3(0.9))=>(P_8(0.7)), it can be represented in the new form (v_1 = Queue_1 is not long)&(v_2 = Queue_2 is long)&(v_3 = Queue_3 is long)=>(d_2 = TM_1). The truth degrees of propositions can be predefined to create different contexts in the product ecosystem. The confidence of a rule 'X => Y' is defined as conf(X => Y) = supp($X \cup Y$) / supp (X) and supp(·) is the proportion of item '·' in the database. Although Eqns. (6-1) and (6-2) take two different

Table 6-3 Generated rules for the interaction activity of buying a ticket

#Rule	Rule	Confidence
1	$(P_1)\&(\neg P_2)\&(P_3)=>(P_9)$	1
2	$(P_1)\&(\neg P_2)\&(\neg P_3)=>(P_9)$	0.5
3	$(P_1)\&(\neg P_2)\&(\neg P_3)=>(P_{10})$	0.5
4	$(\neg P_1)\&(P_2)\&(\neg P_3)=>(P_8)$	0.5
5	$(\neg P_1)\&(P_2)\&(\neg P_3)=>(P_{10})$	0.5
6	$(\neg P_1)\&(\neg P_2)\&(\neg P_3)=>(P_8)$	0.33
7	$(\neg P_1)\&(\neg P_2)\&(\neg P_3)=>(P_9)$	0.33
8	$(\neg P_1)\&(\neg P_2)\&(\neg P_3)=>(P_{10})$	0.33
9	$(P_1)\&(P_2)\&(\neg P_3)=>(P_{10})$	1
10	$(\neg P_1)\&(\neg P_2)\&(P_3)=>(P_8)$	0.5
11	$(\neg P_1)\&(\neg P_2)\&(P_3)=>(P_9)$	0.5
12	$(P_1)\&(P_2)\&(P_3)=>(P_8)$	0.33
13	$(P_1)\&(P_2)\&(P_3)=>(P_9)$	0.33
14	$(P_1)\&(P_2)\&(P_3)=>(P_{10})$	0.33
15	$(\neg P_1)\&(P_2)\&(P_3)=>(P_8)$	1
16	$(\neg P_2)\&(\neg P_3)\&(P_4)\&(P_7) =>(P_{12})$	1
17	$(P_4)\&(P_5)\&(\neg P_6)\&(P_7)=>(P_{12})$	1
18	$(\neg P_1)\&(\neg P_4)\&(\neg P_6)\&(\neg P_7) =>(P_{12})$	1
19	$(P_1)\&(P_2)\&(P_3)\&(P_4)\&(\neg P_6)=>(P_{12})$	1
20	$(\neg P_1)\&(\neg P_2)\&(\neg P_4)\&(P_5)\&(\neg P_7) =>(P_{12})$	1
21	$(P_1)\& (\neg P_3)\&(P_4)\&(\neg P_5)\&(P_7) =>(P_{12})$	1
22	$(\neg P_4)\&(P_7)=>(P_{13})$	0.87
23	$(P_1)\&(P_3)\&(\neg P_4) =>(P_{13})$	0.91
24	$(P_1)\&(\neg P_4)\&(P_7)=>(P_{13})$	0.91
25	$(P_1)\&(P_2)\&(P_3)\&(P_6)=>(P_{13})$	1
26	$(\neg P_3)\&(\neg P_4)\&(P_7) =>(P_{13})$	0.82
27	$(P_2)\&(P_3)\&(\neg P_4)\&(P_6) =>(P_{13})$	1
28	$(P_1)\&(P_2)\&(\neg P_4)\&(P_5)\&(P_6)=>(P_{13})$	1
29	$(P_4)\&(\neg P_7) =>(P_{11})$	0.82
30	$(\neg P_3)\&(P_4)\&(\neg P_7) =>(P_{11})$	0.91
31	$(\neg P_1)\&(P_4)\&(\neg P_7) =>(P_{11})$	0.90
32	$(\neg P_2)\&(P_4)\&(\neg P_7) =>(P_{11})$	0.88
33	$(\neg P_1)\&(P_4)\&(\neg P_5)\&(\neg P_6)=>(P_{11})$	0.92
34	$(P_1)\&(\neg P_2)\&(P_3)\& (P_4)\&(\neg P_5)=>(P_{11})$	0.90

Note the propositions are defined as: P_1: The queue of TM_1 is long; P_2: The queue of TM_2 is long; P_3: The queue of TM_3 is long; P_4: The operation of buying a ticket is easy; P_5: The noise level is high; P_6: The lighting condition is low; P_7: The price to take the subway train is expansive; P_8: The user is choosing TM_1; P_9: The user is choosing TM_2; P_{10}: The user is choosing TM_3; P_{11}: The user is pleasant; P_{12}: The user is neutral; P_{13}: The user is unpleasant.

forms, they express the same rule. In order to mine rules, the rough set software system (RSES 2.2.2) is applied (Bazan and Szczuka, 2005). With the decision table (Table 6-2) as input, and the refining measure of minimum support at 0.6, it generates 34 rules for buying a ticket shown in Table 6-3. Therefore, concerning all the interaction events, the possible rules concerning both affect and cognition can be mined using the similar method mentioned above (See Appendix B for the rules of necessary interaction events).

6.5 User Experience Modeling Based on FRPN Model

6.5.1 FRPN Definition

In order to model UX with the rules mined previously, a technique named FRPN is applied, which can deal with fuzzy variables. FRPN is defined as an 8-tuple (Gao *et al.*, 2003): $\text{FRPN} = \left(P, R, I, H, O, \theta, \gamma, C\right)$, where

(1) $P = \{p_1, p_2, ..., p_n\}$ is a finite set of *n* propositions, called places, describing the status of entities in the product ecosystem.

(2) $R = \{r_1, r_2, ..., r_m\}$ is a finite set of *m* rules, called transitions, representing the fuzzy rule base.

(3) $I : P \times R \to \{0,1\}$ is an $n \times m$ input matrix defining the non-complementary directed arcs from non-negation propositions to rules; for $1 \le i \le n$, $1 \le j \le m$, $I\left(p_i, r_j\right) = 1$, if there is a directed arc from p_i to r_j and $I\left(p_i, r_j\right) = 0$, otherwise.

(4) $H : P \times R \to \{0,1\}$ is an $n \times m$ matrix defining the complementary directed arcs from negation propositions to rules; for $1 \le i \le n$, $1 \le j \le m$, $H\left(p_i, r_j\right) = 1$, if there is a complementary arc from p_i to r_j and $H\left(p_i, r_j\right) = 0$, otherwise.

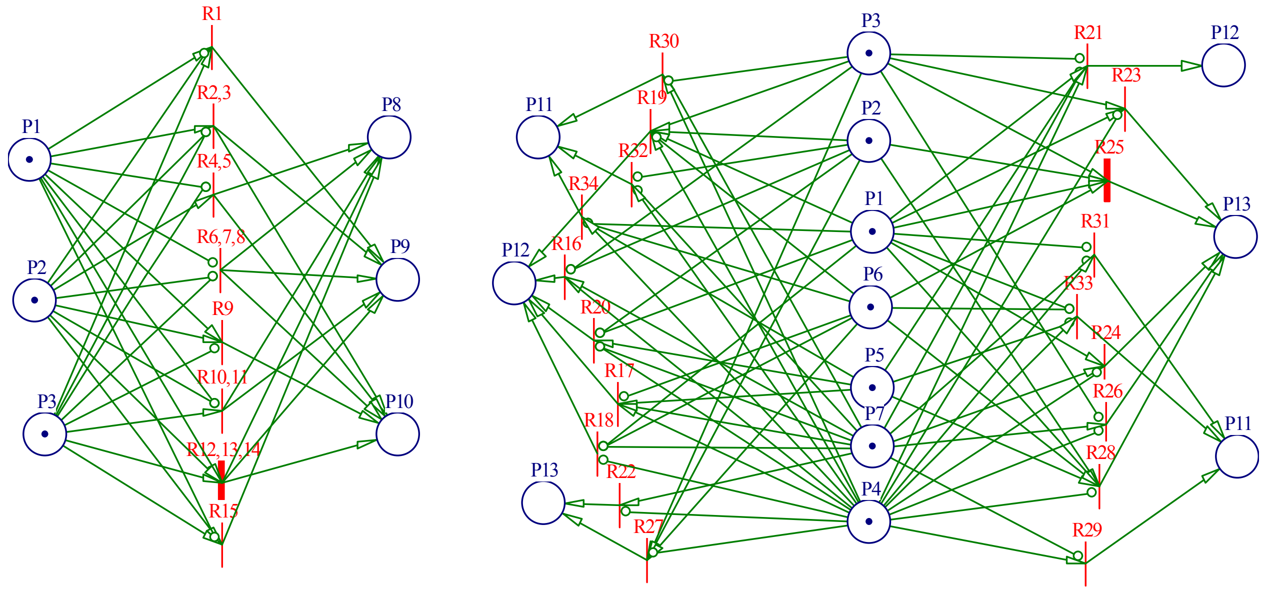
(5) $O: R \times P \rightarrow \{0,1\}$ is an $n \times m$ output matrix defining the directed arcs from rules to propositions; for $1 \leq i \leq n$, $1 \leq j \leq m$, $O\left(r_j, p_i\right)=1$, if there is a directed arc from r_j to p_i and $O\left(r_j, p_i\right)=0$, otherwise.

(6) θ is a truth degree vector, $\theta=\left(\theta_1, \theta_2, \ldots, \theta_n\right)^{\mathrm{T}}$, where θ_i $(1 \leq i \leq n)$ denotes the truth degree of p_i.

(7) $\gamma: P \rightarrow\{0,1\}$ is a marking vector, $\gamma=\left(\gamma_1, \gamma_2, \ldots, \gamma_n\right)^{\mathrm{T}}$. For $1 \leq i \leq n$, $\gamma_i=1$, if there is a token in p_i and $\gamma_i=0$, otherwise.

(8) $C=\operatorname{diag}\left\{c_1, c_2, \ldots, c_m\right\}$, where c_j is the confidence of r_j, $1 \leq j \leq m$, and $c_1, c_2, \ldots, c_m$ is the main diagonal of the confidence matrix *C*.

As an example, the fuzzy production rules for the interaction activity “buying a ticket” can be converted into the FRPN model, as shown in Figure 6-4. Note that complementary and non-complementary arcs are represented by a directed arc terminated with a small circle and a small triangle, respectively; In Figure 6-4, ‘|’ denotes transitions to which both complementary and non-complementary arcs are directing while ‘**|**’ denotes transitions to which no complementary arcs are directing. For example, rule 1: (P_1)&(¬P_2)&(P_3)=>(P_9) is represented as two non-complementary arcs from P_1 and P_3 and one complementary arc from P_2 directed to transition R1 and then an arc from transition R1 to P_9; the associated truth degree is omitted here.



(a) **(b)**

Figure 6-4 FRPN model of the interaction activity "buying a ticket"

(a) Predicting user's cognitive decision over choosing a ticketing machine; (b) Predicting the user's affective state. The detailed definitions of propositions are defined in Table 6-3

6.5.2 Rule Execution Mechanism

For any rule $r_j \in R$, it is enabled if and only if all the input propositions of r_j are marked. Unlike ordinary PNs, the number of token cannot be larger than one, and the token is not removed from the input places of a transition after firing in FRPNs (Gao *et al.*, 2003). All enabled rules can be fired in parallel. Assume the initial marking and truth degree vector are γ^0 and θ^0, respectively, the new marking γ^1 and truth degree vector θ^1 are calculated below after firing all the enabled rules once:

$$\gamma^1 = \gamma^0 \oplus \left[O \otimes \mu^0 \right], \tag{6-3}$$

where $\mu^0 = \left(\mu_1^0, \mu_2^0, \ldots, \mu_m^0\right)^{\mathrm{T}}$ is a firing vector such that $\mu_j^0 = 1$ if r_j fires, $1 \le j \le m$; $\oplus$ and $\otimes$ are max algebra operators (Cuninghame-Green and Butkovic, 2004):

$$\left[A_{m\times n} \oplus B_{m\times n}\right]_{ij} = a_{ij} \oplus b_{ij} = \max\left(a_{ij}, b_{ij}\right);\ \left[A_{n\times k} \otimes B_{k\times m}\right]_{il} = \oplus_{j=1}^{k}\left(a_{ij} \otimes b_{ij}\right) = \max_{j\in\{1,2,\ldots,k\}}\left(a_{ij} + b_{jl}\right).$$

$$\theta^1 = \theta^0 \oplus \left[\left(O \cdot C\right) \otimes \rho^0 \right] \tag{6-4}$$

where $\rho^0 = \left(\rho_1^0, \rho_2^0, ..., \rho_m^0\right)^{\mathrm{T}}$ is a control vector and $\rho_j^0 = \min_{p_i \in {}^\bullet r_j} \left\{ x_i \middle| x_i = \theta_i, \text{ if } I\left(p_i, r_j\right) = 1; \ x_i = 1 - \theta_i, \text{ if } H\left(p_i, r_j\right) = 1 \right\}$, where ${}^\bullet r_j$ represents all the input proposition of rule r_j and ${}^\bullet r_j = \left\{ p_j \middle| I\left(p_i, r_j\right) = 1 \text{ or } H\left(p_i, r_j\right) = 1 \right\}$.

For the illustration purpose, the first 15 rules in Table 6-3 are analyzed. In this example, $P = \{P_1, P_2, P_3, P_8, P_9, P_{10}\}$, $R = \{r_1, r_2, ..., r_{15}\}$. Based on the FRPN definition, the output matrix O is

$$O = \begin{bmatrix} 0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0\,0 \\ 0\,0\,0\,1\,0\,1\,0\,0\,0\,1\,0\,1\,0\,0\,1 \\ 1\,1\,0\,0\,0\,0\,1\,0\,0\,0\,1\,0\,1\,0\,0 \\ 0\,0\,1\,0\,1\,0\,0\,1\,1\,0\,0\,0\,0\,1\,0 \end{bmatrix};$$

the confidence matrix C = diag ([1 0.5 0.5 0.5 0.5 0.33 0.33 0.33 1 0.5 0.5 0.33 0.33 0.33 1]); its initial marking is γ^0 = [1 1 1 0 0 0]$^{\mathrm{T}}$ and assume the initial truth degree vector θ^0 = [0.4 0.9 0.8 0 0 0]$^{\mathrm{T}}$. As illustrated in Figure 6-4(a), all the fifteen rules are enabled, therefore, μ^0 = [1 1 1 1 1 1 1 1 1 1 1 1 1 1 1]$^{\mathrm{T}}$ and ρ^0 = [0.1 0.1 0.1 0.2 0.2 0.1 0.1 0.1 0.2 0.1 0.1 0.4 0.4 0.4 0.6]$^{\mathrm{T}}$. Based on Eqns. (6-3) and (6-4), γ^1 = [1 1 1 1 1 1]$^{\mathrm{T}}$ and θ^1 = [0.4 0.9 0.8 **0.6** 0.132 0.2]$^{\mathrm{T}}$. If the marking is updated again, we find that $\gamma^2 = \gamma^1$ and $\theta^2 = \theta^1$. Therefore, the update is halted. This example demonstrates that the user will most probably (θ_1^4 = 0.6 as the highest truth degree) utilize the TM with the shortest queue (θ_0^1 = 0.4).

6.5.3 Reasoning Algorithm

According to the FRPN model and the mechanism of rule execution, it is possible to predict users' behavior and affective states from the initial marking and truth degrees of the input propositions. In this regard, a reasoning algorithm of FRPNs is proposed (Gao *et al.*, 2003, Gao *et al.*, 2004). First, a neg operator is introduced (Tzafestas and Čapkovič, 1997) so that $\text{neg}\,\theta^0 = \overline{\theta^0} = \mathbf{1}_m - \theta^0$, where $\mathbf{1}_m = [1, 1, ..., 1]$, for example. Then, based on the definition of the firing vector and the control vector, for the k-th reasoning step, μ^k and ρ^k can be calculated as follows (Gao *et al.*, 2003):

$$\mu^k = \text{neg}\left((I+H)^{\mathrm{T}} \otimes \overline{\gamma^k}\right) = \overline{(I+H)^{\mathrm{T}} \otimes \overline{\gamma^k}}, \tag{6-5}$$

$$\rho^k = \overline{\left(I^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \overline{\theta^k})\right) \oplus \left(H^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \theta^k)\right)}. \tag{6-6}$$

Based on the discussion above, the reasoning algorithm of FRPNs is summarized in Table 6-4. Consider the example in Figure 6-4, where $P = \{P_1, P_2, ..., P_{13}\}$, $R = \{r_1, r_2, ..., r_{34}\}$, matrices I, O, and H are obtained based on the definition of FRPNs. and C = diag([1 0.5 0.5 0.5 0.5 0.33 0.33 0.33 1 0.5 0.5 0.33 0.33 0.33 1 1 1 1 1 1 1 0.87 0.91 0.91 1 0.82 1 1 0.82 0.91 0.90 0.88 0.92 0.90]) according to the rule base in Table 6-3; the initial marking vector, γ^0 = [1 1 1 1 1 1 1 0 0 0 0 0 0]$^{\mathrm{T}}$; suppose the initial truth degree vector, θ^0 = [0.4 0.9 0.8 0.2 0.2 0.4 0.6 0 0 0 0 0 0]$^{\mathrm{T}}$ that describes the first 7 propositions concerning "buying a ticket" in the subway station ecosystem. According to the reasoning algorithm, the final θ^{k+1} = [0.4 0.9 0.8 0.2 0.2 0.4 0.6 0.6 0.132 0.2 0.184 0.4 0.522]$^{\mathrm{T}}$, when k = 2. With the highest truth degree of propositions among P_8, P_9, and P_{10} and among P_{11}, P_{12}, and P_{13} as criteria, respectively, the user's choice over "buying a ticket" is most likely TM_1 with the probability of 0.6 and the user's affective state is most likely unpleasant with the probability of 0.522. Likewise, all other interaction events can be modeled using FRPNs, and users' cognitive decisions and affective states can be obtained with the reasoning algorithm. According to Gao *et al.* (2003), the reasoning algorithm for the acyclic FRPN terminates at the (h + 1)-th step for the worst case, where h is the number of transitions in the longest place-transition direct path. Thus the computational complexity in the worst case is $O(mnh)$, where m and n are the numbers of transitions and places, respectively. Therefore, both users' affective states and cognitive decisions can be predicted efficiently as *m*, *n*, and *h* are all small numbers in this research.

Table 6-4 Reasoning algorithm of FRPN

Input: I, H, O, C, and the initial truth degree vector θ^0 and the initial marking vector γ^0
Output: the final truth degree vector θ^{k+1}
$k = 0$; do { $\mu^k = \overline{(I+H)^{\mathrm{T}} \otimes \overline{\gamma^k}}$; $\rho^k = \overline{\left(I^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \overline{\theta^k})\right) \oplus \left(H^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \theta^k)\right)}$; $\theta^{k+1} = \theta^k \oplus \left[(O \cdot C) \otimes \rho^k\right]$; $\gamma^{k+1} = \gamma^k \oplus \left[O \otimes \mu^k\right]$; $k = k+1$; }while ($\theta^{k+1} \neq \theta^k$ or $\gamma^{k+1} \neq \gamma^k$);

6.6 User Experience Simulation

With regard to all the interaction events that one user experiences, the complete UX can be constructed by connecting individual FRPNs that model the individual interaction events accordingly with appropriate sequencing and branching relations. The UX thus formed is characterized by a series of interaction events with a number of what-if scenarios. Since it is difficult to validate decisions on the product ecosystem using analytical methods, simulation methods are appropriate.

In this research, the design of the product ecosystem involves determining the product attributes and the service processes that contribute to positive UX. Among the entities that constitute the product ecosystem, assumptions are made for the simulation as shown in Table 6-5. Moreover, the chain of interaction events in accordance with the UX is partially controllable, i.e., some interaction events are indispensible while others are flexible in view of the business process. Additional constraints are exerted on diverse relationships among users, the ambience, as well as the cause and effect relations between the ecosystem configuration and the user affect and cognition. With all these considerations, the objectives of ecosystem design are to (1) model UX quantitatively and thus connect UX and design elements for informing system design, and to (2) reduce the operational cost by maximizing the utilization of the ecosystem capacities.

6.7 Simulation Based on SIMUL8

With the above objective, a FRPN simulation based on the software SIMUL8 (SIMUL8 Corporation, Boston, MA, USA) is conducted. Figure 6-5 shows the corresponding PN structures, where the FRPN model is codified using the Visual Logic programming in SIMUL8. The simulation is run based on the assumptions made in Table 6-5, which can be preset in SIMUL8.

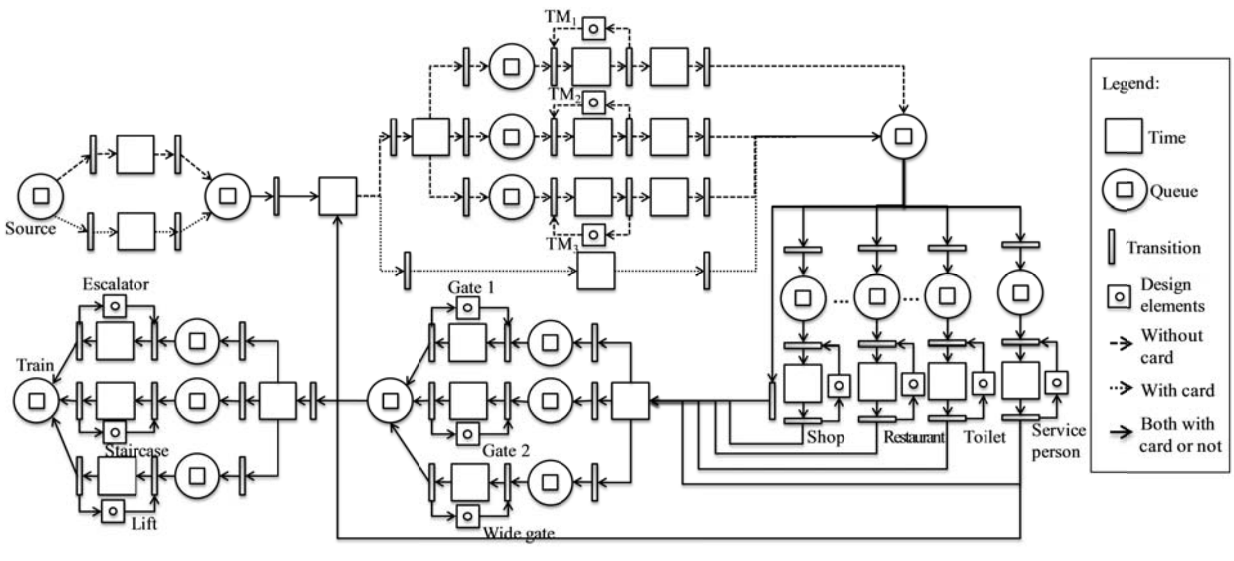


Figure 6-5 Petri net simulation in SIMUL8

In order to deal with the fuzzy variables, membership functions are applied to produce truth degrees of fuzzy variables, including queue length, ticketing machine operation, ticket price, crowdedness of shop, restaurant, lift, escalator, and staircase, stop information, lighting intensity, and noise level (see Table 6-1). For example, the membership function of the queue length is shown in Figure 6-6, and the membership implies the truth degree of the queue length (i.e., long vs. not long).

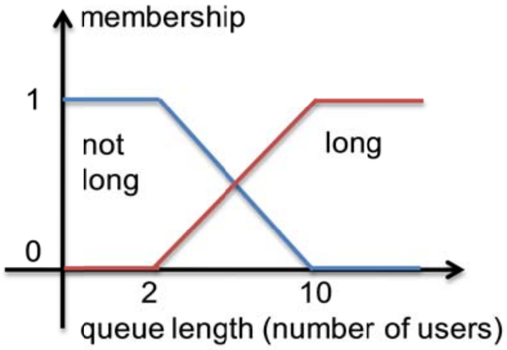


Figure 6-6 Membership function of queue length

Table 6-5 Assumptions made during the simulation

Interaction events	Variables (or initial truth value)	Distribution or probability
Generating users	Generation interval time	Exp (10)
User type	Users without a card (need to buy tickets)	P = 1/4
Buying a ticket	The operation of buying a ticket is easy	U (0.2, 0.5)
	Noise level is high	U (0, 1)
	Lighting intensity is low	U (0.2, 0.6)
	The price to take the train is expansive	U (0.2, 0.8)
	Processing time	N (30, 15)
Entering a gate	Gate is working	P = 9/10
	The luggage size is large	P = 1/3
	The user brings along luggage	P = 1/4
	Processing time	N (20, 10)
Going to the platform	The escalator or lift is working	P = 9/10
	Processing time	N (30, 10)
Boarding the train	Waiting time	Exp(60)
	Stop information is clearly updated	U (0.5, 0.8)
Go to the toilet	Direction information is clear	U (0.2, 0.8)
	Waiting time	Exp (10)
Go to restaurants	Direction information is clear	U (0.2, 0.8)
	Waiting time	Exp (200)
Go to shops	Direction information is clear	U (0.2, 0.8)
	Waiting time	Exp (10)

N (μ, σ^2): Normal distribution, where μ is mean and σ is variance; U (a, b): Continuous uniform distribution, where a and b are two boundaries; Exp (λ): Exponential distribution, where λ is the rate parameter

During the simulation, the performance of the subway ecosystem is measured by system capacity utilization and UX. System capacity utilization is computed from the average utilization of the major design elements, including TMs, gates, service persons, escalators, lifts, staircases, toilets, information boards, shops, and restaurants. In the simulation environment, all these performance factors can be monitored and computed automatically. UX is measured with users' affective states and cognitive decisions, which are indirectly evaluated with user stay-time (or processing time) due to cognitive decisions made in the subway station. Assume that these two parts have the same weight, and thus UX is the mean of them. Further, they are quantified between –1 and 1 with an initial value of 0, and the larger the value, the more positive UX. An individual user's affective state at a particular time is defined as: $AF_i = AF \times \theta_i$, where $AF = \begin{cases} 1 & \text{if affective state=pleasant} \\ 0 & \text{if affective state=neutral} \\ -1 & \text{if affective state=unpleasant} \end{cases}$, and θ_i is the truth degree associated with the affective state. Thus, the average affective state ($\overline{AF_i}$) of an individual user during his/her stay-time T_i is given as $\overline{AF_i} = \frac{1}{T_i}\int_0^{T_i} AF_i \, dt$. Then the affective UX (AUX) of M users in the product ecosystem is computed as:

$$\mathrm{AUX} = \frac{1}{M}\sum_{i=1}^{M}\overline{AF_i}\ . \tag{6-7}$$

And the cognitive UX (CUX) according to the user stay-time is given as:

$$\mathrm{CUX} = \frac{1}{M}\sum_{i=1}^{M}\left(1 - \frac{T_i}{T_{\exp}}\right), \tag{6-8}$$

where $T_{\exp}$ is the expected user stay-time (i.e., average processing time) that is assumed to be no perceptible influence on UX. Assuming that $0 \le T_i \le 2T_{\exp}$, $-1 \le \mathrm{CUX} \le 1$. Then, UX is the aggregated sum of AUX and CUX with the same weight, i.e.,

$$\mathrm{UX}=\left(\mathrm{AUX}+\mathrm{CUX}\right)/2\,. \tag{6-9}$$

6.8 Results

The simulation was conducted with regard to the configuration of the subway ecosystem specified in Table 6-1. The performance was evaluated against UX as well as the system capacity utilization. These results bring about useful implications of the subway ecosystem design in the following aspects.

Figure 6-7 shows the aggregated UX evolving along the simulation time during which about 6000 users utilized the subway ecosystem. Overall, the ecosystem produced an average negative UX of – 0.013 (standard deviation = 0.024), indicating an unacceptable service process. Further, capacity utilization of major design elements in the ecosystem was also calculated as depicted in Figure 6-8. Note that the capacity utilization of trains, restaurants, shops, toilets is defined as the current numbers of users divided by their amounts to hold people while the capacity utilization of other products is defined as the busy time divided by the total simulation time. As seen from Figure 6-8 (a), escalator, lift, trains, wide gate, gates 1 and 2, and restaurant are characterized by high utilization rates. However, the design elements in Figure 6-8 (b), including three TMs, staircase, information boards, and service persons, show relatively low utilization rates. Although a higher average utilization rate indicates a lower unit cost per service process, it suggests a possible bottleneck of the service process, provided that UX is significantly reduced by the product. In addition, the general influence of individual design elements on the average UX of all the users is also illustrated in Figure 6-9.

While service persons, shops, and toilet lead to positive UX substantially, TMs, two gates, escalator, trains, and restaurants lead to UX deterioration.

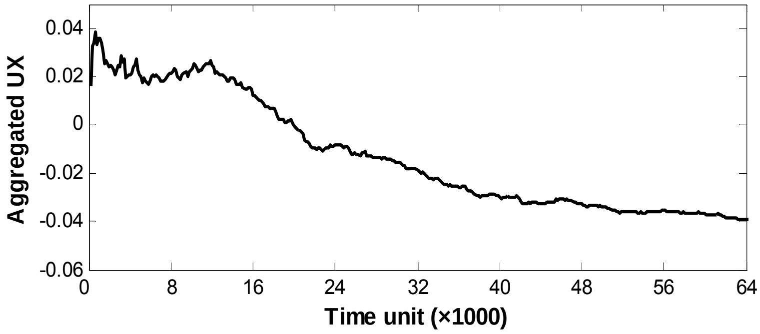
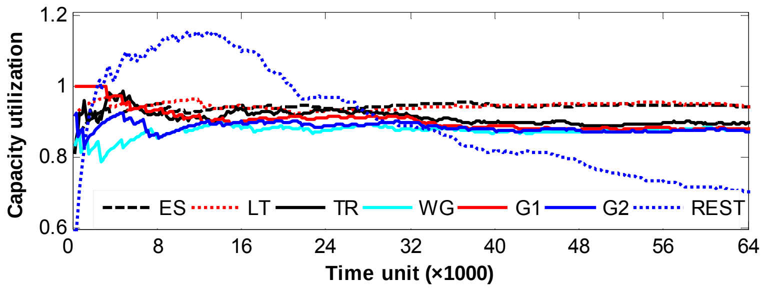
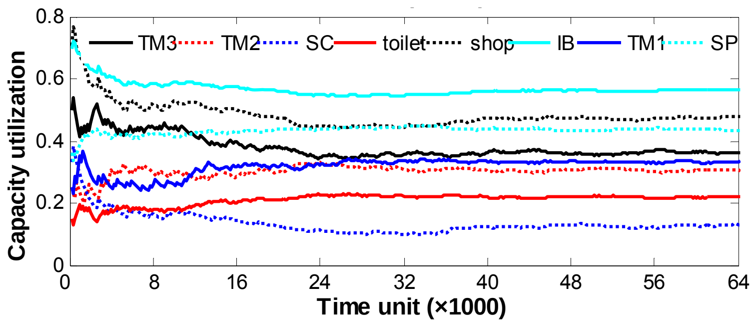


Figure 6-7 Aggregated UX of 6000 users evolving during the simulation time



(a) High capacity utilizaiton



(b) Low capacity utilizaiton

Figure 6-8 Capacity utilization of major design elements during simulation. Note: ES: escalator, LT: lift, TR: train, WG: wide gate, G1: gate 1, G2: gate 2, REST: restaurant, TM1: ticketing machine 1, TM2: ticketing machine 2, TM3: ticketing machine 3, SC: staircase, IB: information board, SP: service person

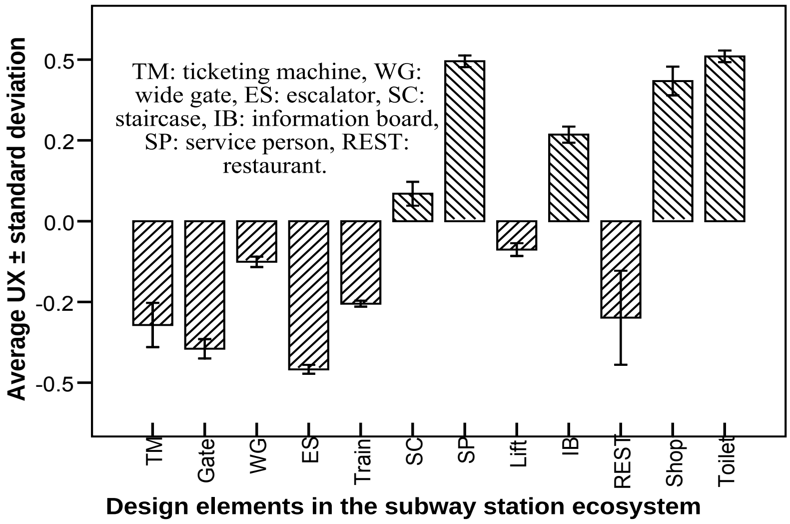


Figure 6-9 Influence of design elements on UX

From the design perspective, it is imperative to examine the causes of the negative UX. Considering the high utilization rates of escalator, lift, trains, gates 1 and 2, as well as restaurants, they seem to be designed with insufficient capacities with regard to the subway ecosystem configuration in Table 6-1. However, it seems implausible that low utilization rates of TMs also give rise to negative UX. Thanks to the reasoning algorithm of the FRPN model, it is able to trace the rules that were fired during the simulation. Table 6-6 shows the rules of major interaction events that cause negative affective UX and the percentages of the users invovled for each rule. Consistent with the fact that TMs leading to negative UX in Figure 6-9, 53.8% of the users (by r_{22}, r_{23}, and r_{24}) reported negative affective UX when "buying a ticket". Thus the major causes are the difficult operation (i.e., $\neg P_4$ in r_{22}, r_{23}, and r_{24}), the long queues of TM_1 (i.e., P_1 in r_{23} and r_{24}) and TM_3 (i.e., P_3 in r_{23}), and the high ticket price (i.e., P_7 in r_{22} and r_{24}). As for "entering the gate", 47.8% of the users reported negative affective UX mainly caused by long queues of gates 1 and 2 and the wide gate (i.e., P_1, P_2, and P_3 in r_{44}). The major antecedents that result in negative affective UX of "going to the platform" are the crowded escalator (i.e., P_1 in r_{14} and r_{19}), the crowded lift (i.e., P_2 in r_{14}), luggage with the users and the low light intensity in the surrounding area (i.e., both P_7 and P_9 in r_{19}). The eighth rule most frequently fired in the interaction activity, "boarding the train" links to negative affective UX, which is due to long waiting time (i.e., P_1), no seats available (i.e., $\neg P_2$), and the high noise level (i.e., P_5). During the interaction activity, "going to the restaurants", 40.2% of the users complained a long waiting time (i.e., P_1 in r_6) and a high level of noise (i.e., P_4 in r_6) that give rise to negative affective UX.

Table 6-6 Summary of rules leading to negative AUX

Interaction activity	Rule	Percentage (%)	Propositions
Buying a ticket	r_{22}: $(\neg P_4)\&(P_7)$=>(P_{13})	11.0	P_1: The queue of TM_1 is long; P_3: The queue of TM_3 is long; P_4: The operation of buying a ticket/top-up is easy; P_7: The price is expansive; P_{13}: The user is unpleasant.
	r_{23}: $(P_1)\&(P_3)\&(\neg P_4)$ =>(P_{13})	26.8	
	r_{24}: $(P_1)\&(\neg P_4)\&(P_7)$=>(P_{13})	16.0	
Entering the gate	r_{44}: $(P_1)\&(P_2)\&(P_3)$ =>(P_{17})	47.8	P_1: The queue of gate 1 is long; P_2: The queue of gate 2 is long; P_3: The queue of the wide gate is long; P_{17}: The user is unpleasant.
Going to the platform	r_{14}: $(P_1)\&(P_2)$=>(P_{15})	16.8	P_1: The escalator is crowded; P_2: The lift is crowded; P_7: The lighting condition is low; P_9: The user brings along luggage; P_{15}: The user is unpleasant.
	r_{19}: $(P_1)\&(P_7)\&(P_9)$ =>(P_{15})	19.6	
Boarding the train	r_8: $(P_1)\&(\neg P_2)\&(P_5)$=>(P_{10})	9.6	P_1: Waiting is too long; P_2: The user is seated; P_5: The noise level is too high; P_{10}: The user is unpleasant.
Going to restaurants	r_6: $(P_1)\&(P_4)$=>(P_8)	40.2	P_1: Waiting is too long; P_4: The noise level is too high; P_8: The user is unpleasant.

6.9 Discussions

(1) Integration of Affect and Cognition. The notion of product ecosystem integrates multiple relevant products and services into a coherent model. Thus, interdependent products and ambient factors co-determine dynamic UX in terms of both the affective and cognitive dimensions along the series of interaction events. In a holistic fashion, it facilitates the integration of affect and cognition and their interactions in one design paradigm. This is

consistent with recent findings that a unity and interrelatedness of the cognitive and affective processes is needed (Storbeck and Clore, 2007). Moreover, UX dynamically evolves along the progression of interaction events. It is important to capture UX within a legitimately valid time horizon so that the relationship between UX constructs and design elements can most likely approximate the fact.

(2) Human-product-ambience Interaction. Consideration of the ambience where users' behavior is contextualized is generally helpful to achieve reliable UX prediction with a relatively high fidelity. It involves interactions not only between the user and a product (object), but also with the ambience, namely, a form of human-product-ambience interactions. Compared with traditional product design for UX, it expands the scope and facilitates UX design both for users and the producer. For users, it is possible to better reflect the causal relationships between UX and design elements in the product ecosystem. For the producer, relevant products and services are designed at a system level that can avoid the design pitfalls where overly narrow optimization of one aspect of UX can be made invalid by a broader context of the design problem (Hewett, 1992).

(3) Complexity, Dynamics, and Uncertainty. For product ecosystem design, it would be often difficult, if not impossible, to find out a comprehensive and unambiguous list of design elements that can significantly influence UX in a broader scope. In addition, since UX is influenced by many factors inside the product ecosystem and UX data are collected by self-reports, UX modeling exhibits high complexity, dynamics, and uncertainty. In order to tackle the complexity issue, various system design elements, including products, ambient factors, and users as well as their interactive relationships should be represented in a systematic form. It is reasonable to model UX as dynamic evolution along individual series of interaction events, in which system elements and their interactive relationships can be specified in a

relatively simple way. Although it is not possible to record UX all the time, it is often adequate to sample dynamic UX at the interval of individual interaction events. With regard to the uncertainty issue, the rough set technique helps generate fuzzy production rules that can be used to represent vague concepts.

In order to effectively predict UX in different contexts of a product ecosystem, the FRPN reasoning algorithm can handle the complexity of decision making with multicriteria. It allows one to exploit the maximum parallel reasoning capacity so that UX with the largest possibility can be predicted. By linking (nesting) individual FRPNs corresponding to individual interaction events under various circumstances, UX can be aggregated to explore the whole product ecosystem.

(4) Simulation. Simulation is used to predict the performance of a predefined subway station ecosystem in terms of two measures, i.e., UX and capacity utilization of individual products. The outcome of simulation analysis can provide designers with decision support to improve UX, enhance the operational efficiency of the product ecosystem, reduce costs, and finally optimize the product ecosystem configuration. For example, it is obvious that the operation of “buying a ticket” is not easy; two gates and the escalator are not adequate to accommodate the current traffic flow; there should be more restaurants; the interval of trains should also be shortened. In this sense, for product ecosystem design, it is easy and cost-effective to obtain re-design solutions by applying simulation for what-if analysis.

(5) Limitations and Future Work. As an exploratory study, the approach proposed in this research also suffers a few limitations, which deserve further investigation. First, this research does not support designers to optimize the ecosystem configuration with respect to the identified system objectives. Therefore, it is desirable to develop methods that can optimize product ecosystem design problem in the future. Such a process might be automated by

applying artificial intelligence for configuration design, such as genetic algorithms and constraint satisfaction techniques. Second, UX modeling based on FRPNs requires profound understanding of human behavior, product information, as well as user affective states and cognitive processes. However, much knowledge related to the FRPN model is based on assumptions. Logical construction of UX necessitates more accurate replication of human affect and cognition in various scenarios. Third, the non-linear nature of the FRPN model makes it difficult to apply analytical methods to study the system behavior. Further work may be directed to study of UX modeling using other possible methods with more flexibility and learning capabilities, such as fuzzy cognitive map (Kosko, 1986). Moreover, it is meaningful to expand the FRPN model to large scale applications with rigorous experimentation and replicable methodologies, such as airport terminals, the iPhone ecosystem, shopping malls, and the like.

6.10 Summary

UX suggests itself to be fundamental to product ecosystem design. In this research, multiple users and relevant system design elements are formulated within a coherent framework. Two important aspects of UX, i.e., the cognitive and affective dimensions, are used to measure UX. Unlike traditional methods that approximate the relationships between different constructs of UX by statistical techniques (e.g., regression), the FRPN model exploits fuzzy production rules and the efficient reasoning algorithm for knowledge-based multi-criteria decision making. It captures the causal relationships between UX and design elements so as to provide design decision support. The simulation results based on the subway station ecosystem design show the feasibility and potential of the FRPN modeling. The FRPN model is an attempt to approximate how UX is predicted when certain key characteristics and behaviors of the subway station are simulated under certain assumptions and constraints.

Therefore, from our perspective, it underscores the modeling of UX in relation to the product ecosystem, and develops a comprehensive modeling and reasoning framework for revealing the rationales of product ecosystem design for UX.

CHAPTER 7
HYBRID ASSOCIATION MINING AND REFINEMENT FOR AFFECTIVE MAPPING

This chapter discusses affective needs fulfillment. It entails a bidirectional affective mapping process between affective needs in the user domain and design elements in the designer domain. To leverage both affective and engineering concerns, this chapter proposes a hybrid association mining and refinement (AMR) system to support affective mapping decisions. The rough set and *K*-optimal rule discovery techniques are applied to identify hidden relations underlying forward affective mapping (FAM). A rule refinement measure is formulated in terms of affective quality. Ordinal logistic regression (OLR) is derived to model backward affective mapping (BAM). Based on conjoint analysis, a weighted OLR model is developed as a benchmark of the initial OLR model for backward refinement. A case study of truck cab interior ecosystem design is presented to demonstrate the feasibility and potential of the hybrid AMR system for decision support to FAM and BAM.

7.1 Introduction

The fulfillment of affective needs involves a tedious elaboration process, referred to as *affective mapping*, enacted between the user domain and the designer domain. Affective needs are qualitative in nature and usually are articulated using abstract, fuzzy or conceptual terms. While users tend to express their emotional perception in a holistic fashion, designers usually interpret affective needs in terms of individual design elements (features). Affective quality is often evaluated according to a (weighted) sum of discrete assessments of each individual design element's contribution to certain emotional aspect of the product (Zhang and Li, 2005). Such contextual mismatching impairs the ability to convey affective needs from users to designers. In affective design, the relationships among affect, functional requirements and existing design parameters are often not clear, which makes it difficult to estimate the consequences (in terms of cost, scheduling and quality) of selecting specific design elements.

Besides, fulfillment of affective needs generally accommodates two key stakeholders: customers and the manufacturer. While meeting customers' affective needs, a manufacturer must seek for economy of scale in product realization (Jiao *et al*., 2006). The manufacturer must also assess affective needs under consideration of a number of potential couplings among various design requirements, along with time and cost constraints (Jiao and Zhang, 2005). Such engineering concerns at the backend of affect require feedback from designers with regard to affective needs, and thus customers may have to compromise or negotiate the 'price' of their affective preferences. This necessitates a reasoning process from the designer domain to the customer domain, namely, BAM. In a holistic view, affective design entails a bidirectional affective mapping process that needs to leverage customers' affective satisfaction with engineering concerns. Moreover, owing to a high degree of subjectivity of affective needs, individual user's preferences may vary significantly. Thus, affective mapping decisions often need to be updated and refined for different business purposes. Therefore, it is imperative to develop affective decision support mechanisms that not only can extract bidirectional mapping relationships between the user domain and the designer domain, i.e., FAM and BAM, but also can refine the extracted relationships in an iterative manner.

7.2 Related Work

Affective needs are usually identified as a set of affective descriptors in the previous studies. A large amount of affective adjectives are collected concerning the consumers' feelings toward a product through user interviews, focus groups or surveys (Nagamachi, 1995). Then, the most relevant and appropriate terms are selected by domain experts, ranging in numbers from several dozens to several hundreds. The selected ones are further scrutinized and structured, either manually or statistically. Kano *et al.* (1984) distinguish affective satisfaction in terms of must-be, one-dimensional, and attractive requirements. Other approaches include intelligence-based methods (Hauge and Stauffer, 1993), knowledge recovery (Chen *et al.,* 2002; Tseng and Jiao, 1998), and physiological responses by measuring galvanic skin response, blood volume pulse, respiration, and electromyogram (Picard, 1997). With the focus being fixed on customers only, the consideration of variances due to different contexts and products is generally missing and can hardly address variances of design during the affect elicitation process.

Kansei engineering has been widely applied as a technique for translating consumers' affective needs about a product into design elements. In essence, there are two types of mapping: qualitative and quantitative mapping. As for qualitative mapping, the simplest way is manual mapping, such as the Category Identification method (Nagamachi, 1995). Focus groups are used to provide reality checks on the usefulness of a new product design (Griffin and Hauser, 1992). Quantitative methods include mainly statistical methods such as multivariate analysis. In addition, it is common to use regression analysis to compare customer characteristics and to determine their overall rankings. Some tools for this task are readily available, including multiple linear regression analysis (Ishihara, 2001) and general linear models (Kim *et al*., 2003). Quality Function Deployment (QFD) has also been widely adopted to translate customer requirements into technical design requirements.

However, most affective descriptors, such as 'beautiful or not', do not exhibit linear characteristics. As a matter of fact, emotional responses to products are fuzzy and vague in nature, thus assuming nonlinear characteristics (Nagamachi *et al*., 2006). As such, more advanced methods, including quantification theory type I, II, III, and IV (Nagamachi *et al*., 2006), neural networks, genetic algorithms, and fuzzy logic (Schütte, 2005), are deemed to be appropriate. Ishihara *et al.* (1995) apply neural network techniques to enhance the inference from Kansei words (affective adjectives) to design elements. Arakawa *et al.* (1999) emphasize the properties of fitness functions for optimization of Kansei using genetic algorithms. Tsuchiya *et al*. (1996) propose a procedure combining genetic algorithms and fuzzy logic for identifying affective needs regarding driving comfortableness of automobiles.

Backward affective mapping from the designer to customer domains has received limited attention. Nagamachi (1995) is one of the pioneers advocating the importance of backward inference in Kansei engineering, whereby design candidates are diagnosed with respect to affective descriptors. Matsubara and Nagamachi (1997) propose a hybrid Kansei engineering system that can support both customers and designers to make their decisions. They employ typical linear regression for analysis and identification based on Quantification Theory Type I. In the process of backward mapping, customer preferences are mainly modelled using market analysis techniques such as conjoint analysis (Green *et al*., 1981; Jiao *et al*., 2007; Tseng and Du, 1998), discrete choice experiments (Green *et al*., 1981), and fuzzy systems (Turksen and Willson, 1992), and the like. The key idea is to assign importance weights or part-worth utilities for multi-criteria decision-making. However, backward mapping can hardly contribute to affective design without proper coordination with forward mapping. It is imperative to develop affective decision support mechanisms that incorporate bidirectional mapping relationships between the user and designer domains.

7.3 Affective Mapping

Figure 7-1 illustrates the general affective mapping process with bidirectional mapping relationships. The user domain depicts how users perceive and respond to the appeal of products. The designer domain delineates how designers achieve affective quality of the products by configuring design elements.

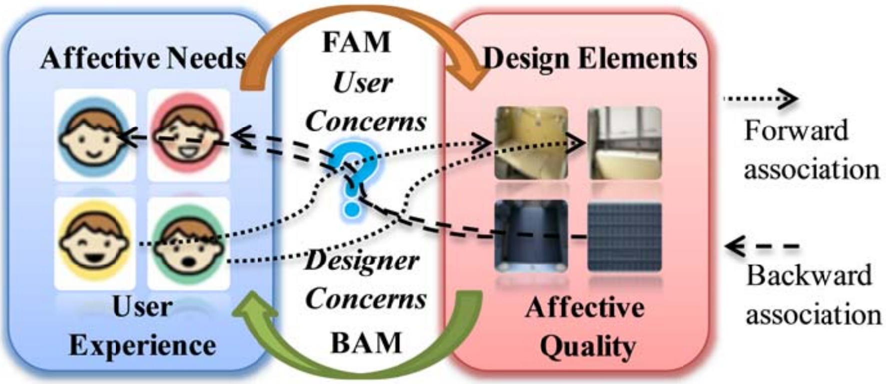


Figure 7-1 Bidirectional affective mapping

Affective needs are represented as a nonempty set of affective descriptors $D = \{d_i\}_I$ in the affective space, where I denotes the total number of affective descriptors. Target users constitute a set, $C = \{c_t\}_T$, where T is the total number of users. An individual user's $(\forall c_t \in C)$ affective needs can be expressed as a subset, $D_t = \{d_j\}_{I_t}$, $D_t \subseteq D$, where $I_t \leq I$ is the total number of this user's affective needs.

Various design elements extracted from product ecosystem documentation can be characterized by another nonempty set, $E = \{e_m\}_M$, where M is the total number of design elements in the product ecosystem. Each design element, $\forall e_m \in E$, may assume several element levels, $E_m^* = \{e_{mk}^*\}_{K_m}, 1 \leq k \leq K_m$, where K_m is the total number of levels (instances) of e_m, and k denotes the k-th level of e_m. For instance, the bunk (a design element) of a truck cab ecosystem may instantiate two element levels, i.e., foldable or not foldable (see Table 7-1).

A combination of design elements with appropriate element levels yields a desired product specification, P_q $(1 \leq q \leq Q)$, for affective needs of c_t, where Q is the total number of products. A product, $P_8 = \{e_{12}^*, e_{41}^*, e_{64}^*\}$, for example, comprises three design elements, $\{e_1, e_4, e_6\} \subset E$, which assume the 2nd, 4th and 6th instance levels of each design element, respectively.

7.3.1 Forward Affective Mapping

A user's affective response results from a holistic impression of the product, rather than a summation of individual achievements of specific design elements towards affective quality. Nonetheless, users may prefer a design element with a specific desired element level. The FAM relationships from affective needs (D_t) to a product (P_q) are denoted as $D_t \Rightarrow P_q$. An individual instance of association, $d_j \Rightarrow e_{mk}^*$, indicates an inference from the antecedent ($d_j \in D_t$) to the consequent ($e_{mk}^* \in E_m^*$). Therefore, the FAM process starts with the mining of all possible associations that constitute the knowledge base from affective descriptors to design elements, i.e., $\Lambda^F = \langle d_j \Rightarrow e_{mk}^* \rangle$, and subsequently refines Λ^F by identifying valuable patterns $\Lambda^{RF} \subseteq \Lambda^F$ according to evaluation criteria.

7.3.2 Backward Affective Mapping

The mapping relationships from a particular product ecosystem specification P_q to a set of affective needs D_t are denoted as $P_q \Rightarrow D_t$, where a correspondence pair, $e_m \Rightarrow d_j$, implies an inference from the antecedent ($e_m \in E$) to the consequent ($d_j \in D_t$). The BAM process includes mining of possible associations for constructing the BAM knowledge base, i.e., $\Lambda^B = \langle e_m \Rightarrow d_j \rangle$, and further for evaluating the associations to differentiate the *significance* and *direction* of those essential associations, i.e., $\Lambda^{RB} \subseteq \Lambda^B$. Note that BAM emphasizes the mapping relationships in terms of design elements, instead of element levels. The reason for this is to control granularity of complexity in handling a large variety of products by underpinning those significant design elements from numerous instances of design elements.

7.4 A Case of Truck Cab Interior Ecosystem Design

The interior ecosystem design of truck cabs is studied as an example to illustrate affective mapping. Considering such factors as cost, material and manufacturability, seven design elements, $\{e_m\}_7$, are identified from six existing long-haul truck models, as tagged in Figure 7-2. Table 7-1 presents 18 instances of these design elements. To describe affective needs, 203 affective adjectives are collected from truck magazines and websites. After consultation with sales experts and human factors specialists, these adjectives are refined to 61 representative affective descriptors, $\{d_i\}_{61}$ (see Appendix C), for the long-haul product line.

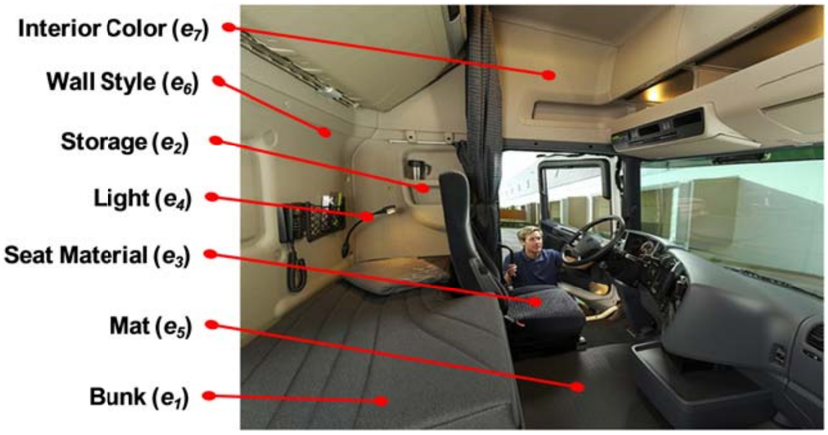


Figure 7-2 Truck cab interior ecosystem design

Table 7-1 Design elements and their levels for truck cabs

Code	Description	Code	Description
e_{11}^*	Bunk-foldable	e_{51}^*	Mat-textile
e_{12}^*	Bunk-unfoldable	e_{52}^*	Mat-rubber
e_{21}^*	Storage-above bed	e_{61}^*	Wall-sponge attached
e_{22}^*	Storage-beside bed	e_{62}^*	Wall-flat
e_{31}^*	Seat material-fabric	e_{71}^*	Interior color-yellow
e_{32}^*	Seat material-leather	e_{72}^*	Interior color-green
e_{33}^*	Seat material-cloth with soft nap	e_{73}^*	Interior color-blue
e_{41}^*	Light-embedded in the wall	e_{74}^*	Interior color-red
e_{42}^*	Light-protruded from the wall	e_{75}^*	Interior color-gray

7.5 Hybrid Association Mining and Refinement

Hybrid AMR entails a combination of mining and refinement processes. Figure 7-3 shows the system architecture of hybrid AMR, consisting of four modules: data pre-processing, forward AMR, backward AMR, and association synthesis and visualization.

The data preprocessing module prepares raw data obtained from sales interviews for subsequent data mining analysis. It relies on domain knowledge and starts with a screening process to minimize ‘garbage’ information, followed by clustering analysis to group individual users’ transaction data by market segments. The output is a transaction database, in which each record represents a correspondence between a user’s preference (E_m^*) and the product (D_t) designed for this customer segment.

The forward AMR module is implemented based on the rough set and *K*-optimal rule discovery techniques. It first produces a pool of reducts (Pawlak, 1991), which contains the characteristic features of design elements for filtering redundant rules. Then, the *K*-optimal rule discovery procedure is executed to generate association rules for each reduct. These rules are further evaluated according to a rule importance measure, and finally the refined rules are derived.

The backward AMR module adopts OLR to construct a basic backward mapping model from design elements to affective needs. Relative importance weights yielded from conjoint analysis are then incorporated into the basic OLR model, resulting in a weighted OLR model. Two OLR models are further compared based on their performance in model fitting, along with controlling variances and noise factors. The one with better overall performance is used to represent backward AMR.

The association synthesis and visualization module compiles AMR results for scrutiny through domain experts’ appraisal. A descriptive synthesis procedure is used to collate and summarize the results. Certain conflicts and inconsistencies among results need to be resolved. Finally, the most useful associations are visualized for decision support.

It is important to note that the AMR system is implemented in an iterative fashion. Each time the system is applied to solve a real-life problem, the results act as feedback to refine the knowledge base and to fine tune the parameters of AMR modules.

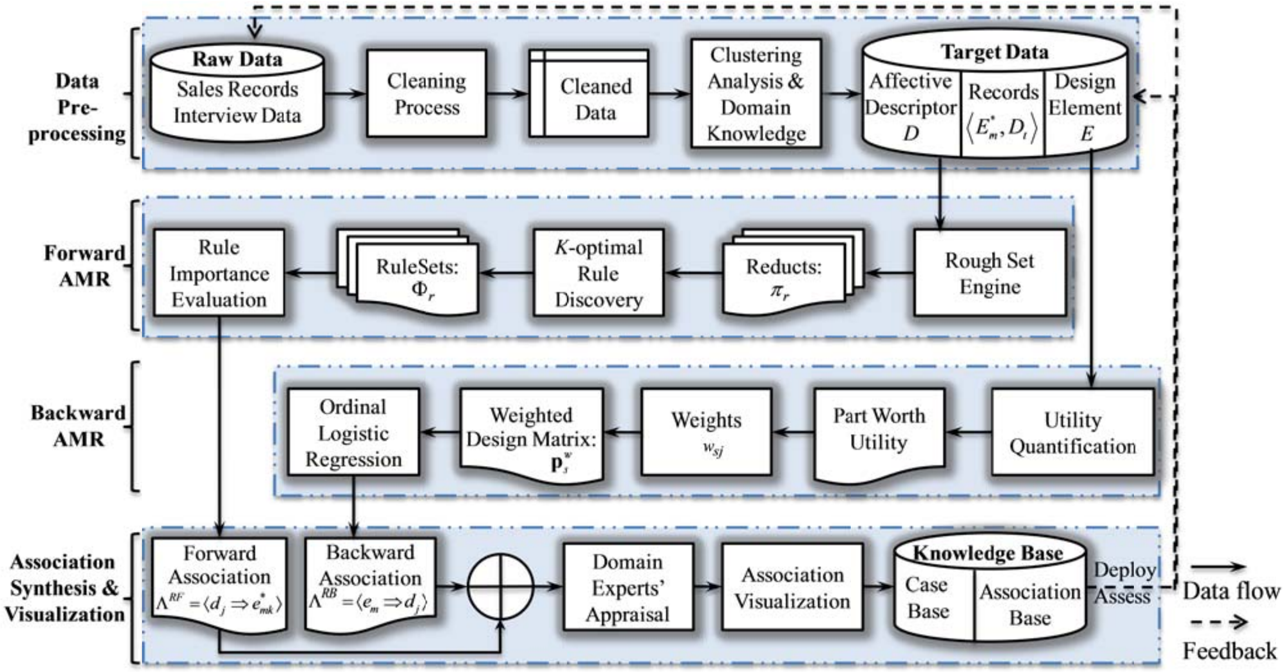


Figure 7-3 System architecture of hybrid AMR

7.6 Affective Descriptor Analysis

The most representative affective descriptors need to be extracted from the 61 affective adjectives identified earlier. Considering vague and fuzzy expressions associated with affective needs, clustering analysis is reported to be advantageous, owing to its large tolerance for ambiguity and a high level of prediction accuracy (Friedman *et al.*, 2001).

First, each affective descriptor is rated by 36 participants for six existing truck cabs using a 7-point Likert differential emotions scale (Osgood *et al.*, 1975), where '1' denotes 'absolutely not' and '7' 'very much'. It thus produces a 216×61 matrix for clustering analysis. A hierarchical clustering analysis with a complete linkage agglomerative method is applied

(Friedman *et al.*, 2001). The results are represented as a dendrogram with 30 clusters or nodes (some correspond to multiple affective adjectives), as shown in Figure 7-4. Each cluster means a group of similar affective descriptor(s). When they are grouped together, one typical affective descriptor is used to represent the whole group of the affective descriptors. The dendrogram forms a hierarchical tree connecting nodes with many inverted U-shaped lines. The height of each inverted-U line represents the distance between two connected nodes. Cutting the dendrogram horizontally at a particular height partitions the data into disjoint clusters represented by the vertical line that intersects it. Empirically, we suggest 10 clusters of affective descriptors cut by the horizontal line (see Figure 7-4). The representative affective descriptors for each cluster are obtained as: clean (d_1), boring (d_2), cool (d_3), modern (d_4), luxurious (d_5), cozy (d_6), comfortable (d_7), cheap (d_8), functional (d_9), and personal (d_{10}).

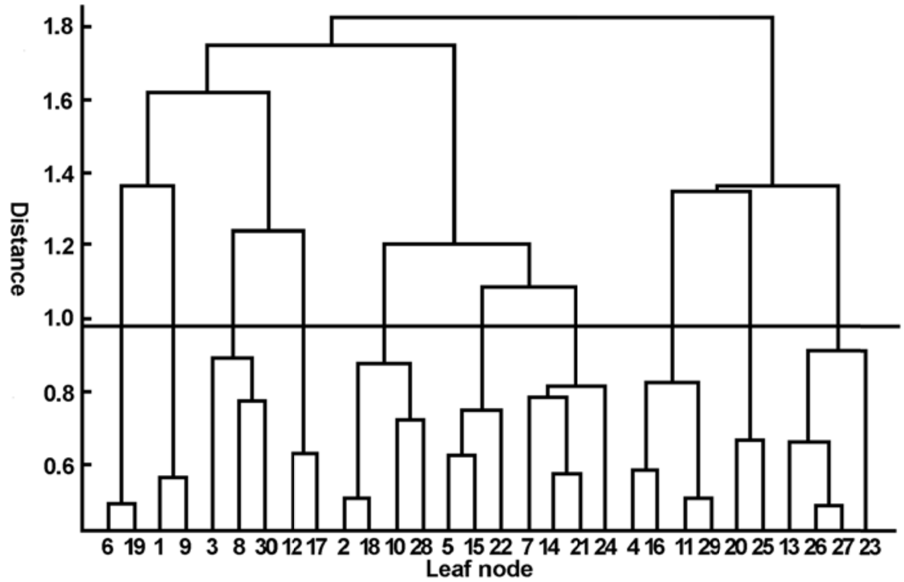


Figure 7-4 Dendrogram of affective descriptors by clustering

7.7 Forward Association Ming and Refinement

7.7.1 K-Optimal Rule Discovery

Based on the specified measure, the *K*-optimal rule discovery process returns at most *K* rules (Webb and Zhang, 2005). This speeds up the rule discovery task by pruning the search space that is devoid of the top *K* most valuable rules. A FAM association rule is generally formulated as $d_i \,\&\, d_j \,\&\cdots\&\, d_k \Rightarrow e^*_{xa} \,\&\, e^*_{yb} \,\&\cdots\&\, e^*_{zc}$, where $d_i, d_j, d_k \in D$, $1 \le i < j < k \le I$, $e^*_{xa} \in E^*_x$, $1 \le a \le K_a$, $e^*_{yb} \in E^*_y$, $1 \le b \le K_b$, $e^*_{zc} \in E^*_z$, $1 \le c \le K_c$, and $1 \le x < y < z \le M$ K_a, K_b, and K_c are the total numbers of element levels with regard to the respective design elements. The rule can be interpreted as the occurrence of affective descriptors $\left(d_i, ..., d_j, ..., d_k\right)$ in accompany with the occurrence of design elements e_x at the *a*-th level, e_y at the *b*-th level, …, and e_z at the *c*-th level. It can be concisely denoted as $X^d \Rightarrow Y^e$, where item set $X^d = \left\{d_i,\ d_j\ ,\ldots,d_k\right\}$ and item set $Y^e = \left\{e^*_{xa}, e^*_{yb}, ..., e^*_{zc}\right\}$ are nonempty sets of conditions called the antecedent and consequent, respectively.

The general principle of *K*-optimal rule discovery can be expressed as a 5-tuple, $\langle C, \Delta, G, \lambda, K\rangle$, where C is a nonempty set of conditions, and $\Delta = \left\{R_h\right\}_H$ is a database of correspondence records between affective needs and design elements, where H is the total number of records. The *h*-th record is represented as $R_h = P_h \cup D_h$, where $D_h = \left\{d^h_i,\ d^h_j, \ldots, d^h_k\right\}$, implying that product P_h configured by certain design elements is used to fulfill affective needs D_h . Set G represents constraints related to association rules, $\left\{X^d \Rightarrow Y^e\right\}$. Function $\lambda : \left\{X^d \Rightarrow Y^e\right\} \times \left\{\Delta\right\} \to R$ maps those hidden association rules in the database to a real value such that the larger the value of $\lambda\left(X^d \Rightarrow Y^e,\ \Delta\right)$, the greater its relevance to association $X^d \Rightarrow Y^e$, within the given database. The number of rules to be discovered is indicated by K .

A *K*-optimal rule discovery system starts with user input to specify λ, G and K values. The system then returns the K rules that optimize λ with regard to database Δ with constraints G. The solution, *s*, to $\{\langle C, \Delta, G, \lambda, K\rangle\} \rightarrow \{X^d \Rightarrow Y^e\}$ is derived by satisfying the following conditions:

$$\begin{aligned}
&\forall s \in \text{solution}\left(\langle C, \Delta, G, \lambda, K\rangle\right): \\
&\left(s \subseteq \text{CSsolution}\left(\langle C, \Delta, G\rangle\right)\right) \wedge \left(|s| \leq K\right) \wedge \\
&\left(\neg \exists r \in \text{solution}\left(\langle C, \Delta, G, \lambda, K\rangle\right):\ |r| < |s|\right) \wedge \\
&\begin{pmatrix} \neg \exists X^d \Rightarrow Y^e \in s, U^d \Rightarrow V^e \in \left(\text{CSsolution}\left(\langle C, \Delta, G\rangle\right) - s\right): \\ \lambda\left(X^d \Rightarrow Y^e, \Delta\right) < \lambda\left(U^d \Rightarrow V^e, \Delta\right) \end{pmatrix},
\end{aligned} \tag{7-1}$$

where CSsolution denotes the solution to a constraint-satisfaction rule discovery task as follows (Webb and Zhang, 2005):

$$\text{CSsolution}\left(\langle C, \Delta, G\rangle\right) = \left\{X^d \Rightarrow Y^e \middle| \left(X^d \subseteq C\right) \wedge \left(Y^e \subseteq C\right) \wedge \left(\text{satisfies}\left(X^d \Rightarrow Y^e, \Delta, G\right)\right)\right\}. \tag{7-2}$$

Leverage is adopted as the value measure λ of rule $X^d \Rightarrow Y^e$ in *K*-optimal rule discovery and is defined as the following (Webb, 2003):

$$\text{leverage}\left(X^d \Rightarrow Y^e\right) = \text{support}\left(X^d \cup Y^e\right) - \text{support}\left(X^d\right) \times \text{support}\left(Y^e\right), \tag{7-3}$$

where $\text{support}(*)$ is the proportion of records that contain item set '$*$'. For example, the support of item set X^d is defined as:

$$\text{support}\left(X^d\right) = \left|\left\{X \mid \left(X \in \Delta\right) \wedge \left(X \supseteq X^d\right)\right\}\right| \big/ H, \tag{7-4}$$

where X is an item set in database Δ and $|*|$ denotes the cardinality of set '$*$'. According to Eqn. (7-2), the *leverage* measure indicates the difference between an observed frequency of $X^d \cup Y^e$ (i.e., $\text{support}\left(X^d \cup Y^e\right)$) and an expected frequency if X^d and Y^e are independent (i.e., $\text{support}\left(X^d\right) \times \text{support}\left(Y^e\right)$). This represents the volume of the interaction between X^d and Y^e, and hence often directly relates to the significance of the interaction between affective needs and the involved product (Webb, 2003).

7.7.2 Rough Set-Based Rule Importance Measure

K-optimal rule discovery uses *leverage* to measure the quality of the rules. However, the real value of a rule, in terms of usefulness and importance, is subjective and depends largely on business concerns *per se*. Furthermore, *K* is often a large number and it is tedious to refine rules manually. Hence, it becomes necessary to establish certain criteria to evaluate the *goodness* of a rule.

Rough set-based methods can be used to filter redundant attributes in the raw data using reducts (Pawlak, 1991) so that rule generation can be more efficient and effective (Li and Cercone, 2006). Referring to Li and Cercone (2006), let $\Pi = \{\pi_r\}_R$ and $\Phi = \{\varphi_r\}_R$ denote the respective sets of reducts and the rule sets, where R stands for the total number of both reducts and rule sets, as each rule set φ_r is generated from reduct π_r. Assume $\varphi_r = \{\phi_i\}_{R_r}$, where R_r is the total number of rules in φ_r. The rule importance measure ρ_i for rule ϕ_i is defined as the total number of this rule generated in all possible rule sets Φ divided by the number of reducts R, namely,

$$\rho_i = \left|\{\varphi_r \in \Phi \,|\, \phi_i \in \varphi_r\}\right| \big/ R, \tag{7-5}$$

where $|*|$ denotes the cardinality of set '$*$'. For example, if there are 4 reducts and ϕ_i appears 3 out of 4 rule sets, then ρ_i is 75%. This rule importance measure provides an objective metric for rule refinement (Li and Cercone, 2006).

7.7.3 Results

Fifteen experienced truck drivers have been invited to evaluate six truck cab interior designs using the extracted ten affective descriptors. The transaction database is obtained by preprocessing these raw data. Excluding two missing records, a total number of 88 valid records are organized into the transaction database. Each record denotes the correspondence of a set of affective needs to the user's selection of design elements. A selected portion of the database is shown in Table 7-2. For example, record #2 assumes e_{11}^*, e_{21}^*, e_{31}^*, e_{41}^*, e_{51}^*, e_{62}^*, e_{71}^*, and d_5&d_9. It means that a particular user perceives a design with *foldable bunk, above-bed storage, fabric seat, embedded light, textile mat, flat wall, and yellow interior*, as *functional and luxurious*.

A Rough Set Exploration System with genetic algorithms (Bazan and Szczuka, 2005) is used to generate reducts. Four reducts are produced, including {bunk, storage, mat, wall}, {bunk, mat, interior color}, {bunk, seat material, interior color}, and {bunk, lights, interior color}. Based on these reducts, a *K*-optimal rule discovery algorithm is employed to generate rule sets for each reduct using MagnumOpus data mining tool (Webb and Zhang, 2005). The system parameters are set as K = 20 for each reduct. Constraints G are restricted by setting the minimum support at 0.04, minimum confidence at 0.2, maximum size of the antecedent of a rule at 4, and a single condition (i.e., one design element) in the consequent only. Table 7-3 shows the identified rules and rule importance measures, along with the corresponding *leverage*, *support*, and *confidence* of each rule.

Table 7-2 Transaction database

ID	Bunk	Storage	Seat Material	Light	Mat	Wall	Interior Color	Affective descriptor
1	e_{12}^*	e_{21}^*	e_{31}^*	e_{41}^*	e_{51}^*	e_{62}^*	e_{71}^*	d_7&d_9
2	e_{11}^*	e_{21}^*	e_{31}^*	e_{41}^*	e_{51}^*	e_{62}^*	e_{71}^*	d_5&d_9
…	…	…	…	…	…	…	…	…
87	e_{12}^*	e_{21}^*	e_{31}^*	e_{41}^*	e_{51}^*	e_{61}^*	e_{74}^*	d_8&d_{10}
88	e_{12}^*	e_{21}^*	e_{33}^*	e_{42}^*	e_{52}^*	e_{62}^*	e_{74}^*	d_6&d_{10}

7.7.4 Analysis

In this case study, there are 29, 34, 24, and 24 rules produced for the four reducts with constraints G, respectively. They are further reduced to 20 for each reduct by setting K = 20 in the *K*-optimal rule discovery process. While *support* can measure how frequently the items of an antecedent and a consequent both appear, it cannot reveal the significance of a rule. The *leverage* measure addresses the degree of interactions between affective needs and design elements.

Table 7-3 FAM relations ranked by rule importance measure

No.	Rules	Rule importance measure	Leverage	Support	Confidence
1	$d_9 \Rightarrow e_{11}^*$	100%	0.050	0.068	0.333
2	$d_8 \Rightarrow e_{12}^*$	100%	0.015	0.273	0.960
3	$d_9 \Rightarrow e_{71}^*$	75%	0.079	0.114	0.556
4	$d_5 \Rightarrow e_{71}^*$	75%	0.056	0.091	0.444
5	$d_8 \Rightarrow e_{75}^*$	75%	0.054	0.102	0.360
6	$d_3 \Rightarrow e_{32}^*$	75%	0.040	0.057	0.556
7	$d_7 \Rightarrow e_{71}^*$	75%	0.039	0.080	0.333
8	$d_6 \Rightarrow e_{32}^*$	75%	0.025	0.068	0.500
9	$d_8 \Rightarrow e_{74}^*$	75%	0.023	0.114	0.400
10	$d_5 \Rightarrow e_{62}^*$	75%	0.015	0.080	0.389
11	$d_9 \Rightarrow e_{51}^*$	50%	0.057	0.159	0.778
12	$d_5 \Rightarrow e_{51}^*$	50%	0.046	0.148	0.722
13	d_9 & $d_5 \Rightarrow e_{51}^*$	50%	0.028	0.057	1.000
14	$d_3 \Rightarrow e_{52}^*$	50%	0.028	0.080	0.778
15	$d_2 \Rightarrow e_{41}^*$	50%	0.023	0.057	0.833
16	$d_7 \Rightarrow e_{52}^*$	50%	0.017	0.136	0.571
17	$d_3 \Rightarrow e_{33}^*$	50%	0.056	0.091	0.444
18	d_7 & $d_5 \Rightarrow e_{71}^*$	50%	0.036	0.045	0.800
19	$d_5 \Rightarrow e_{11}^*$	50%	0.036	0.045	0.800
20	$d_6 \Rightarrow e_{42}^*$	50%	0.027	0.045	0.222
21	$d_2 \Rightarrow e_{74}^*$	50%	0.025	0.068	0.500

The efficacy of the mined rules to predict FAM mapping relationships for future affective design depends on two critical measures, i.e., accuracy and generalizability. Accuracy is often validated using historical data while generalizability should be tested for future data. The *leverage* measure coincides with weighted relative accuracy, which reflects the tradeoff between generalizability and relative accuracy (Todorovski *et al.*, 2000). Furthermore, the rule importance measure considers the semantic meaning of data and evaluates the significance of a rule based on the attribute significance (Li, 2007). For example, rules 1 and 2 (*if the bunk is foldable, then it is functional; if the bunk is unfoldable, then it is cheap*) have an importance of 100%, which are said to be more important than other rules. Concerning the computational complexity, the worst-case is exponential on the number of conditions in the antecedent and consequent, when no pruning is possible and the entire rule space must be explored. , i.e., if there are k conditions that may appear in an antecedent then the space of possible antecedents is 2^k and if any one of these k conditions may also appear in the consequent, then the space of possible rules is of order $O(2^k)$ (Webb and Zhang, 2005). However, due to the constraints on G, as the experiments above have demonstrated, for a number of larger real-world datasets, efficient search by leverage is a reality.

7.8 Backward AMR

7.8.1 Ordinal Logistic Regression

An OLR model is based on the posterior probability of V categories resulting from each affective descriptor $d_i \in D$ being rated on a V-point Likert scale. Assuming there are S participants and one specific product specification rated by the s-th participant is expressed as a vector, $\mathbf{P} = \mathbf{p}_s = \left(p_{1s}, p_{2s}, ..., p_{Js}\right)$, where J is the total number of the design elements specified in the product. In a proportional odds model (Hosmer and Lemeshow, 2000), the logit of the cumulative probability of response variable $d_i \le v$ is given as:

$$c_v(\mathbf{p}_s) = \ln\left(\frac{\Pr(d_i \le v \mid \mathbf{P} = \mathbf{p}_s)}{\Pr(d_i > v \mid \mathbf{P} = \mathbf{p}_s)}\right) = \alpha_v - \sum_{j=1}^{J} \beta_j p_{js} = \alpha_v - \mathbf{p}_s \boldsymbol{\beta}^T , \tag{7-6}$$

where $v=1,...,V-1$, $s=1,...,S$. Intercept α_v indicates the probability that d_i assumes a low scale (close to 1), instead of a high scale (close to *V*), when no design element is involved in the model. The logit change, $c_v(\mathbf{p}_s)$, corresponding to a unitary increase in p_{js}, is denoted as β_j, where $1 \le j \le J$, $\boldsymbol{\beta}=(\beta_1,...,\beta_J)$. The minus sign before β_j is used for convenience of interpretation. In such a way, positive values of β_j correspond to higher probabilities when the dependent variable assumes high scales, and vice versa. Inherent to this model is the proportional odds assumption that β_j is constant across response categories (i.e., different scales of *v*), such that the only difference is α_v.

A weighted OLR is to introduce the *s*-th participant's weights, w_{js}, into independent variable $\mathbf{p}_s$ as correction coefficients in order to filter noise factors in the design element space, as shown in the following equation:

$$c_v^w(\mathbf{p}_s)=\alpha_v^w-\sum_{j=1}^{J}\beta_j p_{js}w_{js}=\alpha_v^w-\mathbf{p}_s^w(\boldsymbol{\beta}^w)^T, \tag{7-7}$$

where $v=1,...,V-1$, $s=1,...,S$ and α_v^w, $\mathbf{p}_s^w$ and $\boldsymbol{\beta}^w$ are the weighted counterparts compared with those in Eqn. (7-6).

7.8.2 Conjoint Analysis for Weight Calculation

Conjoint analysis is one of the well-established tools for obtaining part-worth utilities (Green *et al.*, 1981). The weights derived from part-worth utilities summarize the differential preference of each participant by their perceived utilities of each design (i.e., an association of affective design). Hence, the AMR system applies conjoint analysis to mitigate influence noises, such as the halo effect – a cognitive bias occurring in psychological rating (Beckwith and Lehmann, 1975). As each level of a design element inherently possesses certain utility for the *s*-th participant's preference, we can obtain a range of utility, R_{js}, for the *s*-th subject of the *j*-th design element. The weights are calculated as individual R_{js} of each design element divided by the overall utility range for all the design elements, i.e.,

$$w_{js} = R_{js} \Big/ \sum_{k=1}^{J} R_{ks} \, , j = 1, \ldots, J, s = 1, \ldots, S \, . \tag{7-8}$$

For the design elements in Table 7-1, there exist a total number of 2×2×3×2×2×2×5 = 480 product profiles. Because it is impractical to examine all possible profiles, orthogonal product profile configurations are formulated through design of optimal experiment (Nair *et al.*, 1995) using software SPSS 15.0. Table 7-4 shows a snapshot of 27 orthogonal product profiles, in which each entry in the column of a design element corresponds to the level of that design element. Each row under 'Conjoint Test' is one specification of a product ecosystem profile with respect to specified design elements. All 36 participants have been asked to evaluate and rank all these profiles. The 'Rank' column indicates ranking of each profile by one participant. All data are compiled as input to SPSS for conjoint analysis. The final part-worth utilities for each level of design elements are given in Table 7-5.

Furthermore, each participant is asked to rate each affective descriptor for each product ecosystem profile in terms of a 5-point Likert scale for OLR, where '5' means 'strongly agree' and '1' 'strongly disagree'. The last column of Table 7-4 shows the ratings of affective descriptor *'cool'*. According to Eqn. (7-8), the weight boxplot for all design elements involved is depicted in Figure 7-5.

Table 7-4 Orthogonal design using SPSS

Conjoint Test								**Rank**	**Scale**
Profile	**bunk**	**storage**	**seat material**	**light**	**mat**	**wall**	**interior color**		
1	1	1	2	1	1	2	1	5	5
2	2	2	3	2	1	2	3	16	2
…	…	…	…	…	…	…	…	…	…
26	1	2	2	2	1	1	1	19	3
27	1	1	2	1	1	1	2	23	1

Table 7-5 Part-worth utilities for element levels

Design elements	Level	Utility Estimate
bunk	foldable	0.079
	unfoldable	-0.079
storage	above bed	0.287
	beside bed	-0.287
seat_material	fabric	-0.093
	leather	-0.250
	cloth with soft nap	0.343
light	embedded in the wall	0.491
	protruded from the wall	-0.491
mat	textile	-0.491
	rubber	0.491
wall	sponge attached	0.211
	flat	-0.211
interior_color	yellow	0.094
	green	0.192
	blue	-0.197
	red	0.678
	grey	-0.767

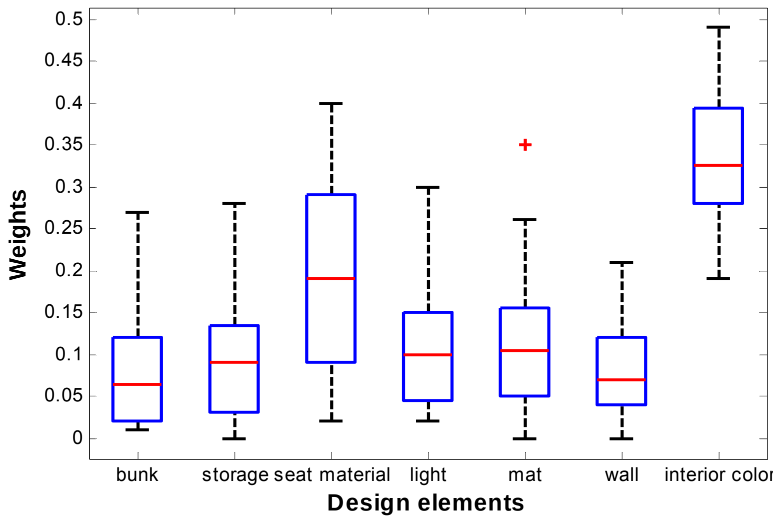


Figure 7-5 Boxplot of design element weights

7.8.3 OLR Model Comparison Study

Table 7-6 summarizes the results of the basic and weighted OLR models for affective descriptor *'cool'*. The Likelihood Ratio Chi-Square test, as shown in Table 7-6(a), suggests that the 'Final' OLR model improves upon the 'Intercept only' model for both basic and weighted models. However, the *p* value for the weighted model is much smaller, indicating more improvement in the weighted model. The Pearson and deviance, as shown in Table 7-

6(b), demonstrate adequate fitting for the weighted model (p > 0.050), whereas the basic model is inferior, as its p value for Pearson is 0.000.

Table 7-6 Ordinal logistic regression model comparison for affective descriptor *'cool'*

(a) Model fitting information

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Intercept Only	76.59/96.16			
Final	59.68/71.66	16.91/24.49	7/7	0.018/0.001

(b) Goodness-of-Fit

	Chi-Square	df	Sig.
Pearson	306.31/100.65	97/97	0.000/0.380
Deviance	71.66/59.68	97/97	0.975/0.999

(c) Parameter estimates

	Scale	Estimate	Std. Error	Wald	Sig.
		α_v			
Intercept	1	-10.88/-9.55	3.10/3.25	12.31/8.64	0.000/0.003
	2	-7.78/-6.88	2.80/2.97	7.72/5.36	0.005/0.021
	3	-4.40/-4.18	2.57/2.77	2.94/2.28	0.086/0.131
	4	-2.10/-1.92	2.49/2.68	0.72/0.52	0.398/0.472
	5 baseline	00/00			
Independent variable	Design Element	β			
	bunk/ bunk	-1.27/-0.04	0.69/0.03	3.40/2.04	0.065/0.153
	storage* / storage**	-0.86/-0.63	0.43/0.23	3.98/7.46	0.046/0.006
	mat/ mat*	-1.28/-0.66	0.75/0.28	2.95/5.50	0.086/0.019
	wall/wall	0.62/0.01	0.73/0.02	0.72/0.44	0.398/0.508
	seat material*/ seat material***	0.27/0.37	0.13/0.09	4.68/16.53	0.031/0.000
	light/light*	0.92/2.00	0.73/0.97	1.60/4.27	0.206/0.039
	interior color***/ interior color**	-1.24/-0.39	0.34/0.12	13.46/10.28	0.000/0.001

Link function: logit; ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$)

(d) Test of parallel lines

Model	-2 Log Likelihood	Chi-Square	df	Sig.
Null Hypothesis	71.66/59.68			
General	41.39/58.56	30.27/1.12	21/21	0.087/1.000

Note the values on the left of '/' are for the basic model while those on the right of '/' are for the weighted model.

The coefficients of independent variables β_j reflect how design elements are associated with dependent variable *'cool'*. The difference between two OLR models also deserves attention, as shown in Table 7-6(c). In the basic model, four design elements (*'bunk'*, *'storage'*, *'mat'*, and *'interior color'*) all have negative coefficients. Among them, *'storage'* (p < 0.050) and *'interior color'* ($p < 0.001$) are significantly attributed to the lower scales of *'cool'*. On the other hand, *'bunk'* and *'mat'* ($p < 0.100$) are marginally associated with the lower scales of *'cool'*. Moreover, *'wall'* and *'light'* ($p > 0.100$) are not correlated with *'cool'*. Likewise, *'seat material'* ($p < 0.050$) is the only variable that is positively related to the higher scales of *'cool'*. For the weighted model, *'light'* ($p < 0.050$) and *'seat material'* ($p < 0.001$) are significantly related to the higher scales of *'cool'*, whereas *'storage'*, *'interior color'* ($p < 0.010$) and *'mat'* ($p < 0.050$) are significantly associated with the lower scales of *'cool'*. And *'bunk'* ($p > 0.100$) is not related to *'cool'*.

Table 7-6(d) depicts the test of parallel lines. The results reveal that the proportional odds assumption holds true for both models and that the p value for the basic model is close to 0.050. Since the ordered logit model estimates one equation over all design elements, the ordered logit coefficients (β_j) turns out to have a high probability of being not equal across levels of the outcome for the basic model.

An overall comparison shows that the weighted OLR model is superior to the basic model in that it improves model fitting by controlling variances and noise factors that cannot be explained by design elements themselves. In other words, it provides designers more insights into the implications of a user's affective semantic space from the perspectives of different design elements. Furthermore, backward AMR provides useful information regarding how to maximize the producer's surplus without sacrificing users' affective satisfaction. For example, the weighted model discovers that associations *'storage'* ↔ *'cool'* and *'interior color'* ↔ *'cool'* are equivalent in satisfying users' perception for *'cool'*. Then it is up to the producer to select which design element (*'storage'* or *'interior color'*) to be used in design at its convenience of cost and manufacturability.

7.9 Association Synthesis and Visualization

Since there is hardly any data mining tool that can solve affective mapping problems automatically, the data mining process requires significant human interactivity (Larose, 2005). Explaining associations by visualization is an effective means to make data mining models comprehensible and accessible to designers (Becker *et al.*, 2001). In addition, possible conflicts among forward and backward association rules need to be resolved.

Figure 7-6 shows an output of FAM visualization, in which the attributes of each association rule, such as rule importance measure, *leverage*, *support* and *confidence*, are labeled graphically. Through visualization, important attributes can be assessed as a whole, facilitating the identification of useful patterns.

The backward associations for affective descriptor *'cool'* with respect to the design elements are plotted in Figure 7-7. Different p values and β values are labeled in the plot, representing the degree of significance and directions of BAM associations, respectively.

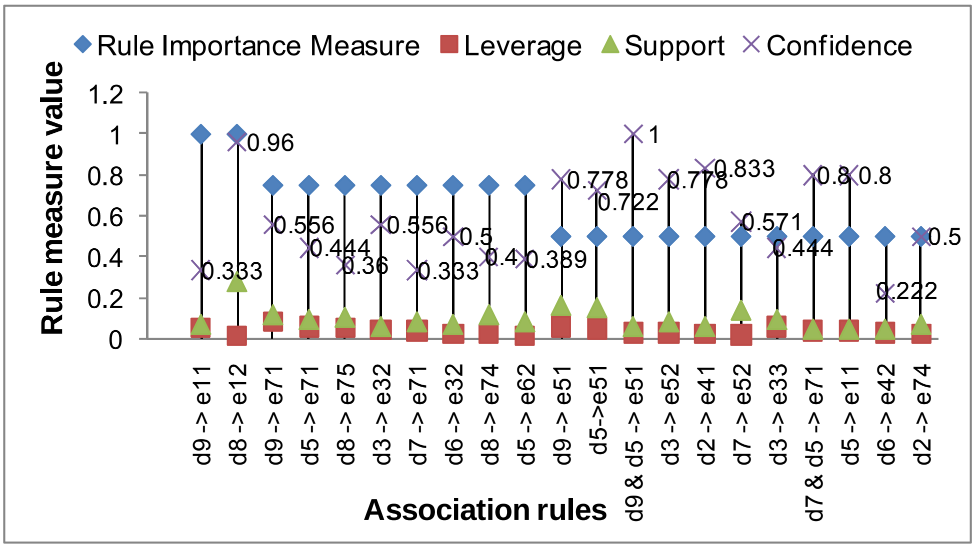


Figure 7-6 Visualization of forward association rules

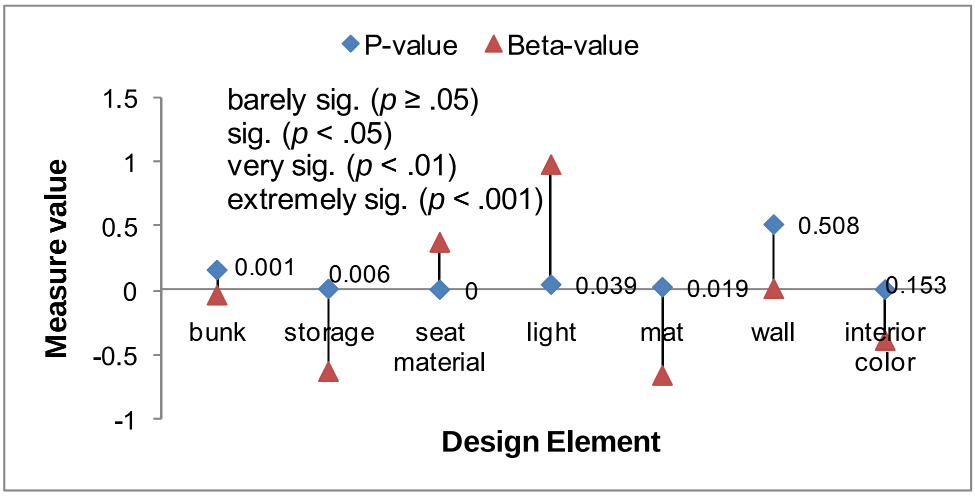


Figure 7-7 Visualization of backward association for affect *'cool'*

For example, three rules, $d_3 \Rightarrow e_{32}^*$, $d_3 \Rightarrow e_{33}^*$ and $d_3 \Rightarrow e_{52}^*$, are related to *'cool'* in Figure 7-6. The first two rules are consistent with such backward associations that *'seat material'* is significantly related to the higher scales (strongly agree) of *'cool'*. The last rule is not consistent in that *'mat'* is significantly related to lower scales (strongly disagree) of *'cool'* in Figure 7-7. The possible reason is investigated by tracing back to the original interaction scenario. It might originate from contextual mismatching between the holistic perception towards affective quality and the summation of individual design elements' contribution to affective satisfaction. Such deviations can be easily spotted through visualization.

7.10 Discussions

Consistent with the bidirectional affective mapping process, the hybrid AMR model comprises forward and backward AMR decision making for affective needs fulfillment. Forward AMR exploits *K*-optimal association mining to return a controllable number of rules according to assessment of rule importance that optimize the rule measure – *leverage* with specified constraints. It not only improves the efficiency of rule mining, but also captures the interaction between affective needs and design elements. The *leverage* measure incorporates generalizability of the rules to support future affective design. The quality of inference rules is further refined through performance evaluation using rough set-based importance measure. This facilitates the incorporation of semantics into rule evaluation, and thus provides a straightforward benchmarking decision support to designers (Li, 2007). The rough set model also helps mitigate the ambiguity underlying affective needs by alleviating the tedious task for domain experts to interpret and judge the validity of the outcome.

An important aspect of users' perception of a product lies in that affective satisfaction does not originate from a weighted sum of single assessments of individual design elements, but rather is reflected as a holistic impression (Ingarden, 1985). In this sense, it is arguable that a negatively-perceived design element alone may jeopardize the positive emotions towards the whole product, regardless of other design elements that may be appealing to users' perception. Although FAM rules associate each individual design element with one or more affective descriptors, derivation of these rules is based on a holistic interpretation of transaction database *per se*. With bidirectional AMR, one particular rule can be traced back to prior design scenarios, and thus by comparing multiple rules involved in each design scenario, possible conflicts between forward and backward associations can be resolved. In addition, negative affective descriptors (e.g., boring) are also encoded in the rules. Such negative association rules indeed act as counterparts to identify good value-added rules and help avoid unintended configuration of certain design elements that finally lead to negative emotions.

The BAM module produces information that helps differentiate various design elements by the significance and direction of the associations. From a designer's point of view, this gives valuable guidelines not only to fulfill user's affective needs effectively, but also to leverage engineering concerns at the backend of design. For example, *'cool'* could be valuable affective needs among male teenagers. When the designer targets this segment of customers, s/he may manipulate those design elements that explicitly appear in the positive associations regarding affect *'cool'* so as to maximize the achievement of affective quality. In the meantime, the designer may rely on those design elements not in the rules for *'cool'* to optimize engineering concerns related to cost and manufacturability. Inevitably, there might be conflicts among design elements, when eliciting positive emotions and minimizing cost. To make tradeoffs, designers may refer to the AMR knowledge base and spot those design elements that evoke similar emotions and launch a product mix (e.g., low- or high-end product lines) in order to target a wider spectrum of market segments.

7.11 Summary

A synergy of forward and backward AMR is conducive to the understanding of affective design decision making from both the users' and designers' perspectives for affective needs fulfillment. The FAM associations provide knowledge about inference and tradeoffs between users and designers. The *leverage* measure can reveal generalizability of association rules proactively to support new designs. The quality of rules can be enhanced through the rule importance measure that incorporates semantics of the associations. To better fulfill each individual user's affective needs, the AMR system architecture enables a configuration model for personalized affective design. The BAM associations support a closed-loop design process and can minimize contextual mismatching throughout the affective mapping process. Backward AMR facilitates the understanding of those factors that influence user choices, and in turn improving design decision making. The hybrid AMR system forms a complementary mechanism enabling the designers to meet users' affective needs while leveraging engineering concerns at the backend of affective design. Proper support of AMR bestows companies with extra values in pursuit of products that are not only functional and safe, but also pleasurable to use, and hence more likely to gain a competitive edge.

CHAPTER 8
CONCLUSIONS AND FUTURE WORK

This concluding chapter summarizes the findings and the contributions of the thesis work. The limitations and possible improvements are also discussed, along with avenues for future research.

8.1 Conclusions

The traditional standpoint of "selling a product to the average customers" has been fundamentally challenged by diverse user requirements nowadays, along with abundant substitute products, and shrinking profit margins of individual products. A new perspective named product ecosystem design is emerging, that is, multiple interdependent products are considered as a consistent whole to create unique UX, where users' cognitive and affective aspects are both accommodated in the design and delivery process of products and systems. While the cognitive aspect focuses on users' information processing and decision-making processes, the affective aspect focuses on users' affective responses and inspirations. Product ecosystem design also extends the traditional boundaries of human-object (product) interactions to encompass the notion of 'ambience' that forms human-object-(product)-ambience interactions. To tackle such a complex design problem systematically, a technical framework is proposed, dealing with issues of ACN acquisition, AC analysis, and AC fulfillment.

ACN acquisition deals with one important methodological issue, i.e., which measures are more effective, for example, between subjective and objective measures. With regard to affective need elicitation, the use of subjective methods often relies heavily on linguistic terms. Therefore, these terms should be concise and easy to understand and takes into account cultural, as well as contextual factors to improve their validity (Larsen and Fredrickson, 1999). By contrast, a major advantage of objective methods, such as physiological measures, is that they are language-independent and can be used in real time so that the system can respond immediately to interaction events to improve UX. On the other hand, the introduction of AmI makes it possible for human cognitive functions to be extended over much larger fields of available information and thus renders human activities to be more optimal for more desirable UX.

AC analysis aims to develop systematic methods that are able to model complex product ecosystems as well as dynamic UX. The proposed method, namely FRPNs, is capable of representing a vast variety of design elements in the product ecosystem and capturing their interactive relationships between them with regard to individual interaction events, during which users' affective states and cognitive task processes are evolving. Simulation methods allow users to interact with different ecosystem profiles of the subway station that would be too difficult, expensive, or impossible to reach physically and analyze what-if scenarios to optimize the tradeoff between UX and operational cost.

AC fulfillment accommodates both UX and engineering concerns. For one thing, the tradeoff between affective UX, cognitive processes and operational costs is studied using simulation methods in Chapter 4, based on which redesign guidelines for product ecosystem profiles are obtained. For another, forward and backward affective mapping techniques using hybrid data mining and refinement methods are proposed to deal with affective UX as well as engineering concerns, respectively, at the back end of affective design. Besides, the application of data mining incorporates both user interaction knowledge and experts' experiences into the projection of mapping patterns from historical data. It thereby maintains both accuracy and generalizability of mined patterns and enhances the ability to explore and utilize domain knowledge more effectively.

Table 8-1 Summary of relations between Chapters 4-7 and Figures 3-3 and 3-4

Chapters	**Relation to Figure 3-3**	**Stage in Figure 3-4**	**Focus**	**Comment**
4	The influence of culture and gender on affect elicitation and prediction is considered	1st and 2nd stage: Affective need elicitation and analysis	Elicitation and predication in real time with wearable sensors	The experiment takes place in the laboratory, but both culture and gender factors are considered. It gives implications on affective design
5	The influence of ambient factors, usability, interactivity, telepresence, and task challenge on cognitive needs acquisition and analysis is considered	1st and 2nd stage: Cognitive need acquisition and analysis	Acquisition and analysis of cognitive needs in real time with ambient intelligence	The experiment mimics a real smart home ecosystem, considering many factors influencing product ecosystem design
6	Affective states and cognitive process are analyzed as a whole, and ecosystem entities, including users, products and ambient factors are considered	2nd and 3rd stage: Affective and cognitive need analysis and fulfillment	User experience modeling, including both affective and cognitive aspects	The simulation is based on a real subway station ecosystem, taking account into all the possible users, products, and ambient factors
7	The influence of affective quality on affective fulfillment is considered	3rd stage: Affective needs fulfillment	Affective need fulfillment with both forward and backward mapping	The case study focuses on a truck cab ecosystem, emphasizing affective quality of the involved products

Although, the examples in different chapters seem isolated, each example is used to show the potential and feasibility of one step in the framework in Figure 3-4 (i.e., affective-cognitive elicitation, affective-cognitive analysis, and affective-cognitive fulfillment) and these steps coherently and holistically form the stages of affective-cognitive design of product ecosystems for UX. Table 8-1 summarize the relations to Figures 3-3 and 3-4 in terms of the factors that influence UX in the conceptual model in Figure 3-3 and their corresponding stage in Figure 3-4. Furthermore, different kinds of case studies are considered in the thesis, including laboratory experiment (Chapters 4 and 7), field experiment (Chapter 6), and simulation (Chapter 5), to demonstrate the potential and applications of the proposed research. Table 8-1 is used to summarize the thesis to help close the loop.

8.2 Contributions

The major contributions of the thesis manifest themselves through the proposal and development of a coherent framework of AC design of product ecosystems for UX. The deliverables are entailed in the strategy, fundamentals, methodology, validation, and application aspects, as elaborated below:

(1) At the strategy level, the following consensuses have been achieved (Chapters 1 and 2):

- Distinguish the important role of UX in terms of affect and cognition in product design;
- Propose the notion of AC design of product ecosystems for UX.

(2) At the fundamental level, the following findings have been obtained (Chapter 3):

- Analyze the fundamentals of AC design of product ecosystems for UX, including the definition of product ecosystems, UX modeling, and underlying operational mechanism of product ecosystem design;
- Identify key research issues along the proposed technical framework with three steps, i.e., ACN acquisition, AC analysis, and AC fulfillment, and accordingly develop the solution strategies.

(3) In terms of the methodology and supporting tools, the following deliverables have been promised (Chapters 4, 5, 6, and 7):

- Discover the possible combination of multiple objective measures for affective need elicitation and prediction and discuss the influence of gender and culture on affective need acquisition (Chapter 4). We utilize standardized affective stimuli to elicit affective states from 42 participants with different backgrounds. These affective states are then predicted by means of three advanced data mining approaches based on the extracted physiological features. Specifically, three different types of models, i.e., the general models, the gender-specific models, and the culture-specific models, are created from numerous participants. It is found that specific models generally outperform the general models and the overall success rates of all the models achieved are comparable to those obtained by previous studies. Therefore, the proposed approach holds promise for robust discrimination of physiological signals among different affective states and for the future affective applications.

- Examine technology-based (i.e., AmI) objective methods for cognitive need acquisition and analysis (Chapter 5). The C-AmI concept implies a unique perspective for home control, security, safety and comfort services, specifically geared towards the elderly. The C-AmI system can also be leveraged to other environments, such as hospital and nursing home ecosystems, with similar hardware and software infrastructures. It has meaningful implications in developing architectures, methods and tools that are capable of combining various technologies into AmI systems across different usage environments, and thus promises personalized services for the elderly.
- Model and simulate combined effects of affective and cognitive aspects of UX on product ecosystem design (Chapter 6). Product ecosystem design entails complex UX that involves interactions among multiple users, products and the ambience. The FRPN is developed to deal with the uncertainty, complexity, and dynamics associated with UX modeling. It is able to capture causal relationships between

UX and design elements and to provide decision support to product ecosystem analysis. Reasoning of diverse constructs of UX is embedded in the fuzzy production rules that are derived from self-reported UX data based on rough set mining. A fuzzy reasoning algorithm is implemented to perform parallel inference by multi-criterion rules and to simulate most likely UX under different ambient factors.

- Explore both forward and backward affective mapping relationships, i.e., FAM and BAM, for affective need fulfillment (Chapter 7). The knowledge gained from FAM can act as an interface between customers and designers and given a particular customer's affective needs, the product can be configured in a personalized way without the tedious elaboration process with the customer and marketing staff. The relationships obtained from BAM try to minimize contextual mismatching by controlling variances that cannot only be explained by design elements, such as halo effect and other noise factors in the process of surveys and interviews, etc. This facilitates the understanding of the factors that influence customer choices and improve the quality of design decisions. Further, it enables the designers to consider other engineering factors to maximize profits of the manufacturers. This hybrid mechanism forms a complementary virtuous cycle for continuous and spiral improvement for affective product design considering both parties in the design process.

(4) As for validation and application, several experimental and case studies have been conducted, including:

- Comparisons studies among the general, gender-specific, and culture-specific models based on a sound experiment design to validate the advantages of multiple objective measures in affective need elicitation and prediction (Chapter 4);
- A case study of EHA in a smart home ecosystem to illustrate the feasibility and potential of the cognitive need acquisition and analysis system based on AmI (Chapter 5);
- A case study of subway station ecosystem design to justify the applicability of product ecosystem design methodology (Chapter 6);
- A case study of truck cab interior ecosystem design to support affective decision making in affective need fulfillment (Chapter 7).

8.3 Limitations and Future Work

(1) Limitations of objective approaches to ACN acquisition. It is reported that physiological measures might only reliably assess a limited set of basic emotions and cannot assess mixed emotions. For pleasures of the mind, it is doubtful if any of the physiological methods will be sensitive enough to capture the subtleness of emotions (Helander and Khalid, 2006). With regard to facial expressions, it is important to make cultural comparisons in terms of statistic tests rather than data mining methods because these behavioural measures are subjective to social and cultural interaction codes (Picard, 1997). Furthermore, a full understanding of the processes involved in the series of affective and cognitive tasks and how they recruit the physiological and behavioral systems are still not very clear. For example, (1) what are the optimal time windows during which to measure different affective and cognitive effects in the interaction events and what factors contribute to their effects? (2) What is the role of the situational context in the interaction events? (3) Is affective and cognitive processing experimentally induced in the laboratory distinct from processing during naturally

occurring encounters? (4) How to disentangle measures of affective effects from those of cognitive tasks when recorded simultaneously? And (5) to what extent, will objective measures correlate with subjective measures? These questions suggest fruitful avenues for new research of ACN elicitation.

(2) Exploration of resilience and coordination in product ecosystem design. As evidenced in Chapter 5, technological powers can tightly couple different parts of a larger system for hyper-efficiency and squeeze systems of human activities to be more optimal. However, as product ecosystems grow larger, they can become more brittle and might fail dramatically when surprising conditions arise in part because of a single anomaly. Therefore, the resilience and robustness of the product ecosystem must be considered. The employment of advanced technologies represents underlying powerful infrastructure but does not create coordination themselves. Instead, it challenges our ability to design soft structures to manage and coordinate non-co-located and asynchronous activities over greater ranges.

(3) Product ecosystem design for UX in a real-world setting. Generally speaking, due to the complexity, uncertainty, and dynamics involved in the affective-cognitive design of product ecosystems for UX, it is often difficult to apply, test, and validate the entire framework (see Figure 3-4 in Chapter 3) in a real-world setting at the current stage. As the exploratory work of product ecosystem design, we are encouraged to take a systems engineering's point of view to use modeling and simulation to validate assumptions or theories on the product ecosystems and the interactions within them. A collections of separate models with specific aspects of a given complex product ecosystem is needed to provide estimates of system effectiveness, performance, and cost from a set of known or estimable quantities. Furthermore, use of simulation can detect possible bad decisions made at the early stage of the product ecosystem design but their implications later in the product ecosystems are not well

understood. The results from simulation allow us to show how the product ecosystem can be redesigned to improve UX, enhance the operational efficiency, and lower costs of the product ecosystem (e.g., Chapter 6). While much work is grounded in the simulation environment, we have been inspired primarily by anthropological and historical approaches to emotion and cognition as two essential aspects of UX. This has led us to move from simulation methods to field studies in the future where UX is regarded as interactionally constructed and subjectively experienced. This requires automatically elicit and analyze user ACNs simultaneously. Consider the work in Chapters 4 and 5, it is necessary combine them in a way that both affect and cognition can be accommodated with AmI in a coherent and resilient manner.

(4) Design for experience value chain in the product ecosystem. We highlight the necessity to accommodate both UX and engineering concerns for AC fulfillment. However, the notion of product ecosystem implies an experience value chain that represents the exchange of experience and value within the network of stakeholders that are required for the production and delivery of a product or service (Edelman *et al.*, 2009). In a global economy, achieving exceptional innovation success of companies is no longer just a matter of making a novel widget, but requires concurrently understanding and redesigning the entire experience value chain (Donaldson *et al.*, 2006). In this regard, Apple, on the one hand, innovatively redesigns consumer electronics products, such as iPhone and iPad, which support enjoyment, sharing, and surprises for their customers, and, on the other hand, redesigns the marketing, distribution and IP protection for their vendors. In doing so, Apple positions its new products to better serve the whole experience value chain while establishing long-term market dominance.

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APPENDIX

Appendix A: Mapping Relationships between Tag IDs and Objects

Time	Tag ID	Object
Mon May 12 13:42:20 SGT 2008	0B E00401001876AC39	all-in-one color for lids, lips and cheeks
Mon May 12 13:42:32 SGT 2008	0B E00401001876AB8F	beans
Mon May 12 13:42:39 SGT 2008	01 E0040100187644BC	blender
Mon May 12 13:42:49 SGT 2008	01 E0040100187689B3	book
Mon May 12 13:43:05 SGT 2008	01 E00401000231D270	bowl
Mon May 12 13:43:33 SGT 2008	01 E00401000231SE38	brow gel
Mon May 12 13:45:48 SGT 2008	0B E004010018768994	butter
Mon May 12 13:46:17 SGT 2008	0B E00401001876A8E2	burner
Mon May 12 13:46:53 SGT 2008	0B E00401001876AC32	CD-ROM
Mon May 12 13:47:54 SGT 2008	0B E004010018766809	chili powder
Mon May 12 13:48:06 SGT 2008	0B E0040100187633BC	coffee
Mon May 12 13:49:25 SGT 2008	01 E004010018768013	coffee maker
Mon May 12 13:50:02 SGT 2008	0B E00401001876A8A7	clothes container
Mon May 12 13:50:13 SGT 2008	0B E00401000231CF25	kettle cover
Mon May 12 13:50:22 SGT 2008	0B E00401001876A8E9	creamer
Mon May 12 13:51:17 SGT 2008	0B E00401001876AC1A	cup
Mon May 12 13:51:28 SGT 2008	0B E00401001876A824	detergent
Mon May 12 13:53:29 SGT 2008	0B E004010018769E0C	dishes
Mon May 12 13:55:46 SGT 2008	01 E0040100187689CB	dryer
Mon May 12 13:57:02 SGT 2008	0B E00401000231CBC0	DVD power switch
Mon May 12 13:57:26 SGT 2008	0B E00401000231CCB8	DVD remoter controller
Mon May 12 13:57:38 SGT 2008	01 E004010018763081	egg
Mon May 12 13:57:53 SGT 2008	0BE0 401000231D49D	eyelash curler
Mon May 12 13:58:16 SGT 2008	0B E00401000231CDE1	filter
Mon May 12 13:59:10 SGT 2008	0B E00401000231CDB4	floss
Mon May 12 13:59:22 SGT 2008	0B E00401000231D1DA	flushing water
Mon May 12 13:59:36 SGT 2008	0B E0040100187630A7	garbage bag
Mon May 12 14:00:44 SGT 2008	0B E004010018769662	grinder
Mon May 12 14:00:57 SGT 2008	01 E00401000231DEB2	handset
Mon May 12 14:01:07 SGT 2008	01 E00401000231D269	kettle
Mon May 12 14:01:45 SGT 2008	0B E004010018765AA7	keyboard
Mon May 12 14:02:02 SGT 2008	01 E004010018763CD9	keypad
Mon May 12 14:02:12 SGT 2008	01 E0040110231C9D1	lid
Mon May 12 14:02:31 SGT 2008	01 E00401000231CB47	mascara
Mon May 12 14:02:49 SGT 2008	01 E00401001876A865	milk
Mon May 12 14:03:01 SGT 2008	01 E00401000231DEB0	mouse
Mon May 12 14:03:38 SGT 2008	0B E00401000231D2CD	mouthwash
Mon May 12 14:03:55 SGT 2008	01 E00401000231D2ED	oatmeal
Mon May 12 14:04:04 SGT 2008	01 E00401000231CFDF	oil
Mon May 12 14:04:13 SGT 2008	0B E004010018766828	orange
Mon May 12 14:04:17 SGT 2008	0B E00401000231D161	pan

Appendix A: Mapping Relationship between Tag IDs and Objects (Cont'd)

Mon May 12 14:04:21 SGT 2008	01 E004010018769DF5	paper filter
Mon May 12 14:05:18 SGT 2008	01 E00401001876800B	pasta
Mon May 12 14:06:10 SGT 2008	0B E00401000231D420	pepper
Mon May 12 14:06:15 SGT 2008	01 E004010018763D17	pill
Mon May 12 14:06:20 SGT 2008	0B E004010018763D00	plate
Mon May 12 14:09:37 SGT 2008	0B E00401000231CCBC	powder foundation
Mon May 12 14:09:58 SGT 2008	01 E004010018765122	light power switch
Mon May 12 14:10:07 SGT 2008	01 E00401001876898B	PC power switch
Mon May 12 14:10:27 SGT 2008	01 E00401000231CEE6	salt
Mon May 12 14:10:49 SGT 2008	01 E00401000231D3DB	sauce
Mon May 12 14:12:38 SGT 2008	01 E00401000231D264	toilet seat
Mon May 12 14:13:04 SGT 2008	01 E00401001876AC0A	kitchen sink
Mon May 12 14:13:17 SGT 2008	0B E00401000231D3A2	toilet sink
Mon May 12 14:13:37 SGT 2008	01 E00401000231D3CF	spatula
Mon May 12 14:13:47 SGT 2008	0B E00401000231D430	strainer
Mon May 12 14:13:54 SGT 2008	01 E00401001876971F	sugar
Mon May 12 14:13:58 SGT 2008	0B E00401000231C9D5	sweetener
Mon May 12 14:14:08 SGT 2008	0B E00401000231CBDA	tablespoon
Mon May 12 14:14:17 SGT 2008	0B E004010018769E1D	tea
Mon May 12 14:14:28 SGT 2008	0B E004010018766820	teapot
Mon May 12 14:15:27 SGT 2008	01 E0040100187633DB	toilet tissue
Mon May 12 14:15:33 SGT 2008	0B E00401000231D1D8	toilet door
Mon May 12 14:15:41 SGT 2008	0B E00401000231D2BF	toothbrush
Mon May 12 14:17:35 SGT 2008	0B E00401000231CEEC	toothpaste
Mon May 12 14:19:41 SGT 2008	0B E00401000231CE56	TV power switch
Mon May 12 14:19:50 SGT 2008	01 E00401000231CD58	TV remote controller
Mon May 12 14:20:17 SGT 2008	0B E0040100187689B4	wash cloth
Mon May 12 14:20:23 SGT 2008	0B E00401001876ABF9	washer
Mon May 12 14:20:34 SGT 2008	0B E00401000231D4B2	water
Mon May 12 14:20:49 SGT 2008	0B E00401000231D2DE	cleanser
Mon May 12 14:24:28 SGT 2008	01 E00401000231CCD8	spoon
Mon May 12 14:33:11 SGT 2008	01 E00401000231D436	teeth brushing cup
Mon May 12 14:35:20 SGT 2008	01 E00401000231D4B0	Mary
Mon May 12 14:35:26 SGT 2008	01 E00401000231DCD1	John
Mon May 12 14:35:31 SGT 2008	0B E00401000231C4B6	Peter
Mon May 12 14:35:38 SGT 2008	01 E00401000231DD43	Luke
Mon May 12 14:35:45 SGT 2008	01 E00401000231CBE8	kitchen
Mon May 12 14:35:50 SGT 2008	01 E00401000231D499	living room
Mon May 12 14:35:53 SGT 2008	01 E00401000231A366	study room
Mon May 12 14:35:56 SGT 2008	01 E00401000231B001	bedroom1
Mon May 12 14:35:58 SGT 2008	0B E00401000231D78A	bedroom2
Mon May 12 14:36:00 SGT 2008	01 E00401000231D78C	bathroom

Note that these mappings from tag IDs to objects enable the identification of objects when the user is doing ADLs with the sensor platform in the smart home ecosystem in Chapter 5.

Appendix B: Rules Mined for Other Necessary Interaction Events

Table B-1 Mined rules for the interaction activity of going to the platform

#Rule	Rule	Confidence
1	$(P_1)\&(\neg P_5)\Rightarrow(P_{10})$	0.95
2	$(P_1)\&(\neg P_9)\Rightarrow(P_{10})$	0.95
3	$(\neg P_1)\&(P_2)\&(\neg P_3)\Rightarrow(P_{10})$	0.96
4	$(\neg P_1)\&(\neg P_9)\Rightarrow(P_{10})$	0.93
5	$(\neg P_1)\&(\neg P_8)\Rightarrow(P_{10})$	0.92
6	$(P_1)\&(P_2)\&(\neg P_8)\Rightarrow(P_{10})$	1
7	$(\neg P_2)\&(P_8)\Rightarrow(P_{11})$	0.95
8	$(P_2)\&(\neg P_4)\&(P_8)\Rightarrow(P_{11})$	1
9	$(P_1)\&(P_2)\&(P_8)\Rightarrow(P_{11})$	0.95
10	$(\neg P_2)\&(\neg P_4)\&(\neg P_8)\Rightarrow(P_{11})$	1
11	$(P_1)\&(\neg P_2)\&(\neg P_3)\&(\neg P_8)\Rightarrow(P_{11})$	1
12	$(\neg P_4)\&(\neg P_5)\Rightarrow(P_{12})$	1
13	$(\neg P_4)\&(\neg P_9)\Rightarrow(P_{12})$	1
14	$(P_1)\&(P_2)\Rightarrow(P_{15})$	1
15	$(P_3)\&(\neg P_4)\&(P_9)\Rightarrow(P_{15})$	1
16	$(P_2)\&(P_3)\&(\neg P_4)\Rightarrow(P_{15})$	1
17	$(P_3)\&(\neg P_4)\&(\neg P_5)\Rightarrow(P_{15})$	1
18	$(P_1)\&(P_7)\&(\neg P_9)\Rightarrow(P_{15})$	
19	$(P_1)\&(\neg P_3)\&(P_9)\Rightarrow(P_{15})$	1
20	$(P_1)\&(\neg P_3)\&(\neg P_5)\Rightarrow(P_{15})$	1
21	$(P_2)\&(\neg P_4)\&(P_8)\Rightarrow(P_{15})$	1
22	$(\neg P_4)\&(P_7)\&(\neg P_5)\Rightarrow(P_{15})$	1
23	$(P_1)\&(\neg P_5)\&(P_7)\Rightarrow(P_{15})$	1
24	$(P_2)\&(P_3)\&(P_7)\&(P_8)\Rightarrow(P_{15})$	1
25	$(\neg P_1)\&(\neg P_9)\Rightarrow(P_{13})$	1
26	$(\neg P_1)\&(\neg P_2)\Rightarrow(P_{13})$	1
27	$(\neg P_2)\&(P_8)\&(\neg P_7)\Rightarrow(P_{13})$	1
28	$(\neg P_3)\&(\neg P_6)\&(\neg P_7)\Rightarrow(P_{13})$	1
29	$(\neg P_2)\&(\neg P_8)\&(\neg P_6)\Rightarrow(P_{13})$	0.92
30	$(\neg P_1)\&(\neg P_8)\&(\neg P_6)\Rightarrow(P_{13})$	0.92
31	$(\neg P_4)\&(P_6)\&(\neg P_7)\&(\neg P_9)\Rightarrow(P_{14})$	0.86
32	$(\neg P_1)\&(\neg P_5)\&(P_7)\&(P_8)\Rightarrow(P_{14})$	0.90
33	$(P_1)\&(\neg P_2)\&(\neg P_7)\&(\neg P_9)\Rightarrow(P_{14})$	1
34	$(\neg P_1)\&(P_2)\&(\neg P_3)\&(P_8)\Rightarrow(P_{14})$	1
35	$(P_1)\&(P_3)\&(\neg P_5)\&(\neg P_6)\&(\neg P_9)\Rightarrow(P_{14})$	1
36	$(\neg P_4)\Rightarrow(\neg P_{10})$	1
37	$(\neg P_5)\Rightarrow(\neg P_{11})$	1

P_1: The escalator is crowded; P_2: The lift is crowded; P_3: The staircase is crowded; P_4: The escalator is working; P_5: The lift is working; P_6: The noise level is high; P_7: The lighting condition is low; P_8: The luggage size is large; P_9: The user bring along luggage; P_{10}: The user is choosing escalator; P_{11}: The user is choosing lift; P_{12}: The user is choosing staircase; P_{13}: The user is pleasant; P_{14}: The user is neutral; P_{15}: The user is unpleasant;

Table B-2 Mined rules for the interaction activity of entering a gate

#Rule	Rule	Confidence
1	$(P_9)\text{=>}(P_{13})$	1
2	$(\neg P_6)\&(P_9)\text{=>}(P_{14})$	1
3	$(\neg P_2)\&(\neg P_4)\&(\neg P_{10})\text{=>}(P_{12})$	1
4	$(\neg P_1)\&(P_2)\&(\neg P_9)\text{=>}(P_{11})$	0.9
5	$(P_1)\&(\neg P_2)\&(\neg P_9)\text{=>}(P_{12})$	0.9
6	$(\neg P_1)\&(\neg P_5)\&(\neg P_{10})\text{=>}(P_{11})$	1
7	$(\neg P_1)\&(\neg P_3)\&(\neg P_{10})\text{=>}(P_{11})$	0.9
8	$(\neg P_2)\&(\neg P_3)\&(\neg P_{10})\text{=>}(P_{12})$	0.9
9	$(P_1)\&(P_2)\&(\neg P_6)\&(\neg P_{10})\text{=>}(P_{11})$	0.5
10	$(P_1)\&(P_2)\&(\neg P_6)\&(\neg P_{10})\text{=>}(P_{12})$	0.5
11	$(P_3)\&(\neg P_4)\&(\neg P_9)\text{=>}(P_{12})$	1
12	$(\neg P_5)\&(\neg P_9)\text{=>}(P_{11})$	0.8
13	$(\neg P_1)\&(P_2)\&(\neg P_9)\text{=>}(P_{11})$	1
14	$(P_1)\&(P_2)\&(\neg P_3)\&(\neg P_9)\text{=>}(P_{13})$	1
15	$(\neg P_2)\&(\neg P_4)\&(\neg P_9)\text{=>}(P_{12})$	1
16	$(P_1)\&(\neg P_2)\&(\neg P_{10})\text{=>}(P_{12})$	1
17	$(\neg P_4)\&(\neg P_5)\&(\neg P_6)\text{=>}(P_{14})$	1
18	$(P_3)\&(\neg P_4)\&(\neg P_5)\text{=>}(P_{13})$	1
19	$(P_1)\&(\neg P_3)\&(\neg P_5)\&(\neg P_{10})\text{=>}(P_{13})$	1
20	$(P_1)\&(\neg P_2)\&(\neg P_6)\&(\neg P_9)\text{=>}(P_{12})$	1
21	$(P_2)\&(\neg P_3)\&(\neg P_4)\&(\neg P_{10})\text{=>}(P_{13})$	1
22	$(\neg P_1)\&(\neg P_3)\&(\neg P_5)\&(P_7)\&(P_8)\text{=>}(P_{16})$	1
23	$(P_1)\&(\neg P_2)\&(P_3)\&(P_7)\text{=>}(P_{16})$	1
24	$(\neg P_1)\&(\neg P_5)\&(\neg P_6)\&(P_8)\text{=>}(P_{16})$	1
25	$(P_2)\&(\neg P_6)\&(\neg P_7)\&(P_8)\text{=>}(P_{16})$	1
26	$(P_2)\&(\neg P_3)\&(\neg P_4)\&(P_7)\&(P_8)\text{=>}(P_{16})$	1
27	$(P_1)\&(P_2)\&(\neg P_3)\&(\neg P_7)\text{=>}(P_{16})$	1
28	$(\neg P_3)\&(\neg P_4)\&(\neg P_5)\&(P_7)\&(P_8)\text{=>}(P_{16})$	1
29	$(\neg P_2)\&(\neg P_3)\&(\neg P_7)\text{=>}(P_{15})$	1
30	$(\neg P_3)\&(\neg P_8)\text{=>}(P_{15})$	0.93
31	$(\neg P_1)\&(\neg P_6)\&(\neg P_8)\text{=>}(P_{15})$	1
32	$(\neg P_1)\&(P_2)\&(\neg P_7)\text{=>}(P_{15})$	1
33	$(\neg P_1)\&(\neg P_7)\&(\neg P_8)\text{=>}(P_{15})$	1
34	$(P_1)\&(\neg P_2)\&(\neg P_7)\&(P_8)\text{=>}(P_{15})$	1
35	$(\neg P_1)\&(\neg P_3)\&(\neg P_7)\text{=>}(P_{15})$	1
36	$(\neg P_3)\&(\neg P_4)\&(\neg P_5)\&(\neg P7)\text{=>}(P_{15})$	1
37	$(P_3)\&(\neg P_5)\text{=>}(P_{17})$	1
38	$(P_1)\&(P_2)\&(\neg P_6)\&(P_7)\text{=>}(P_{17})$	1
39	$(P_2)\&(P3)\&(\neg P_4)\&(P_7)\text{=>}(P_{17})$	1
40	$(P_3)\&(\neg P4)\&(\neg P_7)\&(P_8)\text{=>}(P_{17})$	1
41	$(P_2)\&(\neg P4)\&(\neg P_6)\&(P_7)\text{=>}(P_{17})$	1
42	$(P_1)\&(P_2)\&(P_3)\text{=>}(P_{17})$	1
43	$(P_1)\&(P_2)\&(\neg P_6)\&(P_8)\text{=>}(P_{17})$	1
44	$(\neg P_4)\&(\neg P_5)\&(\neg P_6)\text{=>}(P_{17})$	1

Note the propositions are defined as: P_1: The queue of gate 1 is long; P_2: The queue of gate 2 is long; P_3: The queue of the wide gate is long; P_4: Gate 1 is working; P_5: Gate 2 is working; P_6: The wide gate is working; P_7: The noise level is too high; P_8: The lighting condition is too low; P_9: The luggage size is too large; P_{10}: The user brings along luggage; P_{11}: The user is choosing gate 1; P_{12}: The user is choosing gate 2; P_{13}: The user is choosing the wide gate; P_{14}: The user is seeking assistance; P_{15}: The user is pleasant; P_{16}: The user is neutral; P_{17}: The user is unpleasant;

Table B-3 Mined rules for the interaction activity of boarding the train

#Rule	Rule	Confidence
1	$(P_2)\&(\neg P_6)\&(P_7)\Rightarrow(P_8)$	0.95
2	$(\neg P_1)\&(P_2)\&(P_7)\Rightarrow(P_8)$	1
3	$(P_2)\&(\neg P_5)\&(P_7)\Rightarrow(P_8)$	0.95
4	$(\neg P_2)\&(\neg P_7)\Rightarrow(P_{10})$	1
5	$(P_1)\&(P_5)\&(P_6)\&(\neg P_7)\Rightarrow(P_{10})$	1
6	$(P_1)\&(P_4)\&(\neg P_7)\Rightarrow(P_{10})$	1
7	$(P_1)\&(\neg P_2)\&(P_4)\&(P_6)\Rightarrow(P_{10})$	1
8	$(P_1)\&(\neg P_2)\&(P_5)\Rightarrow(P_{10})$	1
9	$(P_1)\&(\neg P_2)\&(\neg P_3)\&(P_7)\Rightarrow(P_9)$	1
10	$(\neg P_1)\&(P_2)\&(\neg P_7)\Rightarrow(P_9)$	1
11	$(P_1)\&(P_2)\&(P_4)\&(P_5)\& (P_6)\&(P_7)\Rightarrow(P_9)$	0.86
12	$(\neg P_1)\&(\neg P_2)\&(\neg P_5)\&(P_7)\Rightarrow(P_9)$	1
13	$(\neg P_1)\&(\neg P_2)\& (\neg P_4)\&(P_7)\Rightarrow(P_9)$	1
14	$(\neg P_1)\& (\neg P_2)\&(\neg P_4)\&(P_5)\Rightarrow(P_9)$	1
15	$(P_2)\&(\neg P_3)\&(\neg P_5)\&(\neg P_7)\Rightarrow(P_9)$	1
16	$(P_2)\&(\neg P_3)\&(\neg P_6)\&(\neg P_7)\Rightarrow(P_9)$	1
17	$(\neg P_1)\&(\neg P_2)\&(P_4)\&(P_7)\Rightarrow(P_9)$	1

P_1: Waiting is too long; P_2: The user is seated; P_3: The user brings along luggage; P_4: The luggage size is large; P_5: The noise level is too high; P_6: The lighting condition is too low; P_7: The stop information is clearly updated; P_8: The user is pleasant; P_9: The user is neutral; P_{10}: The user is unpleasant;

Appendix C: Affective Descriptors Collected and Distributed in Ten Clusters

#Cluster	Affective descriptors								
1	clean	organized	tidy						
2	boring	narrow							
3	cool	matched	quiet	silent	calm				
4	modern	distinct	ergonomic						
5	luxurious	high-class	long-lasting	exciting	safe	secure	soft	deluxe	fashionable	bright
6	homey	classy	elaborate	elegant	good	quality	home-like			
7	cosy	comfortable	durable	nice	peaceful	practical	relaxed	stylish	well-made	
8	cheap	dim	dull	normal	obsolete	simple	ugly	uncomfortable	washable	
9	functional	fine	high-tech	spacious	warm					
10	personal	natural	neat	personalized	private	reliable	special	stain-resistant		

Note that there are 61 affective descriptors in total after consultation with industrial designers and human factors specialists before they are used for clustering analysis. Based on the hierarchical clustering analysis, ten clusters are obtained and the first column under 'affective descriptors' are the most representative affective descriptors for subsequent analysis in Chapter 7.