Res Eng Design (2011) 22:43–61
DOI 10.1007/s00163-010-0096-z

ORIGINAL PAPER

Fundamentals of product ecosystem design for user experience

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Received: 29 January 2010 / Revised: 24 September 2010 / Accepted: 27 September 2010 / Published online: 16 October 2010

Abstract Recognizing the importance of user experience (UX) in product ecosystems, this paper examines the fundamental issues underlying product ecosystem design, including implications of a product ecosystem, the notion of the ambience, as well as UX in terms of affect and cognition. A conceptual model is outlined to elucidate the critical factors and the operational mechanism of product ecosystem design for user satisfaction. A technical framework of product ecosystem design for UX is presented, consisting of three consecutive and iterative stages, namely, affective-cognitive need acquisition, affective-cognitive analysis, and affective-cognitive fulfillment. An application to subway station design is reported to illustrate the key techniques for product ecosystem design, including ambient intelligence, data mining, Petri-net modeling, and simulation.

Keywords Product ecosystem design · User experience · Affective-cognitive integration · Ambience modeling

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1 Introduction

With the advent of experience economy, strategic business advantages depend less on the power of technology embedded in a given product, but more on a totality of user experience (UX) it offers (Pine and Gilmore 1999). An experience is the interaction process of a customer's purchase of a company's product or service. However, if the company can improve that experience by providing easy accesses to complementary products and/or services, the entire experience can become far more valuable both to the customers and the company than if the customer had merely purchased one good or service. Such a combination of multiple interdependent products and services constitutes the essential factors of a *product ecosystem* (Jiao et al. 2007). One good example is the Apple's iPhone® ecosystem, where a central smartphone product is upholstered by a suite of software, hardware, services, retailing stores, and developer and user groups. Among many factors that consolidate the iPhone's leading position in the smartphone market, the ecosystem notion has been credited for its contribution to such a great UX and a high economic margin that other more disjointed offerings could not match.

The term product ecosystem has been informally used by researchers and industry practitioners to signify the consideration of multiple related products in a coherent process, compared with the conventional viewpoint of static, isolated products (MacQueen 2006). Jiao et al. (2007) adopt this term to highlight human–product–ambience interactions in their work of designing products for affective user satisfaction. In order to support product ecosystem design for UX, this paper introduces the fundamental concepts underlying the product ecosystem and the factors that contribute to UX. Notably users' cognitive and affective aspects are accommodated in the design and delivery process of products and systems. While the cognitive aspect focuses on users' information processing and decision-making processes (Clark and Estes 1996), the affective aspect focuses on users' affective responses and inspirations (Jiao et al. 2007). Both aspects have major impacts on each other, and importantly influence users' satisfaction and purchasing decisions (Khalid and Helander 2006). Product ecosystem design also extends the traditional boundaries of human–object (product) interactions to encompass the notion of the ambience where human–object (product) interactions are operating (Jiao et al. 2007). In order to advance product ecosystem design for UX, a coherent technical framework is proposed, within which various key research issues are identified.

2 Background review

2.1 User-centered design

Product ecosystem design has its origin in designing products with centeredness on human users. This notion is consistent with user-centered design (UCD), which has been typically addressed in the fields of human–computer interaction (HCI), and human factors and ergonomics (HFE). Nevertheless, product ecosystem design differs from UCD in at least two perspectives, namely (1) the notion and scope of products and (2) the implications of UX through human–product–ambience interactions.

UCD primarily concentrates on the functionality and usability aspects of products rather than the affective aspects of users and limits interactions between users and a single product. In particular, UCD is mainly concerned with interactive digital products and systems, and reflects an awareness of the importance of human–computer interface design (Carroll 2000). Similar comments can also be made on traditional methods in HFE (Talbot 2005), although more types of products are involved in HFE. Law et al. (2009) recommend the term UX to be scoped to products, systems, services, and objects that a person interacts with through a user interface. This is also echoing the ISO definition of UX: a person's perceptions and response that result from the use or anticipated use of a product, system, or services (ISO-9241-210 2008). Consistent with these notions, in the context of product ecosystem design, multiple interdependent products (objects) and services co-determine UX. In this line of thought, the interaction paradigm is not constrained to the user and a single product, but rather the user, multiple products and services as well as the ambience where the interaction is performing.

2.2 Design for user experience

UX is an important concept that connects users with product ecosystem quality. Hassenzahl and Tractinsky (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.

2.2.1 *Cognitive factors*

Capitalizing on cognitive factors offers a principled approach to the design and development of human-centered products and systems (Roth et al. 2002), especially in the design of information systems (Helander 2005). It accounts for human capabilities, limitations, and tendencies in the information processing tasks to lower cognitive workloads, reduce errors, and improve efficiency and UX (Wickens and Hollands 1999).

It is important to uncover cognitive requirements of a particular task in a particular domain (Roth 2008). In this regard, cognitive analysis methods are widely applied, such as interviews, observation, process tracing methods (e.g., think-aloud, critiquing), critical decision methods, and conceptual methods (e.g., hierarchical sort) (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 in order to preserve lessons learned by retiring engineers.

Empirical investigations of cognitive requirements are subsequently used to inform system analysis and design (Roth 2008). This process is often implemented according to human information processing rules and principles, such as stimulus–response compatibility (Heuer 2001), cognitive fit theory (Vessey 1991), selective attention (Wickens and Hollands 1999), and limited capacities in human working memory (Wickens and Hollands 1999). Examples of successful design applications include design of auditory displays for anesthesia monitoring (Watson and Sanderson 2007), marketing research (Crandall et al. 2006), computer systems, training, and usability testing (Schraagen et al. 2000), etc.

2.2.2 *Affective factors*

Design for UX that solely focuses on cognitive efficiency has been repeatedly challenged. Khalid (2006) argues to embrace diverse human affective needs (e.g., surprise, excitement, and intimacy). The reason for this is that affect essentially influences human information processing, such as judgment (Zajonc 1980), decision making (Damasio 1994), and problem solving (Norman 2004). These ideas have been disseminated into various research practices in order to improve affective UXs, as demonstrated in the areas of HCI, marketing and consumer research, and engineering design. For example, affective computing in HCI mainly focuses on how systems can be designed to aid irritated users, manage their frustrations or prevent other negative emotions (Picard 1997; Picard et al. 2001). In marketing community, a large number of studies focus on consumers' affective responses to advertisements and brands (e.g., Morris et al. 2002). The role of affect in consumer behavior is also emphasized, such as purchase decision making and judgment (e.g., Yeung and Wyer 2004). In engineering design, Kansei engineering mainly leverages positive emotions to improve UX and has been applied to various industries, such as garment, automotive, and electronics industries (e.g., Jiao et al. 2006, 2007). Many design studies are also devoted to hedonic pleasure (Jordan 2000), and emotional responses and aspirations (Jiao et al. 2007). In this fashion, designers can capitalize on this perspective by conceptualizing affect-engendering products and by focusing on users' affective needs in order to promote UX.

2.2.3 *Affect-cognition integration for UX*

Affect and cognition have long been treated as independent entities (Zajonc 1980). Nevertheless, in the current view, it is suggested that affect and cognition are highly interdependent (Storbeck and Clore 2007), because the phenomena themselves are integrated (Parrott and Sabini 1989). Both laboratory findings and everyday observation call for a unity and interrelatedness of the cognitive and affective processes (e.g., 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 UX. 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 an affective-cognitive decision 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. An integrated view of cognition and affect is also addressed in Citarasa engineering (Helander et al. 2007). It provides systematic procedures that uncover user needs, measure user satisfaction, and identify the mapping relationship between user needs and design elements.

To summarize, it is imperative to accommodate both affective and cognitive factors to improve different facets of UX, i.e., *affective-cognitive integration*. However, in this regard, there is a paucity of published work and a lack of good, well-documented case studies in terms of design for UX in the context of product ecosystem. Therefore, negative UXs might be elicited if there is no systematic planning and coordination among multiple interdependent products.

3 Fundamental issues

3.1 Implications of product ecosystems

A *product ecosystem* is defined as a dynamic unit that consists of all interdependent products and users, functioning together with its surrounding ambience, as well as their interactive relations and business processes. 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 the 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 UXs 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 when users are interacting with products as well as the ambience. Specifically, it should explicitly define the entities of the product ecosystem (i.e., the 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 using simulation methods, for example.

Toward this end, this research elaborates product ecosystem design based on the appraisal theory (Ellsworth and Scherer 2003). It states that human evaluates stimulus events 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 and 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 Fig. 1. Rather than including comprehensive factors individually, this paper discusses critical ones in terms of their interrelatedness and dynamics, which in turn shape UX with its two inherent dimensions: the affective and cognitive dimensions.

3.2 Human–product–ambience interaction

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). However, the interaction can be directly influenced by other factors in the user's ambience so that it forms a paradigm of human–product–ambience interactions. Hence, *ambience* is defined according to the user's relationships with his/her surroundings, including other users, products, as well as environmental, social, and cultural factors. For example, in Fig. 2, 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 ambience. 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 2 depicts the entities and relations in the product ecosystem,

Fig. 1 A conceptual model of product ecosystem design for UX

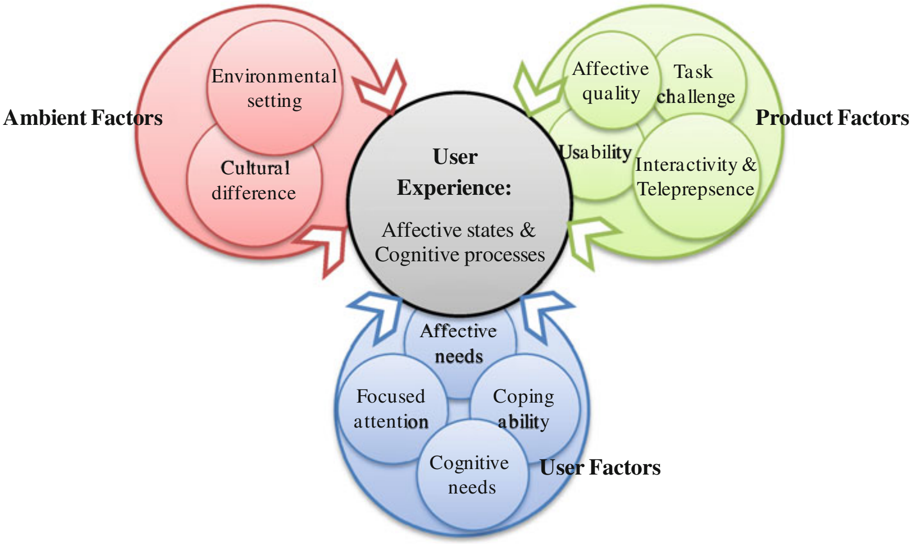
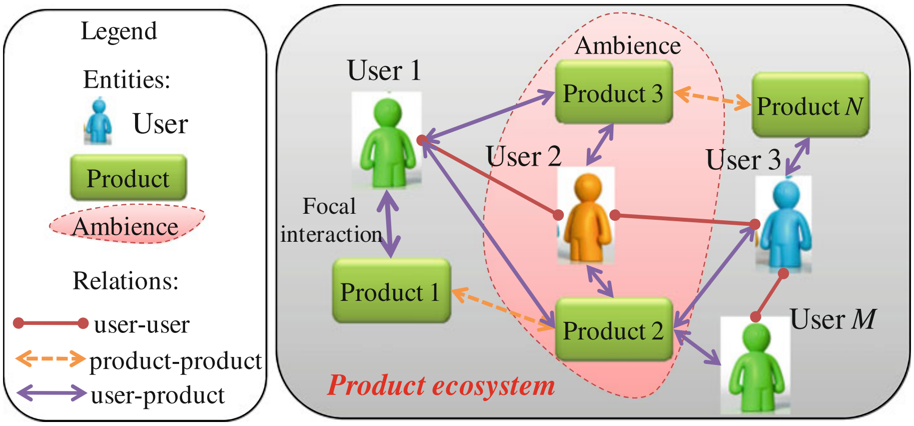


Fig. 2 Entities and relations that form a product ecosystem



where it primarily includes users, products, and ambient factors (also see Fig. 1) that collectively engender UX through human–product–ambience interactions.

3.3 User experience modeling

Based on the product ecosystem formulation, *user experience* is described as an evolution of the user's internal states (i.e., affective states and cognitive processes) along the chain of stimulus events as a result of human-product-ambience interactions. Figure 3 shows the possible UX of User *k* evolving along the stimulus event sequence in the product ecosystem. Therefore, UX, in the context of product ecosystem, is more than the consequence of a single interaction regarding one stimulus event, but rather of a sequence of interactions regarding all the events 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.

3.3.1 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 events 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).

3.3.2 Cognitive processes

Human cognition deals with the information processing tasks with respect to the stimulus events 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, and 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 UXs, either within the cognitive systems (the human thinks positively) or toward the stimulus events (the events are positively evaluated) (Reber et al. 2004).

In summary, UX is elicited by multiple stimulus events in the product ecosystem via human–product–ambience interactions. It has two essential dimensions, namely the affective dimension and the cognitive dimension and influenced by various factors as shown in Fig. 1. These

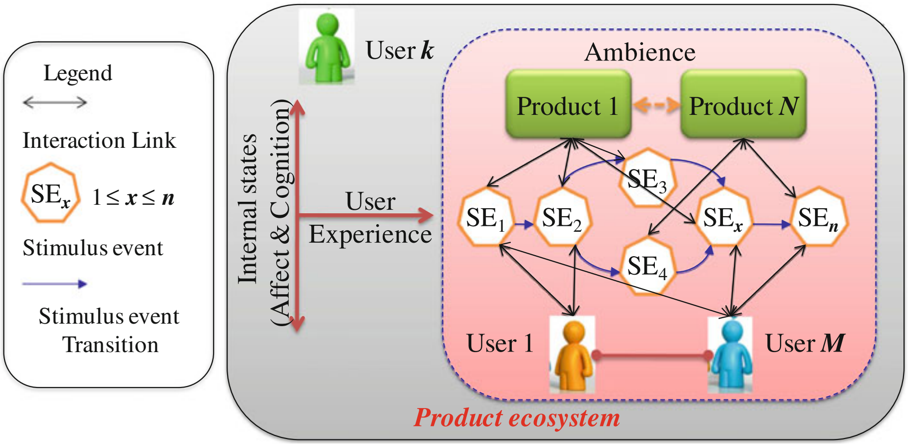


Fig. 3 User experience evolution in a product ecosystem

factors and their operational mechanisms are important to understand, predict, and reason about processes of UX to inform product ecosystem design as elaborated below.

3.4 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 UXs.

Affective quality has two dimensions, i.e., valence and arousal (Russell 2003). *Valence* means the intrinsic pleasantness (positive valence) or aversion (negative valence) of a product feature coded in perception (Ellsworth and Scherer 2003). These features often determine 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 (Schneirla 1959). Pleasant features produce likes and preferences, such as aesthetic pleasure. For instance, product features that follow Gestalt principles of perceptual organization make a design coherent and orderly and, therefore, pleasant to look at (Hekkert and Leder 2007). From the information processing point of view, the aesthetically most pleasing one is the one with least encoded information, given the observer's pervious knowledge and his/her encoding method (Schmidhuber 1997). The stimuli with less information are not only more pleasing but also easier to process, indicating high processing fluency (Reber et al. 2004). In this sense, it is important that multiple interdependent products are compatible with each other and with ambient factors of the product ecosystem so as to result in simple and organized fashions to improve UX.

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). For example, the arousal level in an airport terminal should be high (e.g., color coding for important information) as information seeking is very important for passengers. On the other hand, when in the Web-based learning session, especially for the ones with high cognitive loads, arousal must be kept low as learners need fully concentrate on the subject matter—too much arousal will only make them overloaded. Although the arousal level is determined by multiple factors, such as stimulus events, incentives, and the task itself, as well as ambient factors, multiple products that appropriately designed in the product ecosystem have the ability to optimize the arousal level for task performance to improve UX.

3.5 Affective and cognitive 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. Most appraisal theorists believe that an interaction event 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 mentioned above 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, usability, and utility, and so on. Taking iPhone® as an example, most users 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, systems can be designed to aid irritated users, manage their frustrations or prevent other negative emotions (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. Hence, product ecosystems that elicit positive affective responses and deal with negative ones are more likely to meet users' affective needs and thus improve affective UXs.

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. It is evidenced that cognitive needs have potential to influence the most difficult aspects of product ecosystems with increased complexities, including the vast amount of available data, the pressure to make timely decisions, and the reduced manpower and cost goal and UX, as a result (Perry et al. 1999). In order to adequately address cognitive requirements, 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 workplace are two interacting components to understand cognitive requirements of users. Additionally, perceived affective quality (PAQ) has a positive effect on both perceived usefulness and perceived ease of use (Zhang et al. 2006a). In this sense, PAQ 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). Critical dimensions have been identified, such as learnability, efficiency, memorability, errors and satisfaction (Nielsen 1994). Assuming user skills are at the average level, the more usable the product is, the more conduciveness the product contributes to positive UXs.

3.6 Coping ability and task challenge

Based on the appraisal 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 product ecosystems that can elicit flow experiences, one needs to consider dynamics among multiple factors. Above all, the elicitation of flow depends on the dynamic relations between user skills and task challenges. The product ecosystem 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 to elicit flow experience (Hoffman and Novak 1996). Take Web-based e-learning ecosystem as an example. One of the crucial factors for focused attention is the motivational forces (e.g., a sense of confidence as one kind of affective needs) and intrinsic interest/curiosity. Further, it is necessary to remove distractions (e.g., instant messengers) within and around the system whenever possible. The inverted-U relationship is also identified between arousal and flow experience (Hoffman and Novak 1996). To improve interactivity and telepresence, one point is to use edutaining methods, such as games, puzzles, simulation tools and provide timely visual and/or auditory feedback in appropriate forms. In such a way, an optimal combination of individual products and ambient factors can lead to effective learning results and positive UXs as well.

3.7 Modulating ambient factors

Although there are multiple ambient factors that influence UX in the interaction process, two typical factors, i.e., environmental settings and cultural differences, are of particular interest in product ecosystem design.

3.7.1 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 undesirable UXs in computer ecosystems. Another factor received much attention in consumer and marketing psychology is the background music in shopping mall ecosystems. 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 experiences. 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.

3.7.2 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). Hence, it is also important to consider these factors in the product ecosystem design process. For example, Zhang et al. (2006b) report that people who are individualistically cultured prefer angular patterns (indicating confrontation) while people who are collectively cultured prefer rounded patterns (indicating compromise).

4 A technical framework

To drive the development of rigorous research methodologies of product ecosystem design for UX, a technical framework is presented below. In essence, the technical framework must account for the multiple factors that contribute to desirable UXs as elaborated in the conceptual model, such as affective quality embodied in the product ecosystem, ACNs and coping abilities of its users, and its ambient factors, as well as the tasks that the product ecosystem affords and users aim to complete for their objectives. Furthermore, it must take into account the interactive relations among multiple factors in favor of decision support for UX. From the perspective of engineering design, it must deal with three issues, namely (1) identify the major elements of the product ecosystem, including the ecosystem structure, user characteristics, and product factors, (2) develop effective affective and cognitive 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 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., affective-cognitive need acquisition, affective-cognitive analysis, and affective-cognitive fulfillment.

4.1 Affective-cognitive need acquisition

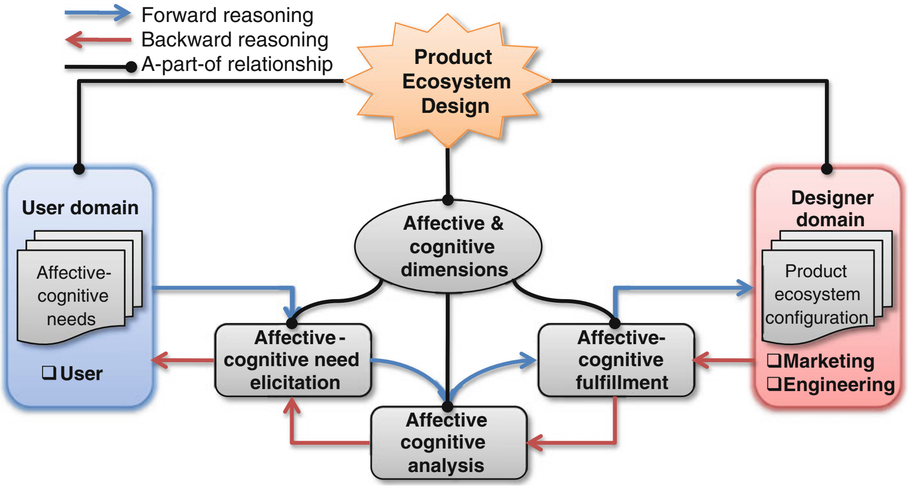
ACN elicitation is to systematically acquire affective and cognitive needs of users, which has significant implications on the design of the product ecosystem. The nature of affect and cognition renders it hard to elicit and measure ACNs. In psychology, affect is considered to be complex, multi-componential, and dynamic so that it requires sophisticated measurement of changes in different components (e.g., physiological reactions, motor expressions, and subjective feelings) (Grandjean et al. 2008). Furthermore, affective needs are often under the influence of physical, socio-cultural, and interpersonal context (Dolan 2002). The cognitive requirements of a task are both the macrocognitive challenges that the task poses (e.g., decision making, replanning, and problem detection) and the requirements to address these challenges (e.g., building mental models and managing uncertainty and attention) (Crandall et al. 2006). Thus, multiple measures that describe different aspects of cognitive performance should be included (e.g., how much, what kinds, when, and for how long).

Traditional measures are often hard, if not impossible, to take all aspects of ACNs into account. Currently, subjective methods, such as knowledge elicitation and cognitive task analysis, are the main accesses to ACNs, such as collecting adjectives that describe affective quality and high processing fluency. While it is convenient to collect adjectives, the verbal accounts of ACNs are usually expressed in abstract, fuzzy, or conceptual terms, and only capture the subjective component of ACNs (Grandjean et al. 2008). Hence, work on ACN acquisition is often based on vague assumptions and implicit inference. Moreover, subjective methods often suffer from recall and selective reporting biases (Stone and Shiffman 1994). Although, on some occasions, the ACN information can be collected concurrently, such as think-aloud protocols (Ericsson and Simon 1993), the problem is the interference with the task or activity during the acquisition process (Detenber 2001).

4.2 Affective-cognitive analysis

Affective-cognitive analysis aims to explicitly and systematically translate ACNs into design elements using engineering methods with an emphasis on UX as well as engineering concerns, i.e., affective-cognitive mapping

Fig. 4 A technical framework for product ecosystem design



(ACM). In particular, the following issues needs to be tackled:

4.2.1 *Non-structured ACNs*

There hardly exists any definitive structure of affective or cognitive needs, despite the fact that there are many models of affect and cognition in psychology and artificial intelligence (e.g., Russell 2003; Salvucci et al. 2005). Further, unlike traditional criteria for functional needs that are often considered as tangible and relatively easy to be quantified, ACNs, especially affective needs, are of a qualitative nature and subjective *per se* and consequently hard to express in a measurable and testable form (Nuseibeh and Easterbrook 2000).

4.2.2 *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, affective and cognitive mapping decisions are intricate and can hardly be consolidated with structured mapping mechanisms.

4.2.3 *Leveraging engineering concerns*

The fulfillment of ACNs should accommodate two key stakeholders: users and the producer. While meeting users' ACNs, 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. 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).

4.2.4 *Assessment and refinement of mapping relationships*

Traditionally, the assessment of ACM 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, noise and variances related to different contexts in interviews, surveys, and questionnaires often weaken model fitting and estimation (Barone et al. 2007). In order to systematically conduct ACM on a scientific basis, it is imperative to develop objective measures to deal with the subjectivity and vagueness of ACNs in the user domain as well as correction methods to filter noise factors in the design element space.

4.3 Affective-cognitive fulfillment

Affective-cognitive fulfillment targets at determining optimal product ecosystem configurations by optimizing UX and minimizing operational costs. It involves modeling users' affective states and cognitive task processes in the interaction process within the product ecosystem with an emphasis on UX as well as product ecosystem behavior. Therefore, the following issues are identified.

4.3.1 *Modeling affective states and cognitive tasks*

Focusing on UX, the users' affective states and the cognitive task processes have to be examined. In particular, it is crucial to develop a model that incorporates multiple dimensions of affect and cognition, and their interactions in the product ecosystem.

4.3.2 *Constructing UX*

The product ecosystem entails a scenario of the entire system design for UX. It emphasizes human–product interactions in the scope of the ambience so as to create the real product usage context and genuine UXs. Therefore, it is imperative to frame the design problem in the related ambience under different stimulus events, thus avoiding the classic pitfall of design divorced from the problem context (Giboin 1999).

4.3.3 *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 ecosystem is desirable.

4.3.4 *Developing efficient solutions for optimal product ecosystem configurations*

Based on the product ecosystem behavior and UX as well as operational cost constraints under the specific business process, an optimal product ecosystem configuration ought to be generated from a large search space of design configurations.

5 An application case

A subway station ecosystem design is presented as a case example to illustrate product ecosystem design that addresses part of the research issues previously discussed.

5.1 Product ecosystem formulation

The product ecosystem is 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 $E^U = \{u_1, u_2, \ldots, u_M\}$ is a set of M users, $E^P = \{p_1, p_2, \ldots, p_N\}$ is a set of N products, and $E^A = \{a_1, a_2, \ldots, a_K\}$ 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 $SE = \{e_1, e_2, \ldots, e_n\}$ is a finite set of events involved in the product ecosystem. Concerning any event $e_k \in SE$, $1 \leq k \leq n$, $\Psi_1 : E^U \times E^U|_{e_k} \rightarrow \mu$, $\Psi_2 : E^U \times \; E^P|_{e_k} \rightarrow \mu$, $\Psi_3 : E^P \times E^P|_{e_k} \rightarrow \mu$, and $\Psi_4 : E^U \times E^A|_{e_k} \rightarrow \mu$ denote the interactive relationships between the involved products, users, and ambient factors with regard to the focal user. Note $\mu \in [0, 1]$, where ‘1’ indicates that the focal user is interacting with another entity, ‘0’, otherwise, and $\mu \in (0, 1)$ implies that the involved entities are located in the focal user’s ambience. The ambience, $Am(u_i)$, for u_i is actually a sub-space of the ecosystem, which consists of the users, products, and ambient factors that are related to u_i. It can be defined as $Am(u_i) = \langle E^U(i), E^P(i), E^A(i) \rangle$, where $E^U(i) = \{u_j | \Psi_1(u_i, u_j) = \mu, u_j \in E^U, i \neq j\}$, $E^P(i) = \{p_s | \Psi_2(u_i, p_s) = \mu, p_s \in E^P\}$, $E^A(i) = \{a_t | \Psi_4(u_i, a_t) = \mu, \; a_t \in E^A\}$, where $\mu \in (0, 1)$for all the interaction relationships.

In the example of subway station design, $E^P = \{$General Ticketing Machines, Information Boards, Control Gates, Luggage, Service Persons, Lifts, Escalators, Staircases, Trains$\}$, $E^A = \{$Lighting, Noise$\}$, and E^U includes all the commuters who travel from one station to another. However, the interactive relationships between entities in the subway station are dynamic and dependent on the focal user involved in a particular stimulus event.

5.2 Ambient intelligent affective cognition

In order to effectively acquire ACNs, three basic criteria should be considered: (1) construct validity (Helander and Khalid 2006), (2) real time, and (3) little interference. Toward this end, Ambient Intelligence (AmI) (Aarts 2004) has emerged as a promising tool to acquire ACNs due to the synergy of knowledge among virtual environment, pervasive computing, wireless sensor networks, HCI, and artificial intelligence. Therefore, in this research, AmI techniques are applied to acquire ACNs.

A virtual environment of a subway station is constructed with EON® software (EON® Reality, Irvine, CA, USA) for a number of 42 participants to navigate. It simulates various actual scenarios of the subway station that facilitates the elicitation of ACNs during the interaction process. In addition, wireless sensor networks can provide distributed and pervasive sensing capabilities to ACNs with little intrusiveness and relatively high construct validity (Picard 1997; Helander and Khalid 2006). It thus allows human affective and cognitive states to be evaluated in real time. 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 mainly because these measures are not susceptible to lingusitic ambiguity (Picard et al. 2001). Therefore, during the navigation process, each participant’s affective and cognitive states are recorded using wearable physiological sensors, including facial electromyography (zygomatic and corrugator muscle activity) using a Myomonitor® Wireless EMG System (Delsys, Boston, USA), respiration rate, electroencephalography (alpha and beta waves), and skin conductance response, using an 8-channel Biofeedback System™ v5.0 (Thought Technology, New York, USA).

Each participant was first briefed to navigate through the virtual subway station from the starting point to the train with four selected stimulus events, including buying tickets, entering control gates, going to the platform either by staircase, lift, or escalator, and boarding the train. Before formal data collection, a practice trial has been conducted by the participant on a 17-inch HP desktop around 1 m away. This enables the participant to familiarize with the experiment protocols. After all the sensors have been installed on the participant, a 2-min resting interval is followed before formal data collection. After finishing one interaction event, the participant was asked to choose one adjective that best describe the emotional response to the event from the given terms, including pleasant, neutral, and unpleasant. The experiment took place in a project room with dim lighting with a range of 10–15 min to finish the task. Through the monitoring process, the physiological signals of the participants are collected concerning the four selected stimulus events, and the related products and ambient factors are also recorded. Figure 5 shows the data acquisition process.

Furthermore, to effectively predict the corresponding UX of the participants, it is reported that predictive models built on physiological data using artificial intelligence are promising (Picard et al. 2001). Such models can be embedded in physiological systems to monitor, quantify, and predict users’ affective and cognitive states in real time in a continuous manner (Fairclough 2009). Consequently, a rough set-based method has been developed to predict participants’ affective states, including pleasant, neutral and unpleasant. Three methods were then used to predict

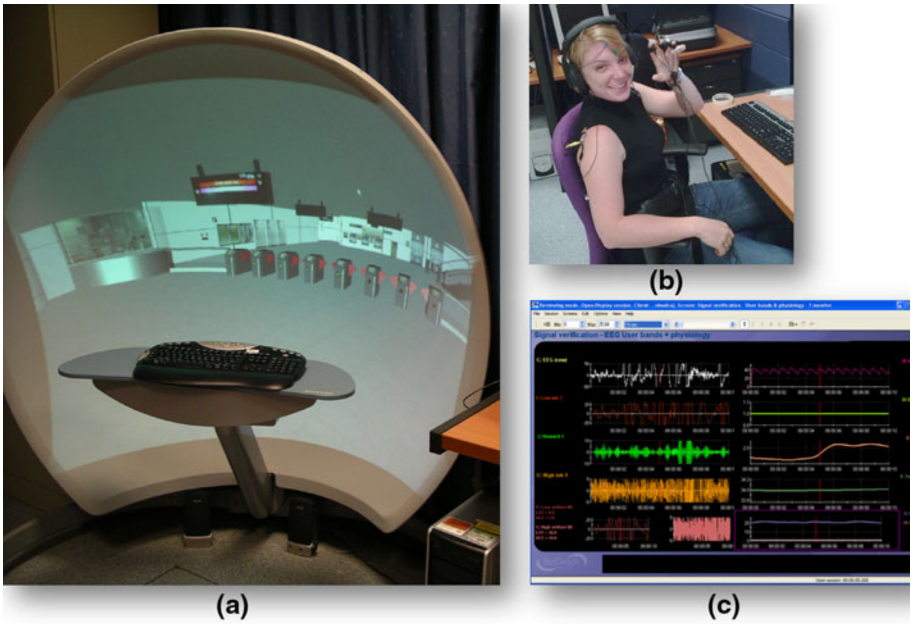


Fig. 5 **a** A virtual subway station; **b** One participant with physiological sensors when navigating; **c** Data acquisition interface

affective states, i.e., *k*-nearest neighbor (*k*-NN), decision rule (DR), and decision tree (DT) based on the rough set theory using the rough set software system (RSES 2.2.2) (Bazan and Szczuka 2000). *k*-NN constructs a distance measure on the basis of training samples and tested samples will make the decision based on the *k* ($k = 5, 10, 20$ in the experiment) training samples that are nearest to the tested ones with respect to the calculated distance (Gora and Wojna 2002). Decision rules are generated based on reducts and the predecessor of the rule takes the conjunction of certain feature values or intervals and the successor takes on specific affect. Decision trees are used to split feature set into fragments not larger than a predefined size as leafs which are supposed to be more uniform and easier to predict affect (Bazan and Szczuka 2000).

In the experiment, there are 126 training entries (42 participants by 3 affect) in the decision table averaged among all the interaction events involved in the virtual subway station. A tenfold cross validation is adopted for all the methods. Table 1 shows the prediction accuracy of all the methods, with mean prediction accuracy ranged from 87.8% by DT to 91.4% by DR, while the results by *k*-NN methods are in between. As for the affective states, the prediction accuracy across different methods of neutral is lowest, 82.6%, while those of pleasant and unpleasant are 91.1 and 94.6%, respectively.

Table 1 Prediction results of affective states

Affect	Pleasant (%)	Neutral (%)	Unpleasant (%)	Mean (%)
DR	96.0	80.2	97.9	91.4
DT	91.3	75.8	96.1	87.7
5-NN	91.9	86.7	92.2	90.3
10-NN	88.9	87.2	93.3	89.8
20-NN	87.4	83.0	93.6	88.0
Mean	91.1	82.6	94.6	89.4

5.3 Data mining for affective-cognitive analysis

As for affective-cognitive analysis, data mining techniques lend themselves to be powerful tools for sifting through layers of seemingly unrelated data for meaningful relationships. These techniques can anticipate user needs and create intelligent and proactive pathways back to users (Larose 2005), such as the rough set theory (Pawlak 1991) and association rule mining (Srikant and Agrawal 1996). They have been successfully applied to construct connections between the user and designer domains. For example, Zhou et al. (2010) apply a *k*-optimal rule discovery method to mine the rules and then propose a rule importance measure based on the rough set theory to further refine the mined rules. Within the data mining methods, objective criteria for selecting and refining mined patterns are often provided, such as *support* and *confidence* in the rough set theory and association rule mining.

In this research, the rough set theory (Pawlak 1991) is applied to mine the fuzzy production rules between the ACNs and different contexts of stimulus events, including status of products and ambient factors. Various contexts about the four interaction events are created, including buying a ticket, entering a control gate, going to the platform, and boarding the train, so as to leverage various entities in the product ecosystem. For example, with regard to the interaction event, "enter a control gate," queue lengths, working status of two narrow gates and one wide gate (denoted as Gate 1, Gate 2, and Gate 3, respectively),

Table 2 Contexts of "entering a control gate" and users' affective states and cognitive decisions

Context#	Queue_1	Queue_2	Queue_3	Luggage size	Noise	Lighting	Affective states	Decision
1	Not long	Not working	Not long	Not large	High	Low	Neutral	Gate 1
2	Long	Long	Not long	Not large	High	Low	Unpleasant	Gate 2
…	…	…	…	…	…	…	…	…
111	Not working	Not long	Not working	No luggage	High	Not low	Pleasant	Gate 2

Queue_i corresponds to the queue of Gate_i (i =1, 2, 3)

luggage size, and surrounding lighting and noise are employed to create the corresponding contexts. A total number of 111 contexts are formulated in the virtual subway station through design of optimal experiment (Nair et al. 1995) using software SPSS 15.0 (SPSS Inc., Chicago, Illinois) as listed in Table 2. Different contexts lead to different affective states which can be predicted from users' physiological data while users' cognitive decisions are indicated by the users' navigating behavior.

In order to mine the patterns behind these data, 17 propositions concerning the stimulus event of "enter a control gate" are shown below. Descriptions about the involved users, products and ambient factors are recorded (P_1–P_{10}), the user's cognitive decisions are reflected by the user's behavior (P_{11}–P_{14}), and the user' affective state is predicted by the physiological data associated with this interaction event (P_{15}–P_{17}). As indicated, some propositions (e.g., P_1–P_3, P_7–P_9) are fuzzy, which are described using terms like *long, low,* and *high*. The classical means to tackle this issue is to employ fuzzy production rules. They are in the form of

$$R_j : P_1(\theta_1)\,\&\,P_2(\theta_2)\,\&\ldots P_{k-1}(\theta_{k-1}) \Rightarrow P_k(\theta_k),\ c_j,\ \theta_k = \min\{\theta_1, \theta_2, \ldots, \theta_{k-1}\} * c_j, \tag{1}$$

where θ_i denotes the truth degree of antecedent/consequent part P_i in a fuzzy rule R_j, and c_j denotes the confidence degree of applying rule R_j. With regard to the data in Table 2, a total number of 47 fuzzy production rules are mined (see below) using the rough set software system (RSES 2.2.2) with the selection measure of *support* over 0.6 (Bazan and Szczuka 2000). These rules are assertions about the status and attributes of users and those of products and the ambience concerning "entering a control gate". For example, Rule 2 '$(\neg P_6)\,\&\,(P_9) \Rightarrow (P_{14})$ 1' means that if Gate 3 is *not* working while the luggage size is too large, then the user is seeking assistance from the service persons with a confidence of 1, where confidence of a rule '$X \Rightarrow Y$' is defined as $\text{conf}(X \Rightarrow Y) = \text{supp}(X \cup Y)/\text{supp}(X)$ and $\text{supp}(*)$ is the proportion of item '*' in the database. The negation of a proposition is represented with the sign '¬', such as '$\neg P_6$' in Rule 2. Therefore, knowledge about predicting users' affective states and cognitive decisions of all the stimulus events in the subway station can be coded as a fuzzy rule set, denoted as Ξ.

Propositions and rules associated with the stimulus event "enter a control gate" are shown below:

P_1: The queue of Gate 1 is long;
P_2: The queue of Gate 2 is long;
P_3: The queue of Gate 3 is long;
P_4: Gate 1 is working;
P_5: Gate 2 is working;
P_6: Gate 3 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 Gate 3;
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;
r_1: $(P_9) \Rightarrow (P_{13})$ 1
r_2: $(\neg P_6)\&(P_9) \Rightarrow (P_{14})$ 1
r_3: $(\neg P_2)\&(\neg P_4)\&(\neg P_{10}) \Rightarrow (P_{12})$ 1
r_4: $(\neg P_1)\&(P_2)\&(\neg P_9) \Rightarrow (P_{11})$ 0.9
r_5: $(P_1)\&(\neg P_2)\&(\neg P_9) \Rightarrow (P_{12})$ 0.9
r_6: $(\neg P_1)\&(\neg P_5)\&(\neg P_{10}) \Rightarrow (P_{11})$ 1
r_7: $(\neg P_1)\&(\neg P_3)\&(\neg P_{10}) \Rightarrow (P_{11})$ 0.9
r_8: $(\neg P_2)\&(\neg P_3)\&(\neg P_{10}) \Rightarrow (P_{12})$ 0.9
r_9: $(P_1)\&(P_2)\&(\neg P_6)\&(\neg P_{10}) \Rightarrow (P_{11})$ 0.5
r_{10}: $(P_1)\&(P_2)\&(\neg P_6)\&(\neg P_{10}) \Rightarrow (P_{12})$ 0.5
r_{11}: $(P_3)\&(\neg P_4)\&(\neg P_9) \Rightarrow (P_{12})$ 1
r_{12}: $(\neg P_5)\&(\neg P_9) \Rightarrow (P_{11})$ 0.8
r_{13}: $(\neg P_1)\&(P_2)\&(\neg P_9) \Rightarrow (P_{11})$ 1
r_{14}: $(P_1)\&(P_2)\&(\neg P_3)\&(\neg P_9) \Rightarrow (P_{13})$ 1
r_{15}: $(\neg P_2)\&(\neg P_4)\&(\neg P_9) \Rightarrow (P_{12})$ 1
r_{16}: $(P_1)\&(\neg P_2)\&(\neg P_{10}) \Rightarrow (P_{12})$ 1
r_{17}: $(\neg P_4)\&(\neg P_5)\&(\neg P_6) \Rightarrow (P_{14})$ 1
r_{18}: $(P_3)\&(\neg P_4)\&(\neg P_5) \Rightarrow (P_{13})$ 1
r_{19}: $(P_1)\&(\neg P_3)\&(\neg P_5)\&(\neg P_{10}) \Rightarrow (P_{13})$ 1
r_{20}: $(P_1)\&(\neg P_2)\&(\neg P_6)\&(\neg P_9) \Rightarrow (P_{12})$ 1
r_{21}: $(P_2)\&(\neg P_3)\&(\neg P_4)\&(\neg P_{10}) \Rightarrow (P_{13})$ 1
r_{22}: $(\neg P_1)\&(\neg P_3)\&(\neg P_5)\&(P_7)\&(P_8) \Rightarrow (P_{16})$ 1
r_{23}: $(P_1)\&(\neg P_2)\&(P_3)\&(P_7) \Rightarrow (P_{16})$ 1
r_{24}: $(\neg P_1)\&(\neg P_5)\&(\neg P_6)\&(P_8) \Rightarrow (P_{16})$ 1
r_{25}: $(P_2)\&(\neg P_6)\&(\neg P_7)\&(P_8) \Rightarrow (P_{16})$ 1
r_{26}: $(P_2)\&(\neg P_3)\&(\neg P_4)\&(P_7)\&(P_8) \Rightarrow (P_{16})$ 1
r_{27}: $(P_1)\&(P_2)\&(\neg P_3)\&(\neg P_7) \Rightarrow (P_{16})$ 1

r_{28}: $(\neg P_3)\&(\neg P_4)\&(\neg P_5)\&(P_7)\&(P_8) \Rightarrow (P_{16})$ 1
r_{29}: $(\neg P_2)\&(\neg P_3)\&(\neg P_7) \Rightarrow (P_{15})$ 1
r_{30}: $(\neg P_3)\&(\neg P_8) \Rightarrow (P_{15})$ 0.93
r_{31}: $(\neg P_1)\&(\neg P_6)\&(\neg P_8) \Rightarrow (P_{15})$ 1
r_{32}: $(\neg P_1)\&(P_2)\&(\neg P_7) \Rightarrow (P_{15})$ 1
r_{33}: $(\neg P_1)\&(\neg P_7)\&(\neg P_8) \Rightarrow (P_{15})$ 1
r_{34}: $(P_1)\&(\neg P_2)\&(\neg P_7)\&(P_8) \Rightarrow (P_{15})$ 1
r_{35}: $(\neg P_1)\&(\neg P_3)\&(\neg P_7) \Rightarrow (P_{15})$ 1
r_{36}: $(\neg P_3)\&(\neg P_4)\&(\neg P_5)\&(\neg P7) \Rightarrow (P_{15})$ 1
r_{37}: $(P_3)\&(\neg P_5) \Rightarrow (P_{17})$ 1
r_{38}: $(P_1)\&(P_2)\&(\neg P_6)\&(P_7) \Rightarrow (P_{17})$ 1
r_{39}: $(P_2)\&(P3)\&(\neg P_4)\&(P_7) \Rightarrow (P_{17})$ 1
r_{40}: $(P_3)\&(\neg P4)\&(\neg P_7)\&(P_8) \Rightarrow (P_{17})$ 1
r_{41}: $(P_2)\&(\neg P4)\&(\neg P_6)\&(P_7) \Rightarrow (P_{17})$ 1
r_{42}: $(P_1)\&(P_2)\&(P_3) \Rightarrow (P_{17})$ 1
r_{43}: $(P_1)\&(P_2)\&(\neg P_6)\&(P_8) \Rightarrow (P_{17})$ 1
r_{44}: $(\neg P_4)\&(\neg P_5)\&(\neg P_6) \Rightarrow (P_{17})$ 1
r_{45}: $(\neg P_4) \Rightarrow \neg(P_{11})$ 1
r_{46}: $(\neg P_5) \Rightarrow \neg(P_{12})$ 1
r_{47}: $(\neg P_6) \Rightarrow \neg(P_{13})$ 1

5.4 Affective-cognitive modeling

In order to carry out affective-cognitive fulfillment, a powerful modeling technique is needed. Graph-based methods suggest themselves to be effective tools to capture fuzzy causal relations between user responses and design elements. Graph-based methods can model multiple entities and relationships in the product ecosystem with arcs and nodes. Thus, the interaction and dynamics between affect and cognition can be revealed. Among many others, Petri nets (PNs) seem suitable to deal with uncertainties inherent in knowledge representation and cognitive reasoning. The dynamic and non-deterministic nature is able to model product ecosystem behavior. PNs and their extensions have been successfully applied to knowledge representation (Pedrycz and Gomide 1994), task sequencing (Cao and Sanderson 1995), and intelligent decision making (Gao et al. 2004), etc. Toward this end, a technique named fuzzy reasoning Petri nets (FRPN) is applied, which is defined as an 8-tuple (Gao et al. 2003): FRPN $= (P, R, I, H, O, \theta, \gamma, C)$, where

1. $P = \{p_1, p_2, \ldots, p_n\}$is a finite set of n propositions called places, describing the status of entities in the product ecosystem.
2. $R = \{r_1, r_2, \ldots, r_m\}$is a finite set of m rules called transitions, representing the fuzzy rule base.
3. $I : P \times R \rightarrow \{0, 1\}$is an $n \times m$ input matrix defining the non-complementary directed arcs from non-negation propositions to rules; for $1 \le i \le n$, $1 \le j \le m$, $I(p_i, r_j) = 1$, if there is a directed arc from p_i to r_j and $I(p_i, r_j) = 0$, otherwise.
4. $H : P \times R \rightarrow \{0, 1\}$is an $n \times m$ matrix defining the complementary directed arcs from negation propositions to rules; for $1 \le i \le n$, $1 \le j \le m$, $H(p_i, r_j) = 1$, if there is a complementary arc from p_i to r_j and $H(p_i, r_j) = 0$, otherwise.
5. $O : P \times R \rightarrow \{0, 1\}$is an $n \times m$ output matrix defining the directed arcs from rules to propositions; for $1 \le i \le n$, $1 \le j \le m$, $O(p_i, r_j) = 1$, if there is a directed arc from r_j to p_i and $O(p_i, r_j) = 0$, otherwise.
6. θ is a truth degree vector, $\theta = (\theta_1, \theta_2, \ldots, \theta_n)^T$, where θ_i $(1 \le i \le n)$ denotes the truth degree of p_i.
7. $\gamma : P \rightarrow \{0, 1\}$, is a marking vector, $\gamma = (\gamma_1, \gamma_2, \ldots, \gamma_n)^{\mathrm{T}}$. For $1 \le i \le n$, $\gamma_i = 1$, if there is a token in p_i, and $\gamma_i = 0$, otherwise.
8. $C = \mathrm{diag}\{c_1, c_2, \ldots, c_m\}$, where c_j is the confidence of r_j, $1 \le j \le m$.

For the illustrative purpose, the rules and propositions concerning "entering a control gate" are converted into FRPN model depicted in Fig. 6. Note complementary arcs are represented by a directed arc terminated with a small circle; for example, the arc directed from P_6 to rule 2 (R2 in Fig. 6) is a complementary arc. '|'denotes transitions to which both complementary and non-complementary arcs are directing while '▌'denotes transitions to which no complementary arcs are directing. For instance, rule 2 has both a complementary arc from P_6 and a non-complementary arc from P_9 while rule 1 only has a non-complementary arc from P_9. Negation propositions are denoted using "Not" operator (e.g., Not(P_{11})).

Based on the FRPN model and execution rules, a reasoning algorithm is proposed below to construct an inference engine that can analyze users' behavior and predict their affective states with regard to a particular configuration of the product ecosystem (Gao et al. 2004)

```
Input: $I, H, O, C$, and the initial truth degree vector $\theta^1$ and the initial marking vector $\gamma^1$
Output: the final truth degree vector $\theta^{k+1}$
  $k = 1$;
  while ($k$)
      $\rho^k = \overline{I^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \overline{\theta^k}) \oplus H^{\mathrm{T}} \otimes (\overline{\gamma^k} \oplus \theta^k)}$ ; // calculate the truth degree vector of rules' preconditions
      $\theta^{k+1} = \theta^k \oplus [\, O \cdot C \otimes \rho^k \,]$ ;// update the truth degree vector
      $\gamma^{k+1} = \gamma^k \oplus [\, O \otimes \overline{I + H^{\mathrm{T}} \otimes \overline{\gamma^k}} \,]$ ; // update the marking vector
      if ($\theta^{k+1} \ne \theta^k$ or $\gamma^{k+1} \ne \gamma^k$ )
          $k = k + 1$;
      else
          $k = 0$;
      end if
  end while
```

Note '$\overline{*}$' is a negation operator of '*', e.g., $\overline{\theta^k} = \mathbf{1}_{\mathrm{m}} - \theta^k$ where $\mathbf{1}_{\mathrm{m}} = (1, 1, \ldots, 1)$; $\oplus$ and $\otimes$ are operators from Max algebra: $[A_{m\times n} \oplus B_{m\times n}]_{ij} = a_{ij} \oplus b_{ij} = \max(a_{ij}, b_{ij})$; $[A_{n\times k} \otimes B_{k\times m}]_{il} = \oplus_{j=1}^{k}(a_{ij} \otimes b_{ij}) = \max_{j\in\{1,2,\ldots,k\}}(a_{ij} + b_{jl})$.

In the example of “entering a control gate”, $P = \{P_1, P_2, \ldots, P_{17}\} \cup \{P_{18}, P_{19}, P_{20}\}$ where $\{P_1, P_2, \ldots, P_{17}\}$ are shown as in Sect. 5.3 and $P_{18} = \neg(P_{11})$; $P_{19} = \neg(P_{12})$; $P_{20} = \neg(P_{13})$; the fuzzy rule base, $R = \{r_1, r_2, \ldots, r_{47}\}$ as shown in Sect. 5.3; matrices I, O, and H can be obtained based on the definition of FRPNs as follows:

I= [00001000110001010011001000100000010001000110000;
00010000110011000010001110000010000001101110000;
00000000010000000100001000000000000010110100000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000011001010000000001101000000;
00000000000000000000010111010000010000010010000;
11000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;];

H = [00001110000010000000010100000011101000000000000;
00110001000000110001001000000100001000000000000;
00000011000001000010110001111100001100000000000;
00100000001000101100100001010000000100111001100;
00000100000100001110010100010000000110000001010;
01000000110000001001000110000010000001001011001;
00000000000000000000000010101001111100010000000;
00000000000000000000000000000110100000000000000;
00011000000111110000100000000000000000000000000;
00100111110000010010100000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;];

O = [00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00000000000000000000000000000000000000000000000;
00010110100110000000000000000000000000000000000;
00101001011000110001000000000000000000000000000;
10000000000001000110100000000000000000000000000;
01000000000000001000000000000000000000000000000;
00000000000000000000000000001111111000000000000;
00000000000000000000011111100000000000000000000;
00000000000000000000000000000000000011111111000;
00000000000000000000000000000000000000000000100;
00000000000000000000000000000000000000000000010;
00000000000000000000000000000000000000000000001;];

where $n = 20$, $m = 47$; and $C = \mathrm{diag}([1\ 1\ 1\ 0.9\ 0.9\ 1\ 0.9\ 0.9\ 0.5\ 0.5\ 1\ 0.8\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0.93\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1])$ according to the rule base in Sect. 5.3; the initial marking vector, $\gamma^1 = [1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0]^{\mathrm{T}}$; suppose the initial truth degree vector, $\theta^1 = [0.8\ 0.9\ 0.7\ 1\ 1\ 1\ 0.6\ 0.8\ 0.2\ 1\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]^{\mathrm{T}}$ that describes first 10 propositions concerning “entering a control gate” in the product ecosystem. According to the reasoning algorithm, the final $\theta^{k+1} = [0.8\ 0.9\ 0.7\ 1\ 1\ 1\ 0.6\ 0.8\ 0.2\ 1\ 0.2\ 0.18\ \mathbf{0.3}\ 0\ 0.2\ 0.3\ \mathbf{0.7}]^{\mathrm{T}}$, when $k = 2$. With the highest truth degree of propositions among P_{10}–P_{14} and among P_{15}–P_{17} as criteria, respectively, the user’s choice over “entering a control gate” is most likely Gate 3 with probability of 0.3 and the user’s affective state is most likely unpleasant with probability of 0.7. Likewise, all the interaction events can be modeled using FRPNs and users’ cognitive decisions and affective states can be automatically obtained with the reasoning algorithm.

5.5 Simulation and result

Based on the FRPNs modeling, simulation methods using virtual product ecosystem models can be implemented to accommodate ACNs of digital human users. It is possible to carry out ‘what-if’ analysis for constructing UX and simulating the business processes. The outcome of the analysis can provide designers with decision support to improve UX in terms of user affect and cognition, enhance the operational efficiency of the product ecosystem, and finally optimize the product ecosystem configuration. Therefore, product ecosystem design for UX can be understood as an optimization problem as shown in Fig. 7:

Toward this end, a simulation model has been developed in the commercial software Flexsim® (Flexsim® Software Products Inc., Utah, USA). Figure 8 shows a screen shot of the subway system in Flexsim®. The performance of the product ecosystem is evaluated according to two criteria, i.e., UX and system capacity utilization (U). In this case study, UX is evaluated with two measures: affective state (AF) and user stay-time (T) due to cognitive decisions made in the subway station. Thus, UX has two parts, i.e., UX_1 and UX_2, due to the effect of the users’ affective states and stay time, respectively. Both of them are quantified between -1 and 1 with initial value of 0, and the higher the value, the more desirable UX is. An individual user’s affective state 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

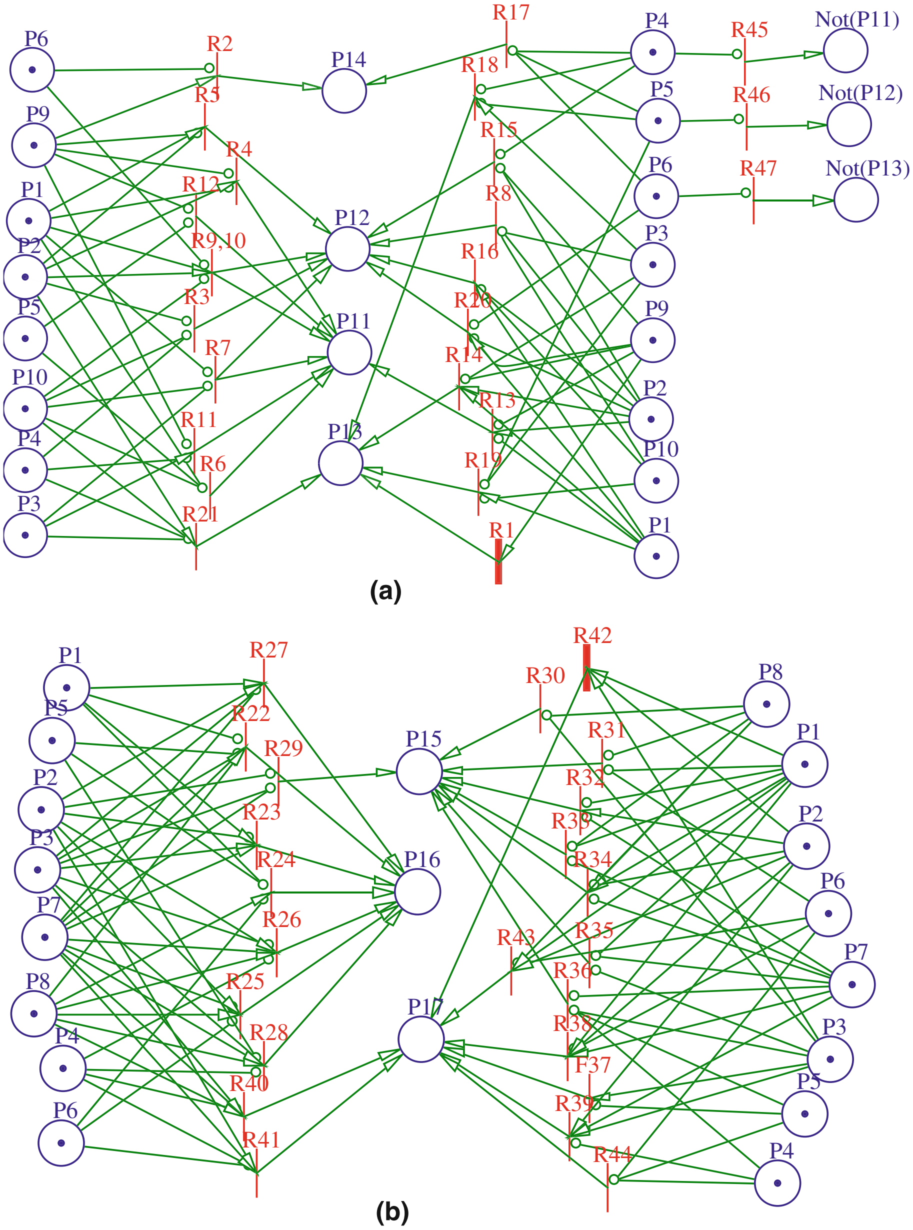


Fig. 6 FRPNs model of the stimulus event "entering a control gate" that transforms the rules and propositions in Sect. 5.3 into Petri net representation: (**a**) choosing a control gate and for (**b**) predicting the user's affective state (some of the propositions are repeated in order for a clearer presentation). For example, rule 1: $(P_9) \Rightarrow (P_{13})$ is represented as an arc from P_9 directed to transition R1 and then an arc from transition R1 to P_{13}; the associated truth degree is omitted here

his/her stay-time T_i is given as $\overline{AF_i} = \frac{1}{T_i}\int_0^{T_i} AF\,dt$. Hence, UX$_1$ is computed as:

$$\mathrm{UX}_1 = \frac{1}{M}\sum_{i=1}^{M}\overline{AF_i}, \tag{2}$$

where M is the total number of users existed in the product ecosystem for the period of the simulation. And UX$_2$ according to the user stay-time is computed as:

$$\mathrm{UX}_2 = \frac{1}{M}\sum_{i=1}^{M}\left(1 - \frac{T_i}{T_{\exp}}\right), \tag{3}$$

where $T_{\exp}$ is the expected user stay-time that has no perceptible influence on UX, i.e., neither positive nor

$\exists P^e = \langle E, \Psi, SE \rangle$

find E^{P^*}, SE^* that $\max(UX)$ and $\min(C)$

where $UX = \langle AF, CG, \Theta \rangle, \Theta = \{e_i \prec e_j\}$

AF = Affective States, CG = Cognitive States, C = Operational Cost

Θ is the stimulus event interaction sequence

Subject to $\Psi|_{e_i}$, *for* $e_i \in SE$, and a fuzzy ruleset Ξ

Fig. 7 Optimization problem of product ecosystem design for UX

negative effect is resulted if the stay-time is $T_{\exp}$. Assuming that $0 \le T_i \le 2T_{\exp}$, $-1 \le \mathrm{UX}_2 \le 1$. If the weights of both affective factors and cognitive factors are the same, then UX can be quantified as

Fig. 8 A screen shot of simulation in Flexsim®

$$\mathrm{UX} = (\mathrm{UX}_1 + \mathrm{UX}_2)/2. \quad (4)$$

System capacity utilization is computed from the average utilization of the subway facilities that require relatively large capital investment or operational cost. These facilities include such major products as shown in Table 3. In the simulation environment, all these performance factors can be monitored and computed automatically.

The effectiveness of the product ecosystem on UX is reflected in Fig. 9 by the average affective state of all users denoted by the solid curve and the average stay-time denoted by the dash curve. Overall, it produces an average affective state of 0.31, which indicates a positive effect of the product ecosystem on the user's affective state. For the user stay-time, it is shown that the users stay in the system for an average period of 6.35 min, which is shorter than the expected stay-time of 6.5 min. This is an indication of acceptable operational efficiency of the service process.

The system capacity utilization is computed to find out the cost-effectiveness of the product ecosystem, as shown in Fig. 10. As can be seen from the results, the lift (LT), the service person (SP), and the train (TR) are characterized by high utilization rates. While a higher average utilization rate of a product indicates lower unit cost per service process, it suggests a possible bottleneck of the service process, provided that the users' affective state is significantly reduced by the respective product.

New product ecosystem configurations can be designed to improve various aspects of the legacy system. Based on Figs. 9 and 10, aggregated UX and aggregated capacity utilization can be calculated with one specific configuration of the subway station. Compared with the legacy system in Table 3, 13 different configurations of subway are computed with the simulation methods and a pseudo-optimal one has been found (see Table 3 and Fig. 11), suggesting the optimal trade-offs between capacity utilization and UX.

Table 3 Product ecosystem configurations

Product	Parameter	Legacy system	Pseudo-optimal
General ticketing machine (GTM)	Number	4	3
	Position	(5, 3) (15, −3) (5, 4) (15, −4)	(5, 3) (5, 4) (5, −3)
Information board (IB)	Number	1	2
	Visibility	High	High
	Position	(3, 0)	(5, 2) (5, −2)
Gate narrow (GN)	Number	8	8
Gate wide (GW)	Number	2	1
Service person (SP)	Number	2	3
Lift (LT)	Speed	Moderate	Moderate
	Position	(25, 0)	(18, 0)
Escalator (ES)	Speed	Slow	Moderate
	Position	(25, 0)	(25, 0)
Staircase (ST)	Position	(25, 1)	(30, 1)
Train (TR)	Interval	6	5

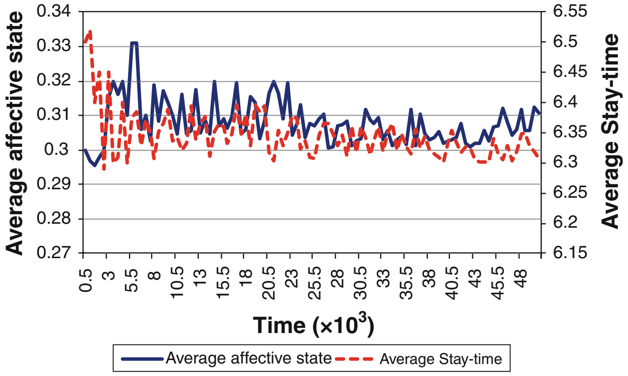


Fig. 9 User experience with respect to affective state and user stay-time

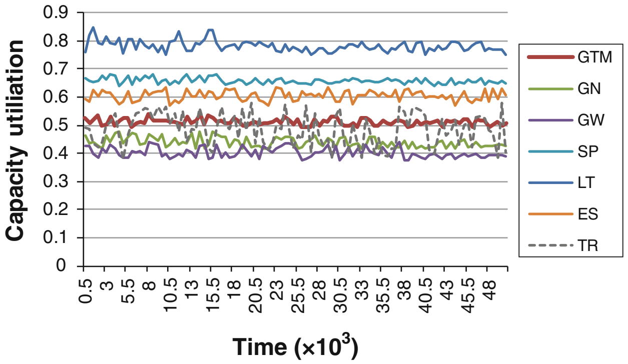


Fig. 10 Capacity utilization of individual products

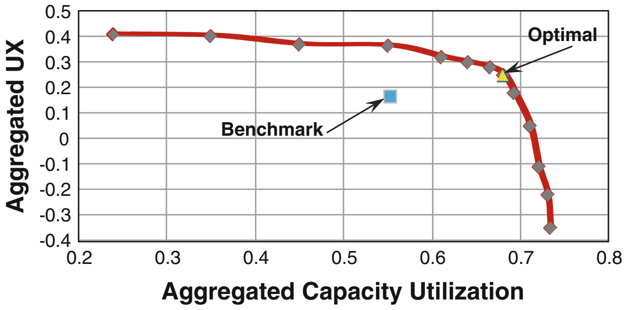


Fig. 11 A pseudo-optimal product ecosystem configuration for the subway station

It should be noted that the optima in the Pareto-frontier may not be found in reality because it is impractical to explore the design space thoroughly. The data points in Fig. 11 are computed manually and are called pseudo-optima.

6 Summary

Product ecosystem design suggests a new paradigm of product design with extended scopes and objectives. It not only emphasizes value-added UX by including users' affect and cognition but also considers the association of one user with multiple products, users, services, environmental settings, and use contexts, i.e., the ambience. Factors that engender UX and their possible underlying interaction mechanisms between affect and cognition are also discussed. These fundamental theories of the model provide a more profound understanding of UX. To tackle such a complex design problem systematically, a technical framework is proposed, dealing with affective-cognitive need acquisition, affective-cognitive analysis, and affective-cognitive fulfillment issues. An application case is presented with possible solution methods to the key research issues identified within each step of the technical framework.

With clear understanding of fundamental issues under product ecosystem design, the product ecosystem vision sheds light on industrial applications, such as cabins of airplanes, trains, yachts, exhibition halls, and shopping malls, and the like. However, product ecosystem design as a new research problem is still at an explorative stage and much work is needed to develop it into a comprehensive methodology. Notably, it remains to address several fundamental issues: (1) How should the product ecosystem be defined and formulated in relation with the nature ecosystem so as to borrow the wisdom of Mother Nature? (2) How do we model and predict the behavior of users in the ecosystem context? (3) How do we integrate the elements of the ambience well with the traditional design process? (4) How do we apply the basic concepts in a broader scenario of systems design, e.g., designing service systems where human involvements become significant? (5) How can we test the product ecosystem design principles under a large scale of experimentation with rigorous, transparent and replicable methodologies, etc? Hence, numerous challenges and opportunities are anticipated in the research and applications of product ecosystem design.

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