An affective-cognitive foundation of user experience design in complex product-service ecosystems

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Abstract
This presentation reviews the theoretical foundation of user experience design. The focus is to develop mathematical models of affective-cognitive decisions for the quantification, evaluation and reasoning of user experience in the context of product-service ecosystem. We will introduce a variety of new methods for understanding human users' subjective experience and affective predication under uncertainty.

Keywords: User experience design, Affective-cognitive foundation, Product-service ecosystem

Introduction
When mobile phones produced by different companies connect people with their friends and family globally, what is the key factor that makes a person select one over another? Here is where the concept of user experience (UX) comes into play. UX includes usability, beauty, overall quality and hedonic, affective and experiential aspects of the use of technology (Hassenzahl and Tractinsky 2006). These experiences define how the connection between two people is realized and unfolds.

Another factor that makes a modern product like an iPhone or iPad works not only because of its inherent UX, but also because of the product-service ecosystem in which it "lives"(Cho *et al.* 2010). This is consistent with the shift to a functional economy where value and UX are delivered through not just by the products themselves but more importantly through a provision of services (Geum and Park 2011). As customers become more connected, products and services are increasingly knitted into a larger ecosystem. Thus, it is important to understand flow patterns and directions of UX within a product-service ecosystem to get "the whole thing" right to delight customers.

As elaborated by Zhou et al. (2011c, 2012), UX has two aspects, i.e., cognitive aspect and affective aspect in the design community. The cognitive aspect 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). The affective aspect focuses on user's emotional responses and aspiration toward high-value added customer satisfaction (Zhou *et al.* 2010). These two aspects play a significant role in human decision making toward product success (e.g., customer purchasing decisions) (Brown 2008). While affective elements are well-known to influence human decision making, the prevailing computational models for analyzing and simulating human perception and evaluation on UX are mainly cognition-based models (Ahn 2010), e.g., expected utility theory (Von Neumann and Morgenstern 1953) and decision and judgment models based on cognitive errors and heuristics (Brandstätter *et al.* 2006). Such a single cognitive perspective is not optimal for analyzing decision behavior towards UX, in which users' affective states experienced at the time of decision making influence their experience and perception (Ahn and Picard 2005). Recent consensus on the integration of emotion and cognition has been driven by the intimate coupling of affective and cognitive decisions (Scherer *et al.* 2001).

In this regard, this paper discusses the theoretical foundation of affective cognitive modeling for UX design. The focus is to develop mathematical and computational models of affective cognition decisions for the quantification, evaluation and reasoning of UX. A technical framework is outlined to understand how users' subjective experience and affective prediction will impact their choice behavior under uncertainty, including (1) Quantitative measure of UX based on cumulative prospect theory; (2) Predication of affective states and cognitive tasks by computational learning through augmented UX information extracted from multimodal physiological and motion data; (3) UX reasoning incorporating affective influence and cognitive tendency by hierarchical Bayesian models with Markov chain Monte Carlo; and (4) Aggregated UX design evaluation using multivariate utility copulas considering multivariate dependence.

Fundamental issues

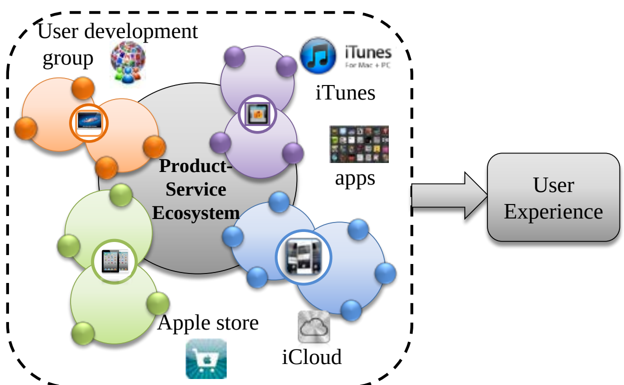

Figure 1 – An example of product-service ecosystem

Product-service ecosystem: A product service ecosystem is defined as a concept of product(s) and service(s) combined in a system that is readily adaptable to changes in their ambience which enables it to stay competitive in the global market and deliver pleasurable UX through continuous improvement and indefinite growth based on the existing technologies. This concept is a combination of a product-service system (Geum and Park 2011) with an open engineering system (Simpson *et al.* 1998). It is an integrated offering of products and services and thus is able to provide sustainability, increased customer value, and positive UX (Mont 2002). Therefore, sometimes the value and UX in the product-service ecosystem is not created by purchasing the product but by offering a service with particular function. It is an open engineering system, because it can adapt to changes in its ambience, including changes in the market, customer needs, technology, resources, system environment, and government/legislation, cultures, and so on in order to stay competitive and offer positive UX (Simpson *et al.* 1998, Zhou *et al.* 2011c). In this sense, it resembles the natural ecosystem in which the biological entities adapt to changes in the environment to stay competitive. One good example is the Apple product-service ecosystem as shown in Figure 1.

User experience: UX 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-object-ambience interactions, where the object refers to a specific design attribute involved in the product-service ecosystem (Zhou *et al.* 2011c). Usually a series of interaction events is involved. Therefore, UX, in the product-service ecosystem, is more than the consequence of a single interaction, 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 include users' (1) affective states and (2) cognitive processes. More details can be referred to (Zhou *et al.* 2011c).

Affective-cognitive decisions for UX design: Figure 2 articulates a scenario of UX design in the context of product-service ecosystem. The UX is enacted as users' affective and cognitive decisions through their interactions with a variety of system design attributes, denoted as a set, $A=\{a_i\}_M$, where M is the total number of design attributes. These design attributes embody the key characteristics of the product-service ecosystem, including tangible or intangible objects or design parameters. Each design attribute may assume a number of element levels, $A_i^*=\{a_{ik}^*\}_{1\le k\le L_i}$, where L_i is the total number of levels (instances) of a_i, and k denotes the k-th level of a_i. For example, leg room in an aircraft cabin can be a design attribute that may assume three instances (e.g., restricted, adequate, spacious). UX with a particular design of the product-service ecosystem can be measured through the user's perception on each individual design attribute, comprising a finite set of partworth UX measures, $\{u_{ik}\}_{M\times L_i}$. The critical challenge of theoretical formulation is how to find a sound measure of the user's perception (u_{ik}) on design instance a_{ik}^*, given all the possible choices of each design attribute; and to derive a holistic UX perception (aggregation of partworth UX measures) as a key performance indicator to differentiate various configurations of design attributes.

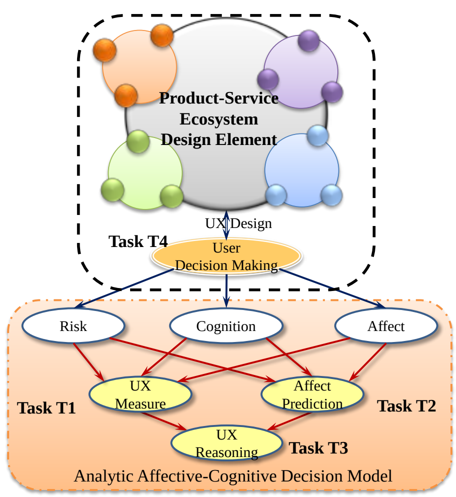

Figure 2 – Affective-cognitive decisions in UX design

Four tasks are identified in Figure 2. We propose to extend prospect theory (Kahneman and Tversky 1979) by (1) formulating cumulative prospect value functions to characterize UX cognitive tendency with risk attitudes and modeling affective influence through the shape parameters of prospect value functions. To elicit affects and proactively incorporate affective influence into UX design, we propose to (2) extract features and predict affective states and cognitive tasks by computational learning from augmented physiological and motion study experiment data. To estimate shape parameters, we propose to (3) model the causal relationships between affective states and UX prospects by hierarchical Bayesian models. Considering multivariate dependence inherent in the aggregation of partworth UX measures, we propose to (4) construct multivariate utility copulas to overcome limitations of traditional multiattribute utility formulation. Therefore, the affective-cognitive decision model manages to incorporate affective influence and cognitive tendency into the quantification of UX within a coherent framework of UX configuration design in the context of product-service ecosystem.

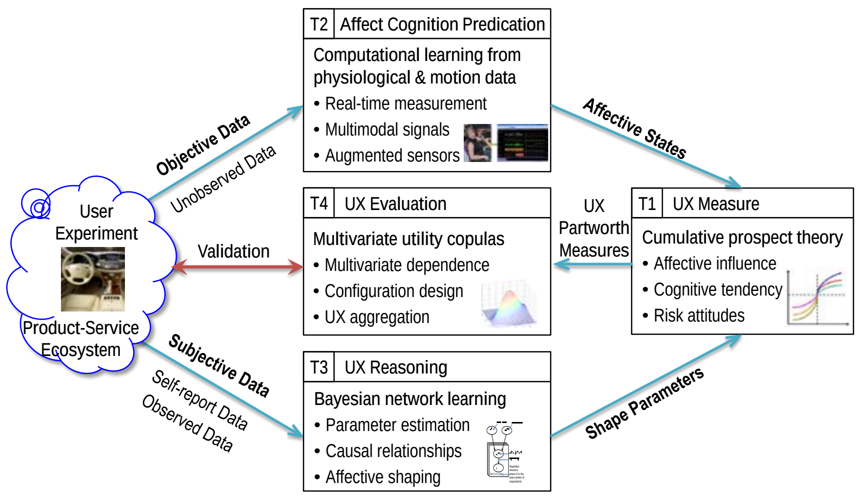

Figure 3 – A technical framework

A technical framework

In order to develop models of affective-cognitive decisions for the quantification, evaluation and reasoning of UX in the context of product-service ecosystem, a technical framework is proposed in Figure 3. We identify four integrated enablers to realize affective cognitive modeling for UX design, including (T1) UX measure, (T2) affect and cognition predication, (T3) UX reasoning, and (T4) UX evaluation.

T1: UX measure based on cumulative prospect theory: We propose a UX choice decision-making model based on cumulative prospect theory (Tversky and Kahneman 1992) in behavioral economics. It incorporates a subjective value function with a decision weighting function to model the subjective evaluation of a design profile. The outcome is relative to a reference point rather than an absolute value. Such an emphasis on the reference point conforms to the human perceptual process, which tends to notice shifts more than resting on static states. Customers choose different product profiles (in which different attributes have different decision weights) with different choice probabilities, resulting in different UX. Unpleasant UX looms larger than pleasant UX. This leads to loss aversion to unpleasant UX. Cumulative prospect theory applies distortions to the cumulative probabilities so that stochastic dominance is not violated. Furthermore, the subjective value function exhibits cognitive tendency for decision making, such as reference dependence, diminishing sensitivity, and loss aversion. However, it does not incorporate affective influences at the time of decision making which is addressed in T3.

T2: Affect and cognition prediction using objective data: On the one hand, in order to have optimal performance and enjoyable UX, 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 states effectively. Traditional methods are typically subjective, such as user interviews, focus groups, and self-report about one's affective states. 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 (Zhou *et al.* 2011b). 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 (Bailenson *et al.* 2008). Therefore, multiple physiological signals will be measured to predict user's affective states in the interaction process.

On the other hand, 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 product-service ecosystem, 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 (Fjeld *et al.* 2002). Hence, through activities that people perform, it is likely to tell their cognitive tasks, goals, and needs. Wearable sensors, such as RFID, motion sensors, and other ambient sensors can be applied to collect objective data to predict user's interaction activities (Zhou *et al.* 2012).

T3: UX reasoning with hierarchical Bayesian models: The purpose of UX reasoning is to justify affective influence on UX measure. Specifically, it is to determine the values of shape parameters for an S-shaped prospect function in accordance with each individual affective state. To support UX reasoning, it is necessary to develop a model that can effectively quantify the causal relationships between affective states and UX prospects in terms of their shape parameters. We propose to estimate these shape parameters by hierarchical Bayesian models with Markov chain Monte Carlo. The formulated UX model conforms to the Bayes theorem such that it is possible to multiply prior probability densities with a likelihood probability to arrive at a posterior distribution of each parameter. It offers a principled and comprehensive way to relate psychological models to experimental data (Lee and Newell 2011). It can identify how, rather than whether, the variables are related, inferring causal influences between UX and product attributes that go beyond regression or correlation analysis (Steyvers *et al.* 2009). It thus helps enforce a true representation of how the participants encode, judge, and make decisions with regard to different design profiles.

T4: UX evaluation using multivariate utility copulas: The purpose of this task is to aggregate multiple dependent UX measures for a holistic evaluation of UX design using multivariate utility copulas. Psychological studies show that UX is reflected as a holistic impression involving unstructured decisions. This suggests that partworth UX measures are dependent on one another, due to the coupling of user interactions with multiple design attributes inside a product-service ecosystem (Zhou *et al.* 2010). Copulas offer a new functional form to model preferences over utility-dependent attributes with arbitrary single utility functions. However, currently methods mainly focus on bivariate functional forms. In order to aggregate numerous dependent UX partworths, we propose to formulate nested multivariate utility copulas. Single utility functions are constructed based on cumulative prospect theory, according to which multivariate Archimedean utility copulas are introduced. A nested structure of Archimedean utility copulas based on the modularized attributes is proposed to formulate multiattribute utility functions (Zhou and Jiao 2013).

An application case

The application case focuses on the vehicle interior design to create positive driving UX. In order to provide proper product and service offering in a profit-maximizing way, automotive manufacturers need to understand driving UX from the perspective of the drivers and passengers and manage their resources to deliver pleasant UX. The key is to develop an affective-cognitive decision making model that can evaluate UX with regard to different vehicle interior design profiles. The design attributes can be user interfaces (UI) of radio, navigation system, steering wheel, air conditioner, and so on. These factors influence passenger's UX in a different ways.

Cumulative prospect theory-based UX measure: Cumulative prospect theory addresses important subjective influence (i.e., cognitive tendency and affective influences) on human choice decision making in UX design using a value function v for an individual design attribute instance (Kahneman and Tversky 1979):

$$v_{ik} = v\left(a_{ik}^*\right) = \begin{cases} \left(\Delta a_{ik}^*\right)^{\alpha}, & \Delta a_{ik}^* \geq 0 \\ -\lambda\left(-\Delta a_{ik}^*\right)^{\beta}, & \Delta a_{ik}^* < 0 \end{cases}, \tag{1}$$

where $\Delta a_{ik}^* = a_{ik}^* - a_{i,ref}^*$, is the difference between the reference attribute instance $a_{i,ref}^*$ and the target design attribute instance a_{ik}^*. The value function is defined with respect to a reference point $a_{i,ref}^*$, rather than an absolute value, and thus is reference dependent. In addition, α and β are parameters between 0 and 1, modulating the curvature of the subjective value function. The degree of curvature of the value function represents a decision maker's sensitivity to, risk attitude to and affective influence on UX. $\lambda > 1$ specifies the degree of aversion to unpleasant UX.

Quantitative modeling to predict choice is an established area of research in marketing and product planning. Using random utility discrete choice models, it is possible to predict customer preferences on different design attribute instances. The value of a design attribute instance a_{ik}^* to the customer is indicated by $v(a_{ik}^*)$. We can construct a closed form of choice probability adapted from the logit model (Train 2003), i.e.,

$$p_{ik} = p\left(a_{ik}^*\right) = \exp\left(\eta\left[v(a_{ik}^*)\right]\right) \Big/ \sum\nolimits_{k=1}^{L_i} \exp\left(\eta\left[v(a_{ik}^*)\right]\right), \tag{2}$$

where $\eta > 0$ is a scaling parameter. As $\eta \to \infty$, the logit behaves like a deterministic model. On the other hand, it becomes a uniform distribution as $\eta \to 0$.

A design attribute a_i with multiple instances, i.e., $A_i^* = \{a_{ik}^*\}_{L_i}, 1 \le k \le L_i$, can be transformed into $m+n+1$ UX outcomes as perceived by one customer. Arrange the outcomes in an increasing order, i.e., $v_{-im} < \cdots < v_{i0} < \cdots < v_{in}$ which occur with respective choice probabilities, $p_{-im}, ..., p_{i0}, ..., p_{in}$. Note that v_{i0} corresponds to the UX outcome of the reference instance; those smaller than v_{i0} are related to the unpleasant UX of design attribute instances; and those larger than v_{i0} are related to the pleasant UX of attribute instances. The user evaluates each attribute instance in conjunction with the associated choice probability, and thus the perceptual UX for a_{ik}^* after probability distortion is

$$u_i = V\left(a_{ik}^*, p_{ix}\right) = \begin{cases} v_{ik}\pi^+\left(p_{ix}\right), & \Delta a_{ik}^* \ge 0 \\ v_{ik}\pi^-\left(p_{ix}\right), & \Delta a_{ik}^* < 0 \end{cases}, \tag{3}$$

where $\pi^+\left(p_{ix}\right) = w^+\left(\sum_{j=x}^{n} p_{ij}\right) - w^+\left(\sum_{j=x+1}^{n} p_{ij}\right)$, $0 \le x \le n-1$, $\pi^-\left(p_{ix}\right) = w^-\left(\sum_{j=-m}^{x} p_{ij}\right) - w^-\left(\sum_{j=-m}^{x-1} p_{ij}\right)$, $1-m \le x \le 0$, $\pi^+\left(p_{in}\right) = w^+\left(p_{in}\right)$, $\pi^-\left(p_{i,-m}\right) = w^-\left(p_{i,-m}\right)$. The weighting function, *w*, takes the following form (Tversky and Kahneman 1992):

$$w(p_{ix}) = p_{ix}^z \big/ (p_{ix}^z + (1-p_{ix})^z)^{1/z}, \tag{4}$$

where $0 \le z \le 1$ specifies the curvature of the weighting function, such that $z = \delta$ stands for pleasant UX (i.e., $w = w^+$) and $z = \theta$ suggests unpleasant UX (i.e., $w = w^-$). This function shows that customers tend to overweigh low probabilities with extreme UX outcomes of attribute instances and underestimate moderate and high probabilities.

Affect and cognition prediction with objective data: To support affect and cognition prediction, we integrate two hardware platforms (physiological measure and motion sensing) into a cohesive augmented sensor platform. During the driving process, 16 participants' affective states are recorded using wearable physiological sensors, including facial EMG (zygomatic and corrugator muscle activity) using a Myomonitor Wireless EMG System, respiration rate, EEG (alpha and beta waves), and skin conductance response, using an 8-channel Biofeedback system TM v5.0. Four different affective states are considered in the driving context, namely, nervous, comfortable, neutral (no particular emotions), and aware (attentive). For cognitive tasks, numerous RFID tags are deployed in the vehicle, such as interfaces of radio, navigation system, steering wheel, air conditioner. Two RFID readers are also attached to the users' hands trying not to interfere driving. Mirametrix® eye tracking device is used to record eye ball movement so that eye retention in seconds can be recorded. The vehicle being tested is a 2006 Nissan Altima. Four different cognitive tasks are identified, including playing music, adjusting temperature, navigating with GPS, and driving with speed limit. Note that driving is the primary task which includes direct control operations, such as navigation, steering, and stabilization while other tasks are secondary. It is observed that when the user is performing multiple tasks simultaneously, his stress level increases.

In order to effectively predict the corresponding affective states and cognitive tasks of the participants, a rough set-based method has been developed (Zhou *et al.* 2011a, Zhou *et al.* 2011b). 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 affective states or cognitive tasks. In the experiment, there are 256 entries extracted from the raw data and tabulated in a decision table for illustration purpose. A ten-fold cross validation is adopted. The *F*-measures (Zhou *et al.* 2011b) for the four affective states are 80.2% (nervous), 78.7% (comfortable), 86.5% (neutral), and 83.6% (aware) and for the four cognitive tasks are 92.1% (playing music), 89.8% (adjusting temperature), 95.6%, and 92.4% (driving with speed limit).

Affective shaping with hierarchical Bayesian models: As shown above, we need to estimate α, β, δ, θ, between 0 and 1, and λ and η in (0, +∞) (see Eqns. (1), (2), and (4)). In Bayesian analysis, the method of implementing a hierarchical model is to use a hierarchical prior. The parent distribution at the top level serves as *a prior*, which is termed as the first stage of the prior. The parameters of the parent distribution also need *a prior* on them for estimation, which is termed as the second stage of the prior. According to Rouder and Lu (2005), a probit transform model is used for a hierarchical prior. Let Φ denote the standard normal cumulative distribution function, and we assume $\alpha_i = \Phi(\alpha_i^{\Phi})$, where $\alpha_i \in [0,1]$ is the *i*-th participant parameter in Eqn. (1), and $\alpha_i^{\Phi} \in R$. Following the probit transform model, we can have $\alpha_i^{\Phi} = \Phi^{-1}(\alpha_i)$. Meanwhile, the probitized parameter is assumed to follow independent normal distribution at the parent level, i.e., $\alpha_i^{\Phi} \sim N(\mu^{\alpha}, (\sigma^{\alpha})^2)$. Then, the parameters at the segment level are called hyper-parameters and can also be assigned to priors. First, for the mean, it is assumed to have a standard normal distribution prior, namely, $\mu^{\alpha} \sim N(0,1)$. For the standard deviation, it is assumed to follow uninformative uniform prior: $\sigma^{\alpha} \sim U(0,10)$. Then β, δ, and θ can also be treated similarly, while λ and η are assumed to follow lognormal distribution. For example, $\lambda \sim LN(\mu^{\lambda}, (\sigma^{\lambda})^2)$ and the mean lies in an interval between 0.1 and 5, i.e., -2.30 and 1.61 on the log scale. Therefore, the mean at the segment level follows $\mu^{\lambda} \sim U(-2.30, 1.61)$, if an uninformative uniform prior distribution is assumed for the lognormal mean, the standard deviation is 1.13. Hence, it is reasonable that the standard deviation follows the uniform distribution: $\sigma^{\lambda} \sim U(0,1.13)$. η has the same treatment of λ. The posterior probability density functions of different parameters are estimated using Markov chain Monte Carlo simulation with WinBUGS software. The mean values and standard deviations of three different affective states are shown in Table 1.

Table 1 – Parameter estimation in three different affective states

Affective states	Parameter mean (standard deviation)					
	α	β	λ	δ	θ	η
Comfortable	0.56 (0.06)	0.60 (0.09)	3.19 (0.73)	0.39 (0.10)	0.52 (0.13)	1.39 (0.75)
Neutral	0.55 (0.07)	0.78 (0.10)	3.12 (0.77)	0.32 (0.07)	0.45 (0.11)	2.14 (0.63)
Nervous	0.46 (0.08)	0.74 (0.08)	2.73 (0.42)	0.36 (0.06)	0.50 (0.13)	1.63 (0.58)

***Aggregating individual UX partworths using multivariate utility copulas*:** The multi-UX measure can be developed by a copula structure and individual UX partworths in Eqn. (3), i.e., $U(a_1,...a_M) = C(U_1(a_1),...,U_I(a_M))$, where a_i, $1 \le i \le M$ is the design attribute, and $u_i = U_i(a_i)$ (see Eqn. (3)) and here u_i is normalized between 0 and 1 (see Zhou and Jiao 2013). Archimedean utility copula (Abbas 2009) can be defined as

$$U(a_1,...a_M) = k_1\varphi^{-1}[\prod_{i=1}^{M}\varphi(l_i + (1-l_i)a_i)] + k_2, \quad (5)$$

where $0 \le l_i < 1$, $k_1 = 1/(1-\varphi^{-1}[\prod_{i=1}^{M}\varphi(l_i)])$, $k_2 = 1-k_1$, and the generator φ is (1) continuous on the domain $a_i \in [0,1]$; (2) strictly increasing on the domain $a_i \in [0,1]$; and (3) $\varphi(0)=0$ and $\varphi(1)=1$. The parameter l_i satisfies $k_1(1-l_i) = 1-U(a_i^{\min}, \bar{a}^{\max})$, where $\bar{a}$ represents the complement attributes (i.e., the remaining alternative attributes) with regard to a_i. $U(a_i^{\min}, \bar{a}^{\max})$ indicates the value of multi-UX when a_i takes the minimum value and its complement attributes take the maximum value. Take the two attributes radio UI and air conditioner UI, (represented as $\Omega = \{a_1, a_2\}$) as an example. We can construct the Archimedean utility copulas. First, the utility values of $U(a_1^{\min}, a_2^{\max})$ and $U(a_1^{\max}, a_2^{\min})$ need to be estimated as: $U(a_1^{\min}, a_2^{\max})$ = 0.53 and $U(a_1^{\max}, a_2^{\min})$ = 0.18. The generator φ takes the form: $\varphi(a_i) = (1 - \exp(-\delta a_i)) / (1 - \exp(-\delta))$, where $\delta \in R \setminus \{0\}$. Based on the available information, we can calculate the values k_1 = 1.54, k_2 = -0.54, l_1 = 0.70, and l_2 = 0.47. δ is estimated as 1. Substituting the obtained parameters into Eqn. (5), we can obtain the bivariate UX function of attributes a_1 and a_2 as shown in Figure 4.

For all the four design attributes, we can group them into two modules based on structural and functional similarity, i.e., $\Omega = \{\{a_1, a_2\}, \{a_3, a_4\}\}$, where a_1, a_2 indicate radio UI and air conditioner UI and a_3, a_4 driving UI and navigation UI, respectively. Each sub-module is considered mutually independent. Then the multivariate UX function can be represented using a nested form

$$U(a_1, \ldots a_4) = C(U_1(a_1), \ldots, U_4(a_4)) = C(C(U_1(a_1), U_2(a_2)), C(U_3(a_3), U_4(a_4))). \quad (6)$$

Thus Eqn. (6) can be used to evaluate the UX for vehicle interior design.

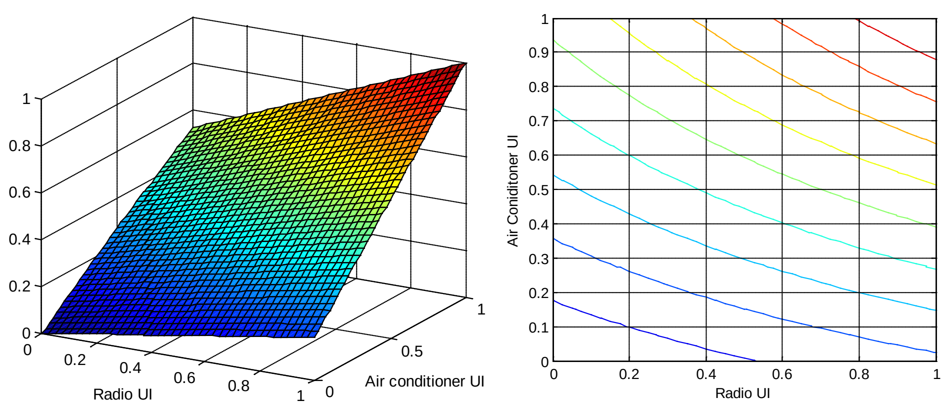

Figure 4 – Bivariate UX function of a_1 and a_2. Left: 3D figure and Right: isopreference curves

Summary

UX design in the context of product-service ecosystem suggests a new paradigm of product design with extended scopes. From a decision analysis perspective, we identify the fundamental issues i.e., developing computational models of affective cognition decisions for the quantification, evaluation and reasoning of UX. An application case is presented to show the proposed framework to deal with the fundamental issues.

References

Abbas, A.E., 2009. Multiattribute utility copulas. *Operations Reserach*, 57 (6), 1367-1383.

Ahn, H., 2010. *Modeling and analysis of affective influences on human experience, prediction, decision making, and behavior*. PhD thesis. MIT.

Ahn, H. & Picard, R.W., 2005. Affective-cognitive learning and decision making: A motivational reward framework for affective agents. *The 1st International Conference on Affective Computing and Intelligent Interaction (ACII 2005).* Beijing, China.

Bailenson, J.N., Pontikakis, E.D., Mauss, I.B., Gross, J.J., Jabon, M.E., Hutcherson, C.a.C., Nass, C. & Oliver, J., 2008. Real-time classification of evoked emotions using facial feature tracking and physiological responses. *International Journal of Human-Computer Studies*, 66 (5), 303-317.

Brandstätter, E., Gigerenzer, G. & Hertwig, R., 2006. The priority heuristic: Making choices without trade-offs. *Psychological Review,* 113 (2), 409-432.
Brown, A.S., 2008. The new point of view: Focus on design for human factors. *ASME Mechanical Engineering Magazine,* (February Issue).
Cho, C.K., Kim, Y.S. & Lee, W.J., 2010. Economical, ecological and experience values for product-service systems. *The 7th Design & Emotion Conference,*. Chicago, USA.
Fjeld, M., Lauche, K., Bichsel, M., Voorhorst, F., Krueger, H. & Rauterberg, M., 2002. Physical and virtual tools: Activity theory applied to the design of groupware. *In* Nardi, B.A. & Redmiles, D.F. eds. *A special issue of computer supported cooperative work (cscw): Activity theory and the practice of design.* 153-180.
Geum, Y. & Park, Y., 2011. Designing the sustainable product-service integration: A product-service blueprint approach. *Journal of Cleaner Production,* 19 (14), 1601-1614.
Hassenzahl, M. & Tractinsky, N., 2006. User experience - A research agenda. *Behaviour & Information Technology,* 25 (2), 91-97.
Kahneman, D. & Tversky, A., 1979. Prospect theory: An analysis of decision under risk. *Econometrica,* 62 (6), 1251-1289.
Lee, M.D. & Newell, B.R., 2011. Using hierarchical bayesian methods to examine the tools of decision-making. *Judgment and Decision Making,* 6 (8), 832-842.
Leont'ev, A.N., 1977. *Activity and consciousness* Moscow: Progress Press.
Mont, O.K., 2002. Clarifying the concept of product-service system. *Journal of Cleaner Production,* 10 (3), 237-245.
Rouder, J.N. & Lu, J., 2005. An introduction to bayesian hierarchical models with an application in the theory of signal detection. *Psychonomic Bulletin & Review,* 12 (4), 573-604.
Scherer, K.R., Shorr, A. & Johnstone, T. eds. 2001. *Appraisal processes in emotion: Theory, methods, research,* Canary, NC: Oxford University Press.
Schiano, D.J., Ehrlich, S.M. & Sheridan, K., 2004. Categorical imperative not: Facial affect is perceived continuously. *Conference on Human Factors in Computing Systems.* Vienna, Austria, 49-56.
Simpson, T.W., Lautenschlager, U. & Mistree, F., 1998. Mass customization in the age of information: The case for open engineering systems. *In* Read, W. & Porter, A. eds. *The information revolution: Current and future consequences.* Greenwich: Ablex Publications, 49-71.
Steyvers, M., Lee, M.D. & Wagenmakers, E.J., 2009. A bayesian analysis of human decision-making on bandit problems. *Journal of Mathematical Psychology,* 53 (3), 168-179.
Train, K.E., 2003. *Discrete choice methods with simulation* Cambridge, UK: Cambridge University Press.
Tversky, A. & Kahneman, D., 1992. Advances in prospect theory: Cumulative representation of uncertainty. *Journal of Risk and Uncertainty,* 5 (4), 297-323.
Von Neumann, J. & Morgenstern, O., 1953. *Theory of games and economic behavior,* 3rd ed. Princeton, NJ: Princeton University Press.
Wickens, C.D. & Hollands, J.G., 1999. *Engineering psychology and human performance,* 3rd ed. New Jersey: Prentice Hall.
Zhou, F., Jiao, J., Chen, S. & Zhang, D., 2011a. A case-driven ambient intelligence system for elderly in-home assistance applications. *Systems, Man, and Cybernetics, Part C: Applications and Reviews, IEEE Transactions on,* 41 (2), 179-189.
Zhou, F., Jiao, J.R., Schaefer, D. & Chen, S., 2010. Hybrid association mining and refinement for affective mapping in emotional design. *Journal of Computing and Information Science in Engineering,* 10 (3), 031010-9.
Zhou, F. & Jiao, R.J., 2013. Modeling dependence among user experience partworths by nesting multivariate archimedean utility copulas. *ASME Journal of Mechanical Engineering,* To appear.
Zhou, F., Jiao, R.J., Xu, Q. & Takahashi, K., 2012. User experience modeling and simulation for product ecosystem design based on fuzzy reasoning petri nets. *Systems, Man and Cybernetics, Part A: Systems and Humans, IEEE Transactions on,* 42 (1), 201-212.
Zhou, F., Qu, X., Helander, M.G. & Jiao, J., 2011b. Affect prediction from physiological measures via visual stimuli. *International Journal of Human-Computer Studies,* 69 (12), 801-819.
Zhou, F., Xu, Q. & Jiao, R., 2011c. Fundamentals of product ecosystem design for user experience. *Research in Engineering Design,* 22 (1), 43-61.