Using Dynamic Bayesian Networks to Model User-Experience

Paul van Schaik[1(✉)], Yifeng Zeng[2], and Iain Spears[1]

[1] School of Social Sciences and Law, Teesside University, Middlesbrough, UK
[2] School of Computing, Teesside University, Middlesbrough, UK
{p.van-schaik,y.zeng,i.spears}@tees.ac.uk

Abstract. This paper presents a new approach to modelling the time course of user-experience (UX). Flexibility in modelling is essential: to select or develop UX models based on the outcome variables that are of interest in terms of explanation or prediction. At the same time, there is potential for (partial) re-using UX models across products and generalisation of models. As a case study, an experience model is developed for a particular consumer product, based on a time-sequential framework of subjective well-being [13] and a theoretical framework of flow for human-computer interaction [23]. The model is represented as a dynamic Bayesian network and the feasibility and limitations of using DBN are assessed. Future work will empirically evaluate the model with users of consumer products.

1 Introduction

Parallel to the spread of personal computing, user-experience (UX) has become a major area in HCI research. Sutcliffe [20] provides a useful definition of UX: users' judgment of product quality arising from their experience of interaction, and the product qualities which engender effective use and pleasure. UX stresses that interactive products do not only deliver functional benefits, they promote experiences too, and users intention to (re)live positive experiences is an important driver of technology use [7]. Because most modern interactive products, such as laptop computers, hand-held devices (e.g. smart phones) and tablets, can be used both for work and leisure, utilitarian aspects (e.g., ease of use and learnability) are widely regarded as important, but insufficient by themselves to give a complete account for the acceptance, use and success of these technologies [3]. Indeed, the main idea behind the concept of UX is that the success of interactive products is fundamentally connected to their ability to promote high-quality experiences, but usability remains important. It is helpful to distinguish between instrumental and non-instrumental factors in relation to UX [22]. Usability of a product, as an instrumental factor, may strongly contribute to negative experiences, if it does not reach a satisfactory level expected by users. However, in order to achieve positive experiences, high levels of non-instrumental factors (e.g. positive and negative affect) are needed.

L. Cao et al. (Eds.): ADMI 2013, LNAI 8316, pp. 3–13, 2014.
DOI: 10.1007/978-3-642-55192-5_1,

Models that represent HCI knowledge are useful to summarize data, formalize relationships between variables and to make predictions, even if or precisely because they possess a degree of incompleteness and falseness. Indeed, HCI models can have theoretical and practical value as long as they fit data well, and make theoretical and practical sense, without actually being entirely truthful in their description of a particular phenomenon or process. Flexibility in modeling is therefore essential: to select or develop UX models based on the outcome variables that are of interest in terms of explanation or prediction, instead of using a single *one-size-fits-all* approach. Usually outcome variables are seen as indicators of success of a particular product, for example satisfaction or overall evaluation of experience. Outcome variables can be derived from, for instance, defined user-requirements (e.g. health improvement) or marketing objectives (e.g. satisfied customers). After UX has been measured it is possible to establish (*a*) to which extent requirements or objectives of the product have been met and (*b*) which other variables mostly contribute to explaining variance in the outcomes, as a basis for potential product improvement. Products that share the same outcome variables may share the same or similar models, thereby facilitating potential (partial) re-use UX models for new products and generalization of models.

With a change in emphasis from usability to experience, it is increasingly important that products promote a high-quality experience. This is particularly important for new technology that users may be unfamiliar with, such as augmented reality (AR). AR systems could promote high-quality UX, but there is a lack of UX research to underpin the design of such systems. Research to inform the design of such products is expected to benefit both product users and product manufacturers.

Existing models of UX have been formulated and tested with techniques based on the general linear model. In particular, multiple regression analysis, variance-based structural equation modeling (partial least-squares path modeling) and covariance-based structural equation modeling have been used. In this paper we explore the use of dynamic Bayesian networks, with the following contributions: (*a*) a flexible, but theory-driven, approach to UX modeling, (*b*) the specification of a particular well-grounded theory-based UX model and (*c*) the representation of the model as a dynamic Bayesian network and analysis of the modeling work. Section 2 presents related work. Section 3 presents the modeling approach, followed by conclusions and future work in Sect. 4.

2 Related Work

Existing research on UX modeling distinguishes instrumental and non-instrumental aspects of experience. However, in this work UX outcomes are usually non-instrumental. In Hassenzahl's user-experience [7,8] model perceptions of product characteristics (pragmatic quality and hedonic quality) are antecedents of global product evaluations (goodness and beauty). In Porat and Tractinsky's environmental-psychology UX model [18], environmental stimuli (classical aesthetics, expressive aesthetics and usability) are antecedents of emotional states (pleasure, arousal and dominance); in turn, these are antecedents of attitudes towards service. In Thüring and Mahlke's [22] CUE model, system properties, user-characteristics, and task/context are antecedents of interaction characteristics; in turn, these are antecedents of perceptions of instrumental qualities and perceptions of non-instrumental qualities, both of which lead to emotional reactions; all three are antecedents of appraisal of the system. In Hartmann *et al.*'s model of user-interface quality assessment [8], three stages are involved in users' judgment of quality assessment. First, users assess an interactive system based on their goals and the task domain. Second, users select decision-making criteria based on their goals and task. Third, users evaluate the system using these criteria.

Tests of these four UX models were in empirical studies used analysis of variance [7,21,22], partial correlation [7], covariance-based structural modeling [18]. Recent work has proposed the use of dynamic Bayesian networks (DBNs) for modeling quality of experience [11]. In their approach, context attributes are antecedents of the context state; in turn, context-state variables are antecedents of the situation state. The approach is illustrated with simulation results. Limitations of this work include the following. The work has no apparent credible theoretical justification; it does not build on existing theory of UX. Furthermore, it does not account for experience of a particular episode of interaction as it happens and global judgment of interaction with a product. Instead it only accounts for the memory of interaction episodes. Moreover, it does not account for causal relations between these three aspects of experience and, in a gross simplification, reduces the measurement of technology acceptance to a Boolean.

A major shortcoming of existing UX research on AR (and interactive products more generally) is that often actual product use and long-term use are not studied [24]. Furthermore, the role of task performance is not addressed; moreover, most research is not experimental, so cause (design) and effect (UX) cannot be established. Therefore, our program of research aims to conduct experimental research that models UX over time to inform the design of AR systems to sustain high-quality UX. We use a time-sequential framework of subjective well-being [13], our methods for modeling UX [23] and our hybrid real-time motion measurement system [19]; this work is expected to lead to new applications and improvements in product design.

3 Modeling Approach

Models of UX specifying determinants of positive experiences have been tested with a range of interactive devices and technologies. However, several challenges in UX modeling remain, in terms of UX theory, research design, technical solution and application of modeling to product design. Based on Kim-Prieto *et al.*'s time-sequential framework of subjective well-being [13], a time-sequential framework of UX can be framed as a sequence of stages over time: from the experience of a particular episode of interaction as it happens (**Level 1**) to the memory of interaction episodes (**Level 2**) to global judgment of interaction with a product (**Level 3**).

The approach taken here to model UX with a product over time uses DBNs [11]. This is illustrated with a consumer product (shaver), but the approach applies without loss of generality to any product. Based on existing work with industry by the research team, a sensor-embedded shaver will be developed. The shaver will communicate with a users existing smart phone to record the users behavior and measure the users experience in terms of memory of experience episodes (shaves) and global judgment of shaving experience.

The use of DBNs for UX modeling over time has several advantages over other techniques such as multiple regression analysis, structural equation modeling (SEM, in particular PLS path modeling and covariance based SEM), multilevel modeling and time series analysis are. DBNs are a dynamic version of probabilistic graphical models - Bayesian networks-that represent cause-effect relations embedded in a domain. They are able to structure the relations over time and provide an intuitive tool for conducting various inference tasks in the domain. To make a functional DBNs, it is always quite tedious to construct the DBNs manually, which requires a large amount of knowledge input from domain experts. Considering the availability of data in our domain, we are using automatic methods to learn DBNs from the accumulated data over subject study. However, it remains important that modeling results are grounded in theoretical understanding in order to build cumulative knowledge; therefore, as a starting point, we derive a well-argued theoretical model by integrating existing theoretical frameworks.

A recent theoretical framework of flow for HCI will be used [23] because the crucial role of task performance in modeling UX and the theory of flow experience (the degree to which a person feels involved in a particular activity) uniquely addresses this performance. In this framework, characteristics of person (user), artifact (product) and task are antecedents of flow experience. Flow experience consists of two main components: preconditions of flow and the dimensions of flow proper. Consequents of flow include objective, subjective and behavioral out-comes. The concept of flow is linked to that of effortless(ness of) performance [2]: the more flow people experience, the more effortless/less effortful their task performance is.

3.1 Data Capture and Variables

At **Level 1**, experience as it happens is inferred from captured sensor data and secondary-task data collected during each interaction episode. The three-dimensional position of the shaver is recorded continuously as well as the force a user applies to the shaver (and, optional, muscle activity). From these, measures of effortlessness are computed, including accuracy of motor performance, frequency and size of (motor) corrections and speed of action (variability) [5]. Performance is more effortless with more accurate motor performance, more frequent and smaller (motor) corrections and greater speed of action [5].

From a secondary task (for example, a reaction-time task where people respond to specific [sound] signal), response time is recorded. Attentional demand is measured as speed of secondary-task performance (timing of response relative to signal). Performance is more effortless with reduced attentional demand (faster secondary-task performance). In sum, online UX variables for DBN-modeling include: U1 Accuracy of motor performance; U2 Frequency and size of (motor) corrections; U3 Speed of action; U4 Speed of secondary-task performance.

Rather than using these variables as nodes in a model, we use a hidden (latent) variable to represent *effortlessness* inferred from these (indicator) variables, with reflective measurement. This is because the latent variable is the *cause* of the variables. At **Level 2**, memory of interaction episode is inferred from captured psychometric-questionnaire data collected immediately after each interaction episode. Flow experience is measured using Guo and Pooles 30-item inventory (or a subset or a similar instrument) [6]. From the 30 items, nine dimensions as hidden (latent) variables are inferred. The first three dimensions are preconditions of flow and the remaining six are dimensions of flow proper. For simplification, from the six dimensions of flow one high-order flow dimension may be inferred, but autotelic experience (Dimension 9) may also be used in the modeling as a variable on its own as it captures most clearly the intrinsically motivational value of flow experience. Visual attractiveness is measured using a single item from Tractinsky *et al.* [17], using a 10-point semantic differential. Affect is measured using PANAS with 10 items for positive affect and 10 for negative affect [1]. From the 20 items, two dimensions (positive and negative affect) are inferred. In sum, online interaction-memory variables for DBN-modeling include: U5 Balance of challenge and skill; U6 Goal clarity; U7 Feedback; U8 Autotelic experience; U9 Visual attractiveness; U10 Positive affect; U11 Negative affect.

Quality of task result (quality of shave) is assessed from a photograph taken of a particular save and satisfaction with task result from psychometric-questionnaire data collected immediately after each interaction episode. Quality of task result is rated by an independent judge or through image interpretation software. Items(5) to measure satisfaction from result are developed, based on existing instruments. From the items the satisfaction with task result as hidden (latent) variables is inferred. In sum, task result variables for DBN-modeling include: U12 Quality of task result; U13 Satisfaction with task result.

At **Level 3**, global judgment of interaction is inferred from captured psychometric questionnaire data collected after a number of interaction episodes. Items to measure utility(4), appearance(4), positive memories(3), pleasure of interaction(2), product attachment(5) and product satisfaction(4) are from Mugge et al. [16]. Items to measure intention(4) of future purchase are adapted from Kowatsch and Maass [14]. From the items the three global-judgment constructs as hidden (latent) variables are inferred. In sum, global-judgment variables for DBN-modeling include: U14 Utility; U15 Appearance; U16 Positive memories;

U17 Pleasure; U18 Product attachment; U19 Product satisfaction; U20 Intention of future purchase.

The role of person characteristics in relation to flow experience is that they moderate the effect of preconditions of flow experience on flow proper [4]. These characteristics are inferred from captured psychometric-questionnaire data collected once at the start of a trial. The constructs of achievement motivation and in particular action orientation (volatility subscale of the Action Control Scale, 12 items) from Diefendorff *et al.* [10] and perceived importance (3 items) from [4] are measured. From the items each of these constructs are inferred as hidden (latent) variables. In sum, person variables for DBN-modeling include: U21 Action orientation (volatility); U22 Perceived importance.

3.2 Static BN

To structure a potential BN, we proceed to specify relations among variables by exploiting their description in the existing literatures.

Level 1. Experience during interaction. The hidden variable *effortlessness* is modeled reflectively as a cause. This is because all measured variables at Level 1 are indicators of and 'caused' by effortless attention. We may abuse the functional relations as follows.

- Accuracy of motor performance = F(Effortlessness)
- Frequency and size of (motor) corrections = F(Effortlessness)
- Speed of action = F(Effortlessness)
- Speed of secondary-task performance = F(Effortlessness)

Level 2. Memory of interaction episode. Peoples memory of flow immediately after an interaction episode reflects the degree of effortlessness of the activity [2]. Therefore,

- Balance of challenge and skill = F(Effortlessness)
- Goal clarity = F(Effortlessness)
- Feedback = F(Effortlessness)

According to the staged model of flow experience [6] preconditions of flow are causes of flow experience proper; according to Engeser and Rheinberg [4] and Keller and Bless [12], achievement motivation is a moderator of the effect of the preconditions of flow on flow proper; according to Engeser and Rheinberg [4], importance is a moderator of this effect. Therefore,

- Autotelic Experience = F(Balance of challenge and skill, Goal clarity, Feedback, Achievement motive, Importance)

Because of cognitive (attention-enhancing) and motivational facilitation [4,23] task performance and the result of task performance are enhanced. Therefore,

- Quality of task result = F(Effortlessness, Balance of challenge and skill, Goal clarity, Feedback)

Level 3. Global judgment of interaction. Consistent with Kim-Prieto *et al.* [13], (immediate) memories of task result provides extrinsically motivational value that contributes to the global judgment of perceived utility. Therefore,

- Utility = F(Satisfaction with task result)

Brief (immediate) judgment of visual attractiveness contributes to elaborate (reflective) judgment of aesthetics [17]. Therefore,

- Appearance = F(Visual attractiveness)

(Immediate) memories of experience contribute to global judgment of experience [13]. Therefore,

- Positive memories = F(Positive affect, Negative affect)

Autotelic experience in a particular interaction episode is an 'intrinsically rewarding experience' [9] and therefore produces pleasure that contributes to a global judgment of pleasure of interaction. Utility and appearance contribute to pleasure [16]. Therefore,

- Pleasure = F(Autotelic experience, Utility, Appearance)

Pleasure partially mediates the effect of utility on satisfaction and fully mediates the effect of appearance [16]. Therefore,

- Product Satisfaction = F(Pleasure, Utility, Appearance)

The effects of utility and appearance on product attachment are fully mediated by pleasure [16]. Positive memories have a positive effect on pleasure [16]. The effects of utility and appearance on product attachment are moderated by positive memories [16]. Therefore,

- Product Attachment = F(Pleasure, Utility, Appearance, Positive Memories)

Satisfaction is an antecedent of intention [15]. Therefore,

- Intention of Future purchase = F(Satisfaction)

By combining the relations specified above, we may present the static BN for the UX in Fig. 1.

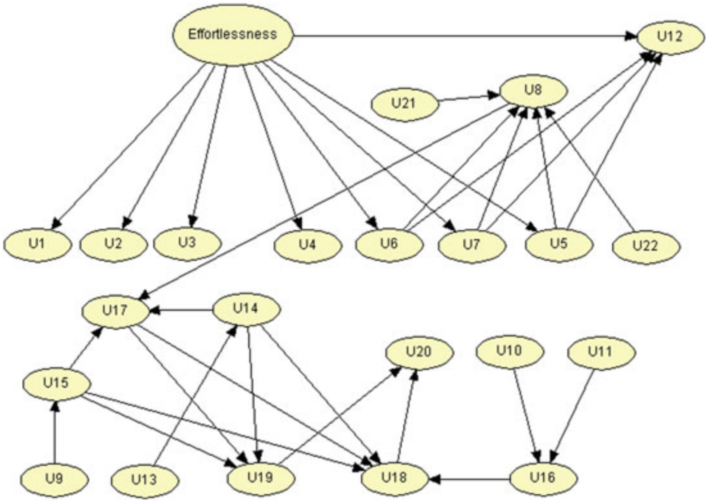

Fig. 1. A static BN represents the UX.

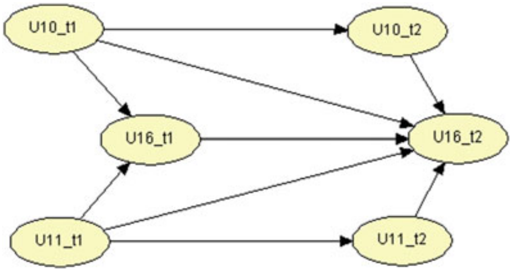

Fig. 2. A dynamic BN represents one relation over time.

3.3 Dynamic BN

To construct a time-dependent framework, we assume a first-order Markov process: the previous experience is an antecedent of next experience. Therefore, each experience variable at the previous time ($t1$) is treated a cause of the same variable at the next time($t2$). The relations (indicated by **F**) can also turn into a first-order Markov process. For example, we may represent the relation below over time in Fig. 2.

- Positive memories = F(Positive affect, Negative affect)

Obviously, the complete DBN will be a very complicated model where all relations are expanded over time. We will further test whether any descendants of the antecedents in the relations are statistically significant. By doing this, we expect to simplify the model by reducing the connectivity over time.

3.4 Discussions

Complicated UX relations always puzzle both domain experts and practitioners as the dimensions grow over time. Resorting to probabilistic graphical models, we intend to provide a more intuitive representation to describe UX over time. Particularly, the model becomes an easy way to convey UX to product designers who can understand the studied domain through a formal language.

By exploiting the previous study on UX, we structure UX variables into one BN and expand the BN into DBN assuming a first-order Markov process. The remaining thing is to specify DBN parameters (conditional probability tables) that normally can be done in an automatic way. Currently, we are gathering domain data from the field study and expect to estimate the parameters through a proper learning method.

4 Conclusions and Future Work

Modeling the time course of UX is important, but an under-researched field of study. The use of DBN is a promising approach to modeling UX over time, but this work needs to be informed by and account for existing theoretical frameworks and new ideas. This will allow existing theories to be refined or replaced by new theories. We have demonstrated the feasibility and limitations of using DBN to model UX. Most important findings were that UX relations can be explicitly represented through BN and can be intuitively understood by researchers and practitioners without different knowledge background; however, learning BN parameters could be a potential issue as a sufficient amount of data shall be gathered. We will exploit domain knowledge to develop a more reliable and efficient learning process.

Future work will include testing the UX flow model that has been presented here in experiments with different products where (the result of) task performance is essential. Furthermore, it is important to realize that modeling needs to be flexible to select or develop UX models based on the outcome variables that are of interest in terms of explanation or prediction, instead of using a single 'one-size-fits-all' approach. Depending on target UX outcomes and the role of task performance for particular products, different models need to be formulated and tested for theoretical understanding and as a basis for design improvement.

References

1. Watson, D., Clark, L.A., Tellegen, A.: Development and validation of brief measures of positive and negative affect: the panas scales. J. Pers. Soc. Psychol. **54**(6), 1063–1070 (1988)
2. de Manzano, O., Theorell, T., Harmat, L., Ullén, F.: The psychophysiology of flow during piano playing. Emotion **3**(10), 301–311 (2010)
3. Dillon, A.: Beyond usability: process, outcome and affect in human-computer interactions. Can. J. Libr. Inf. Sci. **4**(26), 57–69 (2001)

4. Engeser, S., Rheinberg, F.: Flow, performance and moderators of challenge-skill balance. Motiv. Emot. **32**(3), 158–172 (2008)
5. Wulf, G., Lewthwaite, R.: Effortless motor learning? an external focus of attention enhances movement effectiveness and efficiency. In: Bruya, B. (ed.) A New Perspective in Attention and Action, pp. 75–101. MIT Press, Cambridge (2010)
6. Guo, Y.M., Poole, M.S.: Antecedents of flow in online shopping: a test of alternative models. Inf. Syst. J. **19**(4), 369–390 (2009)
7. Hassenzahl, M.: The thing and i: understanding the relationship between user and product. In: Blythe, M.A., Overbeeke, K., Monk, A.F., Wright, P.C. (eds.) Funology, pp. 31–42. Kluwer Academic Publishers, Norwell (2003)
8. Hassenzahl, M.: The interplay of beauty, goodness, and usability in interactive products. Hum. Comput. Interact. **19**(4), 319–349 (2004)
9. Jackson, S.A., Marsh, H.W.: Development and validation of a scale to measure optimal experience: the flow state scale. J. Sport Exerc. Psychol. **18**(1), 17–35 (1996)
10. Diefendorff, J.M., Hall, R.J., Lord, R.G., Strean, M.L.: Action-state orientation: construct validity of a revised measure and its relationship to work-related variables. J. Appl. Psychol. **85**(2), 258–263 (2000)
11. Mitra, K., Zaslavsky, A., Ahlund, C.: Dynamic bayesian networks for sequential quality of experience modelling and measurement. In: Proceedings of the 11th International Conference and 4th International Conference on Smart Spaces and Next Generation Wired/Wireless Networking, Anonymous Smart Spaces and Next Generation Wired/Wireless Networking, pp. 135–146 (2011)
12. Keller, J., Bless, H.: Flow and regulatory compatibility: an experimental approach to the flow model of intrinsic motivation. Pers. Soc. Psychol. Bull. **34**, 196–209 (2008)
13. Kim-Prieto, C., Diener, E., Tamir, M., Scollon, C., Diener, M.: Integrating the diverse definitions of happiness: a time-sequential framework of subjective well-being. J. Happiness Stud. **3**(6), 261–300 (2005)
14. Kowatsch, T., Maass, W.: In-store consumer behavior: how mobile recommendation agents influence usage intentions, product purchases, and store preferences. Comput. Hum. Behav. **26**(4), 697–704 (2010)
15. Lin, W.-S.: Perceived fit and satisfaction on web learning performance: is continuance intention and task-technology fit perspectives. Int. J. Hum. Comput Stud. **70**(7), 498–507 (2012)
16. Mugge, R., Schifferstein, H.N.J., Schoormans, J.P.L.: Product attachment and satisfaction: understanding consumers' post-purchase behavior. J. Consum. Mark. **27**(3), 271–282 (2010)
17. Tractinsky, N., Cokhavi, A., Kirschenbaum, M., Sharfi, T.: Evaluating the consistency of immediate aesthetic perceptions of web pages. Int. J. Hum. Comput. Stud. **64**(11), 1071–1083 (2006)
18. Porat, T., Tractinsky, N.: Its a pleasure buying here: the effects of web-store design on consumers' emotions and attitudes. Hum. Comput. Interact. **27**(3), 235–276 (2012)
19. Spears, I.: Development and evaluation of an 'exergaming' intervention to target cardio-vascular and quality of life outcomes in a deprived area of the north-east. Grant Ref: EP/I001891/1. Research Councils UK Digital Economy Programme (2010)
20. Sutcliffe, A.: Designing for User Engagement: Aesthetic and Attractive User Interfaces. Morgan and Claypool, San Rafael (2009)

21. Hartmann, J., Sutcliffe, A., De Angeli, A.: Towards a theory of user judgment of aesthetics and user interface quality. ACM Trans. Comput. Hum. Interact. **15**(4), 15:1–15:30 (2008)
22. Thüring, M., Mahlke, S.: Usability, aesthetics and emotions in human-technology interaction. Int. J. Psychol. **4**(42), 253–264 (2007)
23. van Schaik, P., Ling, J.: A cognitive-experiential approach to modelling web navigation. Int. J. Hum. Comput Stud. **9**(70), 630–651 (2012)
24. Bai, Z., Blackwell, A.F.: Analytic review of usability evaluation in ismar. Interact. Comput. **24**(6), 450–460 (2012)