Kay Connelly

On Developing a Technology Acceptance Model for Pervasive Computing

Received: date / Accepted: date

Abstract Since the majority of proposed pervasive computing applications rely heavily on infrastructure that is not yet widely available, understanding long-term usage and acceptance is of utmost importance for determining if a technology/application is worth the required investment. Yet performing such an evaluation is difficult before the necessary infrastructure is available. We propose developing a mathematical model to predict user acceptance over time of pervasive computing applications based on the user's perception of usefulness, ease-of-use, social influence, trustworthiness and integration. This paper is a first step towards a predictive model of user acceptance in pervasive computing environments. We conclude the paper outlining the next steps to fully instantiate the model. Ultimately, the model can be used to direct research efforts and resources towards those applications most likely to be used by people.

Keywords ubiquitous computing, pervasive computing, formal models, evaluation, user acceptance

1 Introduction

Pervasive computing embeds computing and information technologies into our environments by integrating them seamlessly into our everyday lives [25]. For over fifteen years, there has been work on novel technologies, infrastructures and applications under the heading of pervasive computing. While design has flourished in this domain resulting in entirely new areas such as *calm technology* [24], *tangible computing* [9], and *context-aware computing* [15], evaluation of pervasive computing has struggled because of the inherent challenges posed by evaluating systems that are designed to be *woven into the fabric of our everyday lives* [25].

Traditional evaluation techniques such as laboratory studies allow researchers to study and refine specific aspects of a design (such as an interface), but are not satisfactory for evaluating a technology's actual use in real life over time. In a laboratory, it is impossible to reproduce the richness of everyday life where unexpected events occur that can affect a person's interaction with a particular system [18]. For example, when evaluating a system that automatically turns off a cell phone ringer depending on the context of the receiver [21], it is difficult to reproduce all factors that would affect a user's experience with the system, such as who is calling, why they are calling, what the receiver is doing, the other people in the vicinity, et cetera. [12].

To compensate for these problems, many researchers have turned to *in-situ* evaluation, where participants interact with the system during their normal lives over a period of time. Researchers utilize techniques such as experience sampling [4], cultural probes [8], observations, recall diaries, logs, questionnaires and interviews to obtain both qualitative and quantitative data about user experiences [17]. In-situ evaluations tend to be resource intensive and of short duration (i.e. a few days or weeks). Indeed, many in-situ studies utilize prototypes that are difficult to deploy for any length of time because portions of the system rely on non-existent infrastructure and must be simulated.

While both laboratory and in-situ studies provide valuable information during the design phase, neither

K. Connelly
150 S Woodlawn Ave.
Bloomington, IN, 47401, USA
Tel.: 812-855-0739
E-mail: connelly@indiana.edu

currently provides insight into user acceptance and usage after the initial novelty wears off. Since the majority of proposed pervasive computing applications rely heavily on infrastructure that is not yet widely available, understanding long-term usage and acceptance is of utmost importance for determining if a technology/application is worth the required investment. Yet performing such an evaluation is difficult before the necessary infrastructure is available. The problem, then, is circular, requiring an evaluation to justify the necessary infrastructure investment and requiring the infrastructure to perform such an evaluation. Thus, a technique for predicting long-term usage after minimal exposure to a prototype system is needed to help direct researchers and industry towards those technologies with the most chance of gaining user acceptance.

We propose building upon existing work in Management Information Systems (MIS) to develop a predictive model that links objective and subjective factors to user acceptance. Such a model can be used in two ways. First, it can be used after an initial prototype is developed to determine if a particular application would gain enough user acceptance over the long term to justify investing in its further development. Second, it can be used to further iterate on a design by identifying weaknesses which need to be addressed in order to increase user acceptance. This approach does not currently cover *adoption*, which includes such factors as marketing and business models, but instead focuses on issues surrounding user acceptance given that the technology is available and affordable.

In this paper, we introduce such a model. In section 2, we present related work. We then describe the existing user acceptance models for desktop computing in Section 3. We propose a hypothesis pervasive technology acceptance model (PTAM) in Section 4, discussing the unique characteristics of pervasive computing which necessitate a change to the existing models. In Section 5, we describe how we will validate this model.

2 Related Work

There have been numerous papers examining the usability or user acceptance of particular pervasive computing applications. These works, however, are limited in scope to a specific application and cannot immediately be generalized. For example, Kaasinen presents a discussion of user acceptance of mobile guides based on seven field studies [11] in which he explores factors such as usability, utility, user trust and reliability. While this paper provides an interesting set of qualitative reflections based on field observations and interviews, and is important for understanding the many design choices for mobile guides, it does not lend itself to a more formal model that can be used by others. A major advantage of a mathematical model is the ability to predict usage based on a handful of Likert scale items. The responses on the items easily translate subjective perceptions into numeric values that are then plugged into the mathematical model, thereby minimizing time and costs associated with making decision about the viability of a particular application.

There have been a number of attempts at providing design guidelines for pervasive computing applications with respect to a particular application-type or specific feature. For example, there are design guidelines for privacy in pervasive computing environments [6,13], small displays [10] and pervasive healthcare applications [3]. While these guidelines are useful for designers during the design phase, they do little to empirically predict the likelihood of long term user acceptance.

Scholtz and Consolvo introduced a framework for evaluating pervasive computing applications that defines nine evaluation areas such as attention, trust and conceptual models [20]. The purpose of the framework was to introduce a common vocabulary and set of metrics so that researchers could start presenting their findings in a commonly accepted format. Thus, it is not surprising that the framework is quite broad and it is not straight forward to operationalize. For example, one of the measures of Schlotz and Consolvo's *conceptual model* is "Awareness of Application Capabilities", defined as "Degree of match between user's model and actual functionality of the application; degree of match between user's understanding of his or her responsibilities, system responsibilities, and the actual situation; degree to which user understands the application's boundary". Eliciting a user's mental model in itself is a heavy undertaking [19]. So while the framework is a good starting point to introduce a language for pervasive computing evaluation, it does not address the need for a model that can be used by practitioners to predict user acceptance.

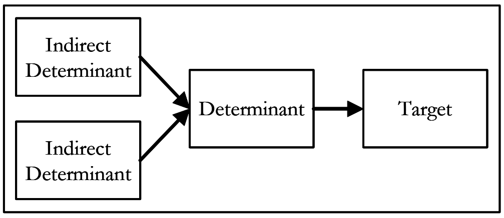

Fig. 1 A model consists of a target construct to be computed as well as direct and indirect determinants to be measured.

3 Theoretical Foundations

In this paper, a ***model*** attempts to predict a target construct (e.g. user acceptance over time) by determining the relationship between it and other measurable constructs. Fig. 1 shows a diagram of a generic model. The target construct, which the model predicts, is on the far right. A ***direct determinant*** of the target is a construct whose value at least partially determines the target. There can be multiple direct determinants in a model. An ***indirect determinant of*** the target is a construct that has an effect on a direct determinant. An indirect determinant is said to ***moderate*** the effect of a direct determinant on the target. An indirect determinant can moderate multiple direct determinants. By measuring both the indirect and direct determinants, a model can often predict more of the target behavior than by measuring the direct determinants alone. Subjective determinants are measured by a series of Likert scale items, which allows their values to be entered easily into a mathematical equation that computes the likelihood of the target behavior. A set of questions to measure a single construct is an ***instrument***.

3.1 Predictive Models of User Acceptance

In the discipline of MIS, there exist several theoretical models of how a user's perceptions of an application predict actual and perceived usage. Fred Davis introduced the most influential of these models, the technology acceptance model (TAM) shown in Fig. 2 [5]. TAM is an adaptation of the theory of reasoned action, a theory in social psychology that explains a person's behavior through their intentions, which in turn is determined by two constructs: attitudes and social norms [7]. While the theory or reasoned action explains general human behavior, TAM specifically addresses computer usage and breaks down the theory of reasoned action's attitude construct into two constructs: perceived usefulness (PU) and perceived ease-of-use (PEU). Perceived usefulness is defined as "the degree to which a person believes that using a particular system would enhance his or her job performance" and perceived ease-of-use is defined as "the degree to which a person believes that using a particular system would be free of effort". The literature reports that TAM typically accounts for around 40% of the variance in behavioral intent.

While TAM explored the attitude construct from the theory of reasoned action, it neglected the social norm construct. Accordingly, TAM was extended to TAM2 to include subjective norm as a third determinant of intent, where subjective norm is defined as "a person's perception that most people who are important to him think he should or should not perform the behavior in question" [22]. TAM2 also introduced the notion of indirect determinants, examining the role of experience, voluntariness, image, job relevance, output quality and result demonstrability in determining perceived usefulness. TAM2 has been shown to account for up to 52% of behavioral intent.

In parallel, Moore and Benbasat adapted innovation diffusion theory from sociology to MIS [14]. While some of their constructs are similar to TAM's PU and PEU, they also include social influence constructs beyond TAM2's subjective norm. By looking at image (defined as "the degree to which use of an innovation is perceived to enhance one's image or status in one's social system") and visibility (defined as "the degree to which one can see others using the system in the organization"), they were able to account for up to 68% of behavioral intent.

There are many overlapping constructs in the various models, and in 2003, Venkatesh et al. presented a unified model that included indirect and direct determinants of intent to use a system and were able to account for up to 70% of behavioral intent [23]. In this paper, we build upon these predictive models, adapting them to pervasive computing environments.

4 Proposed PTAM Model

With technologies becoming pervasive in our lives, both at work and at play, there is a need to extend technology acceptance models to account for this broader domain and user group. Pervasive computing moves away from the traditional desktop model of computing towards having technology embedded in the environment. Pervasive computing environments differ significantly from traditional workplace and academic settings in several ways:

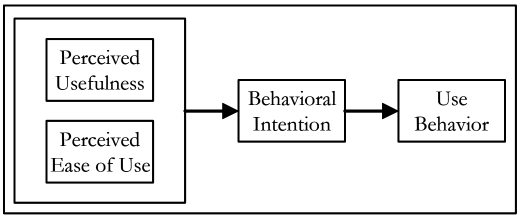

Fig. 2 In the technology acceptance model (TAM), perceived usefulness (PU) and perceived ease-of-use (PEU) are direct determinants of behavioral intent to use a system, which in turn, determines actual usage of a system.

Work Environments

All of the MIS models were developed for work environments, where it is assumed that the reason individuals use a particular technology is directly related to their job. The instruments to measure the various constructs have this assumption built in. For example, one of the items in TAM's instrument for measuring perceived usefulness is "Using X would improve my job performance.", where X is replaced by the name of the application being investigated [5], and one of the items in the instrument to measure image in innovation diffusion theory is "Because of my use of X, others in my organization see me as a more valuable employee." [14]

Pervasive computing, however, aims to embed computing devices into our everyday environment. Work applications are no longer the central focus. In this domain, researchers investigate applications to be used anytime, anywhere, including homes, public spaces (e.g. malls and theatres), parks and even automobiles. As such, one can no longer assume that an individual is using an application to improve their job performance. Applications can be used to communicate with loved ones, make life more convenient, improve one's health, or for simple entertainment. Thus, a pervasive-technology acceptance model must account for a person's *motivation* to use an application beyond job-related reasons.

Trust

Pervasive computing introduces an entirely new set of issues related to trust. First, pervasive computing environments often gather very intimate and personal data about its users. Indeed, many pervasive computing applications rely on gathering information about a user's physical and social context. Trusting the system to keep that information confidential and not to abuse it is an aspect of trust that must now come to the fore.

Second, the applications studied in the MIS domain have been relatively simple, static applications that behave according to users' expectations (once trained). Many pervasive computing applications, however, attempt to tailor their behavior based on the context of the user and physical environment, resulting in behavior that is not always predictable. An application that does not behave as a user expects causes the user to believe the application is not functioning properly. Thus, the notion of trusting an application to behave a certain way may play into user acceptance.

Integration

Pervasive technologies are no longer situated on the desk, but are embedded in the environment around us requiring interactions as we go about our daily lives. It

is essential for a model to account for how well the technology is integrated into our lives. A person may reject a technology if it unduly distracts from or interferes with their other activities.

Demographics

The demographics of participants in existing MIS studies have been somewhat homogenous because of the focus on work and academic settings. These models have yet to incorporate varied age, education and socio-economic status. Pervasive computing, by definition, will be integrated into our physical world where people of all ages, from all walks of life will interact with the technology.

Accordingly, we propose a Pervasive Technology Acceptance Model, hereafter called PTAM, which extends the TAM model in the following specific ways. First, PTAM redefines Perceived Usefulness, Perceived Ease of Use and Social Influence for pervasive computing environments. Second, it adds the *Trust* and *Integration* constructs as direct determinants of behavioral intention. Third, it adds *Usage Motivation* as a moderator of Perceived Usefulness with an instrument to measure impact on health, work, learning, entertainment and communication. Fourth, it includes *gender*, *age, experience* and *socio-economic status* as moderators.

Fig. 3 shows the diagram for PTAM. The constructs in white are part of an extended version of TAM (TAM-2). The constructs in light gray have been

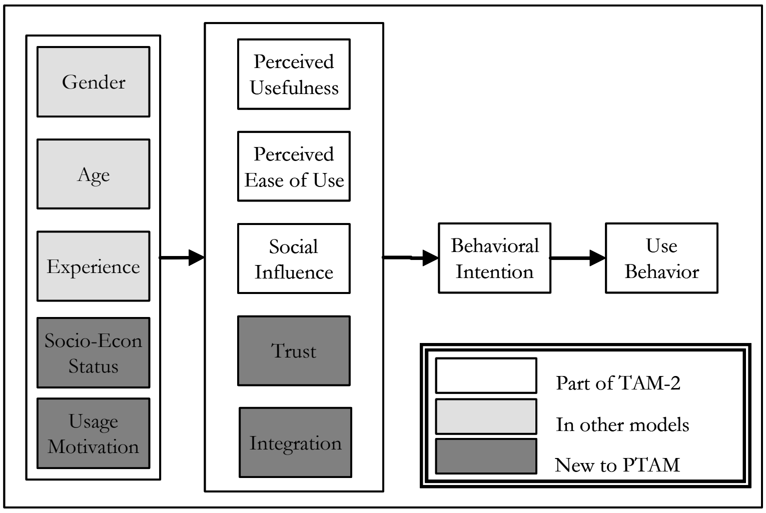

Fig. 3 In the pervasive technology acceptance model (PTAM), trust, socio-economic status and usage motivation are new constructs required by the pervasive computing domain.

studied in other user acceptance models. The constructs in dark gray have not previously been studied in a model. Table 1 provides the definitions for the direct determinants of behavioral intent in PTAM, where the wording is no longer job-specific.

5 Model Validation

There are two steps to validating the model. The first is to develop the instruments used to measure the subjective factors listed in Table 1. The second step is to use the instruments to study technology over time in order to instantiate the model, determining how much influence each factor has on long term user acceptance.

5.1 Instrument Development

We have completed the instrument development [26]. Here, we provide an overview of the basic approach we used, which is similar to that which was used to develop the original TAM instruments. The goal was to identify a minimal set of items, thereby reducing the effort required by participants.

The Spearman-Brown prophecy formula and previous work in MIS suggest that 6 items will be required for each subjective construct to obtain a reliability of at least .80. For each construct, we first proposed a set of 12-14 candidate items based on the definitions of the constructs and a review of the literature.

We then conducted a series of interviews with a small group or participants (n=15) to assess the semantic content of each item. Based on a cluster analysis of the results, we reduced and refined the items to ensure content validity and proper coverage. Subsequently, we performed a larger field study (n=150) of an existing pervasive technology (i.e. text messaging) to assess reliability of the proposed instruments. We further refined and reduced the items based on the results.

5.2 Validation

The next step is to instantiate the model by performing long-term user studies of pervasive and mobile computing technologies in order to calculate how much of the variance in usage is determined by each of the constructs in the model. This returns us to the circular question posed in the introduction: How do we perform the long-term studies required to instantiate this model?

Our approach consists of two phases. First, we must have large enough studies for statistical significance given the number of constructs we have in the model. It is not feasible to conduct such studies with prototype systems; instead, we will look at existing products, such as the Nike/iPod shoe [2] and the ambient orb [1]. These products have the flavor of pervasive computing applications (e.g., personalized information use and display), but do not require some of the more extensive infrastructure upon which the more academic-oriented projects depend. In this phase, it will be important to examine instances of technology acceptance *and* abandonment. So we must be careful to study these niche products with a wide demographic, not just early adopters; e.g., give the Nike/iPod shoe to *all* runners, from marathon runners to weekend warriors. By utilizing commercially available products, we can feasibly study a large group of users over time.

These commercial products, however, are not as visionary as the current research in the field; and thus, may not accurately represent them. Our second phase is to deploy a smaller number of research prototypes in order to validate the model derived from the commercial projects. This level of deployment is

Table 1: Definitions of direct determinants of proposed PTAM.

Determinant	Definition
Perceived Usefulness	The degree to which a person believes that using the application will enhance their life.
Perceived Ease of Use	The degree to which a person believes that using the application would be free of effort.
Social Influence	The degree to which a person believes that using the application would enhance their image or social status.
Trust	The degree to which a person believes they can trust the application.
Integration	The degree to which a person believes the application can be integrated into their normal life activities.

consistent with the more intense prototype deployments currently pursued in the field. In this way, we will instantiate PTAM so that new pervasive computing projects can be evaluated in terms of user acceptance without requiring large-scale deployments.

Acknowledgements

The author would like to thank Yvonne Rogers's for her valuable feedback during the development of this model. This work was supported in part by an NSF grant EIA-0202048 and by a grant from the Lilly Endowment.

References

1 Ambient Devices: http://www.ambientdevices.com
2 Apple: http://www.apple.com, Nike: http://www.nike.com
3 Consolvo, S., Everitt, K. M., Smith, I. and Landay J. A. "Design Requirements for Physical Activity-Enabling Technologies". In the *Proceedings of the SIGCHI conference on Human Factors in computing systems (CHI2006)*, 2006, pages 457-466.
4 Consolvo, S. and Walker, M.: Using the experience sampling method to evaluate ubicomp applications. In IEEE Pervasive Computing Mobile and Ubiquitous Systems, vol. 2(2), (2003) 24-31
5 Davis, F.D. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology". In *MIS Quarterly*, 13:3, 1989, pages 319-339.
6 Dourish, P., Grinter, R., Delgado de la Flor, J., and Joseph, M. "Security in the Wild: User Strategies for Managing Security as an Everyday, Practical Problem". In *Personal and Ubiquitous Computing*, 8:6, 2004, pages 391-401.
7 Fishbein, M. and Ajzen, I. *Belief, Attitude, Intention and Behavior: An Introduction to Theory and Research*, Addison-Wesley, Reading, MA, 1975.
8 Gaver, W., Dunne, T., and Pacenti, E. Cultural probes and the value of uncertainty. In Interactions 11(5), 2004, 53-56
9 Ishii, H., and Ulmer, B. "Tangible bits: towards seamless interfaces between people, bits and atoms". In *Proceedings of the SIGCHI conference on Human Factors in computing systems (CHI1997)*, 1997, pages 234-241.
10 Karkkainen, L. and Laarni, J. "Designing for Small Display Screens". In the *Proceedings of the second Nordic conference on Human-computer interaction*, 2002, pages 227-230.
11 Kaasinen, E. "User Acceptance of Location-Aware Mobile Guides Based on Seven Field Studies". In *Behavior and Information Technology*, 24:1, 2005, pages 37-49.
12 Khalil, A. and Connelly, K. "Context-aware Telephony: Privacy Preferences and Sharing Patterns". To appear in the *Proceedings of Computer Supported Collaborative Work (CSCW)*, November 2006.
13 Langheinrich, M. "Privacy by Design - Principles of Privacy-Aware Ubiquitous Systems". In *Proceedings of Third International Conference on Ubiquitous Computing (Ubicomp 2001),* LNCS 2201, Springer-Verlag, 2001, pages 273-291.
14 Moore, G. C., and Benbasat, I. "Development of an Instrument to Measure the Perceptions of Adopting an Information Technology Innovation". In *Information Systems Research*, 2:3, 1991, pages 192-222.
15 Moran, T. P. and Dourish, P. "Introduction to this Special Issue on Context-Aware Computing". *Human-Computer Interaction*, 16:2-4, 2001, pages 87-95.
16 Nunnaly, J. (1978). Psychometric theory. New York: McGraw-Hill.
17 Preece, J., Rogers, Y., Benyon, D., Sharp, H., Carey, T. and Holland, S.(1994) Human Computer-Interaction. Addison-Wesley, Wokingham, Berks.
18 Rogers, Y., Connelly, K., Tedesco L., Hazlewood, W., Kurtz, A., Hall, B. E., Hursey, J., and Toscos, T. "Why It's Worth the Hassle: A Case Study in Using In-Situ Studies during Design". To appear in the Proceedings of Ubicomp, 2007.
19 Sasse, M. A. "Eliciting and Describing User's Models of Computer Systems". PhD Thesis, School of Computer Science, University of Birmingham, April 1997.
20 Scholtz, J. and Consolvo, S. "Toward a Framework for Evaluating Ubiquitous Computing Applications". In *Pervasive Computing*, 3:2, 2004, pages 82-88.
21 Schmidt, A., Takaluoma,, A. and Mantyjarvi, J. "Context-Aware Telephony Over WAP". In *Personal and Ubiquitous Computing*, 4:4, 2000, pages 225-229.
22 Venkatesh, V. and Davis, F.D. "A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies". In *Management Science*, 45:2, 2000, pages 186-204.
23 Venkatesh, V., Morris, M.G., Davis, G.B., and Davis, F.D. "User Acceptnace of Information technology: Toward a Unified View". In *MIS Quarterly*, 27:3, 2003, pages 425-478.
24 Weiser, M and Brown, J. "Designing Calm Technology". In *PowerGrid Journal*, 1:1, 1996.
25 Weiser, M. "The Computer for the Twenty-First Century". In *Scientific American*, 265:3, 1991, pages 94-104.
26 Connelly, K. "Towards a Pervasive Technology Acceptance Model." Under review.