POST-ACCEPTANCE OF ELECTRONIC MEDICAL RECORDS: EVIDENCE FROM A LONGITUDINAL FIELD STUDY

Completed Research Paper

Tobias Mettler
University of St. Gallen
Müller-Friedberg-Strasse 8, 9000
St. Gallen, Switzerland
tobias.mettler@unisg.ch

Abstract

Many studies investigating post-acceptance of electronic medical records (EMR) assume that healthcare professionals exclusively base their continuance behavior on reasoned actions. While rational considerations certainly affect the intention to use an EMR, it does not fully explain the definitive user continuance behavior. Evidence exists that also subliminal effects such as habits and emotions play an important role. Consequently, we propose to investigate post-acceptance of EMR applying three different, but complementary views: (i) continuance behavior as result of reasoned actions, (ii) continuance behavior as result of emotional responses, and (iii) continuance behavior as result of habitual responses. The results from a longitudinal field study showed that automatic behavior, enabled by sufficient facilitating conditions and a good task-technology-fit, as well as positive emotions considerably affected healthcare professionals EMR continuance behavior. It also showed that a user's computer literacy level didn't play a significant role regarding the post-acceptance behavior.

Keywords: Electronic medical records, health informatics/health information systems/medical IS, adoption, IS continuance, longitudinal research

Introduction

In many countries the healthcare sector is facing considerable challenges as related to costs, efficiency, safety, and patient-centricity. The adoption of information technology (IT) and domain-specific information systems (IS) is, amongst other things, seen as potential leverage in responding to problems concerning the availability and quality of medical information, simplification and security of medical routines, or overcoming distance and budget restrictions (World Health Organization 2005).

In parallel to the diffusion of new technological advancements, an increasing body of research on healthcare-focused IS/IT adoption and use has been conducted in the recent years (Spil et al. 2011). Special attention has been given to studies that examine the cognitive beliefs and affects that motivate healthcare professionals (especially physicians) to accept a newly implemented IS, such as electronic medical records (EMR) or electronic health records (EHR) (e.g. Ash and Bates 2005; Hennington and Janz 2007; Morton and Wiedenbeck 2009; Sherer 2010).

However, evidence exists that despite strong encouragement and interest from governmental authorities and firms, many hospitals and physicians are lagging behind in the adoption of electronic documentation (Jha et al. 2009; Venkatesh et al. 2011). Reasons for that are not yet well understood (Goh et al. 2011). Up to now, great part of the research literature is focusing on measuring and predicting "acceptance" or "first-time use" of EMR (e.g. Handy et al. 2001; Kazley and Ozcan 2007; Schectman et al. 2005). While these articles provide a foundation for better understanding "IS success" in healthcare (i.e. according to DeLone and McLean (1992) an organizational impact induced by individual systems use and user satisfaction), they do not shed much light with respect to long-term viability and continued usage (Bhattacherjee 2001).

In this paper, we therefore aim at investigating EMR "post-acceptance" or "continued use" effects. A core challenge in accomplishing this is the fact that in healthcare different educational backgrounds (medical vs. non-medical) and conflicting missions (cure vs. care) always had a strong impact on how processes and systems were incorporated into the day-to-day work environment (Ramanujam and Rousseau 2006). Continued use of EMR might therefore be considerably influenced by the characteristics of extant or habitual work patterns (Goh et al. 2011), social norms and imposed "world views" (Glouberman and Mintzberg 2001) as well as emotional affects towards IS/IT in general (Shaw and Manwani 2011).

Drawing on an extensive review of the relevant literature, we thus define the following overarching research questions: (i) *what are the key factors influencing post-acceptance of EMR*, and (ii) h*ow do unconscious or habitual responses affect the users' continuance behavior?* In order to answer these questions, we conducted a longitudinal field study of an EMR implementation in a large hospital, including both, a quantitative survey as well as further in-depth qualitative interviews for clarifying outliners in measured user behavior. Based on our findings, we propose an adaptation to the post-acceptance model of IS continuance (Bhattacherjee 2001) by also including emotional and habitual affects that help to better explicate healthcare-specific differences in the adoption behavior of IS/IT users.

Theoretical Background

Expectation confirmation theory (ECT), also referred to as expectation disconfirmation theory (EDT), has been adopted in many different fields for studying cognitive beliefs and affects influencing the continuance intention, for instance with respect to repurchasing (Atchariyachanvanich et al. 2006) or usage (Limayem and Cheung 2008) of a particular product or service. Having its roots in consumer behavior research (Cronin and Taylor 1994; Oliver 1980), satisfaction is a key determinant of continuance and can be described as function of prior expectations and post adoption performance perception and confirmation/disconfirmation (Susarla et al. 2003).

While disconfirmation arises from a negative disparity between expectations formed during the pre-consumption phase and post-consumption performance experiences, confirmation is the result of a considerable "overfulfillment" of these initial expectations (Kopalle and Lehmann 2001). In this sense, lower expectation and/or higher perceived performance may lead to a greater confirmation. It assumed that high rates of confirmation positively affects satisfaction, which in turn influences the intention to continue using and/or purchasing a particular product or service (Hayashi et al. 2004). Because expectation provides the baseline or reference level with which customers evaluate products and services, also a direct link between expectation and satisfaction is postulated (cf. left side of Figure 1).

One of the first studies adopting ECT to the field of Information Systems was conducted by Bhattacherjee (2001). Main reasons for conceptualizing a new model for studying IS adoption was seen in the deficiency of existing research models – such as the Technology Acceptance Model (TAM) by Davis (1989) – to measure long-term IS use or "routinization" (Cooper and Zmud 1990). As opposed to measuring first-time use, where typically users accept or reject a system (Shaw and Manwani 2011), the proposed "post-acceptance model of IS continuance" stipulates the fact that users who are negatively disconfirmed and dissatisfied with prior IS/IT usage may still continue using the system if they consider it to be useful in their work (Bhattacherjee et al. 2008). The mentioned research model has several variations as to the original ECT model (cf. right side of Figure 1): First, instead of measuring perceived performance, the IS-related model assesses perceived usefulness since evidence exists that performance is only one of several factors for specifying the value of IS/IT (Mirani and Lederer 1998). Second, because the model focuses on post-acceptance, expectation is rather understood as being an inherent part of perceived usefulness and is therefore not operationalized by a separate construct. Third, perceived usefulness is seen has having a direct influence on satisfaction and IS continuance intention (Bhattacherjee 2001). In order to better measure temporal patterns or cognition changes in IS/IT usage, (2004) extended the initial post-acceptance model of IS continuance to a two-stage model by linking perceived usefulness and initial attitude towards using IS/IT in the *pre-usage* stage and presupposing satisfaction and disconfirmation as emergent constructs influencing *post-usage* usefulness and modified attitude.

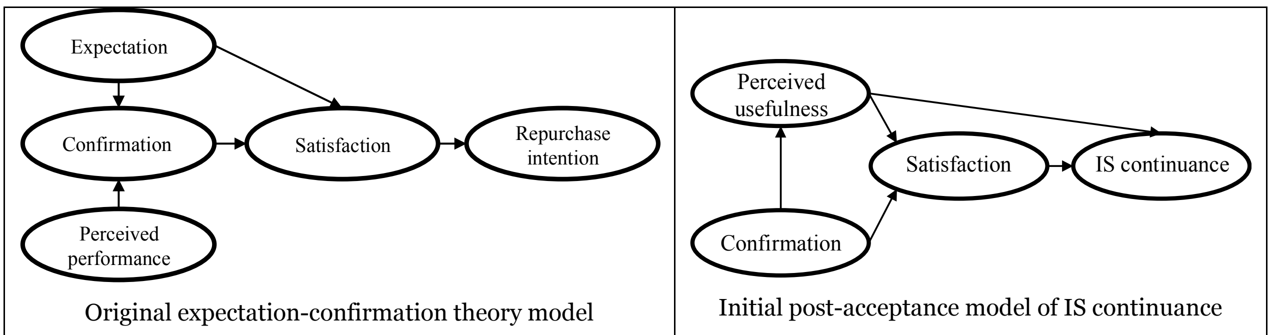

Figure 1. Research models on post-acceptance

Different Perspectives on Continuance Behavior

The initial post-acceptance model of IS continuance has been argued by several authors of not being able to fully explain routinization of IS/IT (e.g. Liao et al. 2006; Limayem and Cheung 2008; Lin et al. 2005). A major criticism was expressed by Ortiz de Guinea and Markus (2009) who found a major limitation in its underlying premise of exclusively viewing continuance behavior as intentional or reasoned, thus ignoring habitual or emotional responses. In light of this critique, we propose to investigate the continued use/post-acceptance of EMR applying three different, but complementary views: (i) continuance behavior as result of reasoned actions, (ii) continuance behavior as result of emotional responses, and (iii) continuance behavior as result of habitual responses.

Continuance behavior as result of reasoned actions

Building upon theories from social psychology, such as the theory of reasoned action (TRA) or the theory of planned behavior (TPB), a great part of post-acceptance studies assume that users behave rationally and are conscious of all their actions. A key assumption is that continuance intention is the result from a reasoned appraisal of the differences in the pre-adoption beliefs regarding the *expected benefits* and the effective post-adoption experiences (cf. previous section; also see Figure 2).

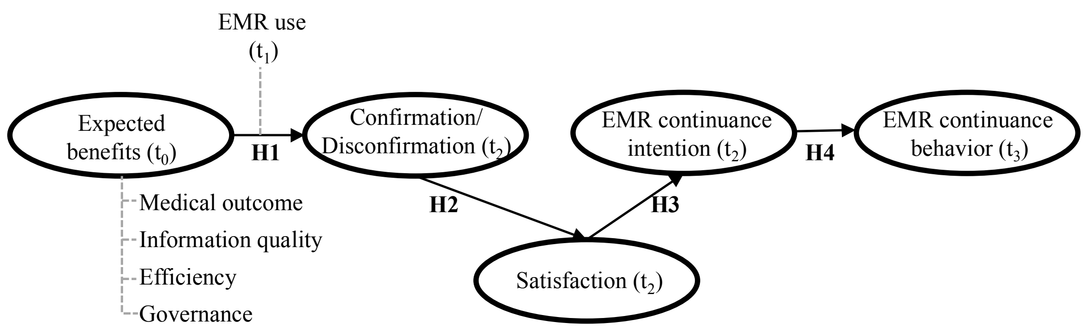

Figure 2. Continuance behavior as result of reasoned actions

According to Mirani and Lederer (1998), benefits can be strategic (e.g. quicker response to change), informational (e.g. more concise information), or transactional (e.g. reduced communication costs). Following Fitterer et al. (2011), archetypal "performance expectation" categories for health information systems are, amongst others, medical outcome (e.g. patient safety, adequacy of treatment), information quality (e.g. consistency, completeness), efficiency (e.g. personal productivity), and governance (e.g. privacy, security, conformity).

Before adopting the EMR (t_0) these expectations tend to be vague, because they generally are based on second-hand information (e.g. vendor claims or word-of-mouth reports). After adopting the EMR and extensively using it for a while (t_1), the pre-adoption expectations are superseded by persistent hands-on experiences. In a reasoned process the users weigh the fulfillment of their expectations (t_2). Lower expectations and/or higher benefits lead to greater confirmation (H1). The greater the confirmation, the more satisfied users are (H2). Since users supposed to be rational, a satisfied EMR user might intend to continue its usage (H3). It also assumed that positive behavioral intentions ultimately lead to a higher continuance behavior (H4). Note that we do not suppose a direct relationship between expectations and satisfaction, since we believe that satisfaction is constantly mediated and determined by the confirmation/disconfirmation construct. Thus, we hypothesize as follows.

Hypothesis 1 (H1): *Pre-usage expectations will positively influence confirmation; respectively negatively influence disconfirmation.*

Hypothesis 2 (H2): *Post-usage confirmation will positively influence satisfaction; respectively post-usage disconfirmation will negatively influence satisfaction.*

Hypothesis 3 (H3): *Post-usage satisfaction will positively influence EMR continuance intention.*

Hypothesis 4 (H4)*: EMR continuance intention will positively influence EMR continuance behavior.*

In this sense, we strongly relate to the original ECT model for conceptualizing EMR continuance behavior as result of reasoned actions (cf. Figure 2). Major differences to Bhattarjee's post-acceptance model of IS continuance (2001) is that we do not assume expectations to be inherent parts of perceived usefulness. Rather we presume that expected benefits are major drivers for a medical professional to be satisfied or dissatisfied after using the EMR. In addition, we also believe that it is important to explain routinization of IS/IT only based on intentions, but also on the actual continuance behavior.

Continuance behavior as result of emotional responses

Unlike the "traditional" notion, which presumes that individual behavior builds on reasoned actions resulting from conscious intentions regarding that behavior, evidence exists that continuance behavior is also affected by a user's *emotional* responses (cf. Figure 3). According to Ortiz de Guinea and Markus (2009) "emotions may drive continuing IT use directly, rather than through behavioral intentions" (p. 438). In contrary to the reasoned rationale, however, a user is not necessarily conscious about its emotions and effects on the continuance behavior.

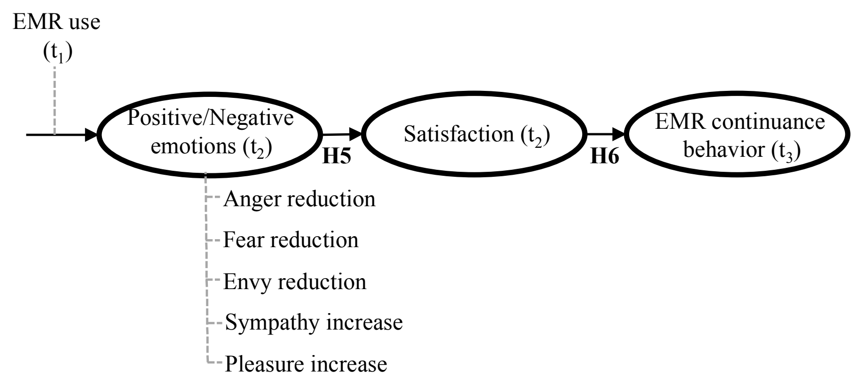

Figure 3. Continuance behavior as result of emotional responses

Following Astleitner and Leutner (2000) five distinct emotional responses to IT use can be distinguished: anger (e.g. a negative feeling from being hindered to reach a desired goal), fear (e.g. a negative feeling arising from judging a situation as threatening), envy (e.g. a negative feeling resulting from the desire to get something that is possessed by others), sympathy (e.g. a positive feeling referring to an experience of feelings and orientations of other people who are in the need of help), and pleasure (e.g. a positive feeling based on mastering a situation). Recent empirical research showed that sentiments, such as fun (Lin et al. 2005) or joy (Van der Heijden 2004), considerably influenced the satisfaction of users (t_2). It thus can be expected that an increase of positive and a decrease of negative feelings will lead to a higher level of satisfaction (H5). More recently, Bhattacherjee and Barfarm (2011) also found indications for a direct relation between satisfaction and continuance behavior. Building on this, in the long run (t_3) it is assumed that a constant high satisfaction level will positively affect EMR continuance behavior (H6). Accordingly, we hypothesize as follows.

Hypothesis 5 (H5): *Positive post-usage emotions will positively influence satisfaction; respectively negative post-usage emotions will negatively influence satisfaction.*

Hypothesis 6 (H6): *Post-usage satisfaction will positively influence continuance behavior.*

Continuance behavior as result of habitual responses

Some evidence exists that continuance behavior is also triggered automatically (cf. Figure 4), without preceding a conscious perceptual or judgmental process (Limayem and Cheung 2008). This *automatic behavior*, also referred to as habit, typically is developed by "learned sequences of acts that have become automatic responses to specific cues, and are functional on obtaining certain goals or end-states" (Verplanken and Aarts 1999, p. 104). However, Ortiz de Guinea and Markus (2009) criticized that in the current post-acceptance literature surprisingly little attention is given to what these specific cues might be. Since IT use is mostly instrumental, they argue that the task a user intends to perform might be one important environmental cue. Another trigger for automatic behavior is, according to them, IS/IT itself. Besides these environmental cues, computer literacy of users tend to be another eminent trigger for behavior, since a user's understanding of the properties and functionality of a EMR strongly influences its use (Shaw and Manwani 2011).

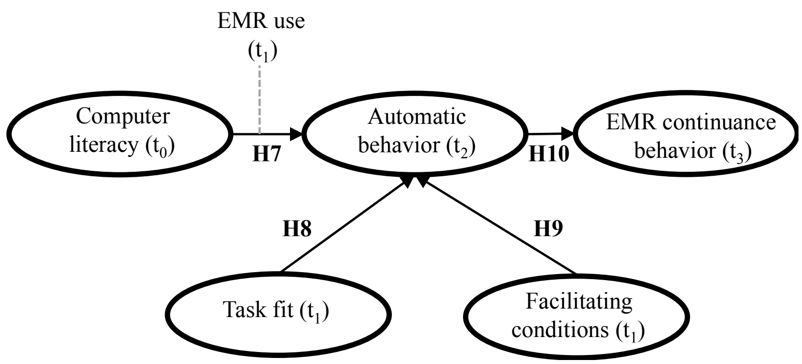

Figure 4. Continuance behavior as result of habitual responses

Prior research on the adoption of IS/IT in healthcare has shown that medical professionals generally have a strong resistance to new systems. Especially since medical routines can be composed of many interlocking individual habits, often a major source of inertia is introduced (Polites and Karahanna 2012). Especially through the repeated use of the previous system, often "cognitive switching costs" are developed that "lock-in" individuals to preferring the actual system over alternatives in the future (Murray and Häubl 2007). Accordingly, having a given set of personal skills for and attitude towards interacting with a new EMR (t_0), it is assumed that users with low levels of computer literacy are more likely to invest cognitive resources toward performing a task. In other words, low computer literacy on the side of the EMR user will lead to more automatic behavior (H7). Contrariwise, medical professionals with high levels of computer literacy with the previous system, thus experiencing a "lock-in" effect, will more likely to slower generate automatic behavior with the new system.

Another influencing factor on the development of automatic behavior is the accuracy of the EMR to support the achievement of a desired outcome. It is assumed that the higher the task fit is, the more likely it is that EMR users do not need to rethink their actions ("it worked 100 times, why shouldn't it work the next time") and thus may develop a habitual response (H8). We think that this assumption holds true for all kinds of systems. However, with the implementation of new IS/IT in healthcare typically also work routines are changed. Since a lower task fit causes medical professionals to constantly rethink their actions, and time in this context is of utmost importance, we believe that this might be another major source for resistance; regardless of the previous matter of "cognitive switching costs".

Considering these narrow time constraints in a medical professional's daily work, we think that facilitating conditions (e.g. hardware, IT-support) also exert an influence whether habits are developed or not. Although it is often related directly to usage behavior (Venkatesh et al. 2003), we think that there is also a direct relation between facilitating conditions and automatic behavior (H9). For instance, when the hardware is poor, certain EMR users might not fully explore all the features of the new system because of long loading times or the fear of a complete system freeze. Hence, it expected that superior facilitating conditions would more likely yield to automatic behavior. Finally, in line with Limayem and Cheung (2008) and Ortiz de Guinea and Markus (2009), there are indications for a direct significant relation between automatic behavior and continuance behavior. Accordingly, it is assumed that when it's easy for the EMR user to develop many habitual responses, it is more likely that a positive continuance behavior is produced (H10). We hypothesize as follows.

Hypothesis 7 (H7): *Pre-usage computer literacy will negatively influence the development of automatic behavior.*

Hypothesis 8 (H8): *Task-fit while using the EMR will positively influence the development of automatic behavior.*

Hypothesis 9 (H9): *Facilitating conditions while using the EMR will positively influence the development of automatic behavior.*

Hypothesis 10 (H10): *Automatic behavior will positively influence EMR continuance behavior.*

The overall proposed three-stage research model is illustrated in Figure 5.

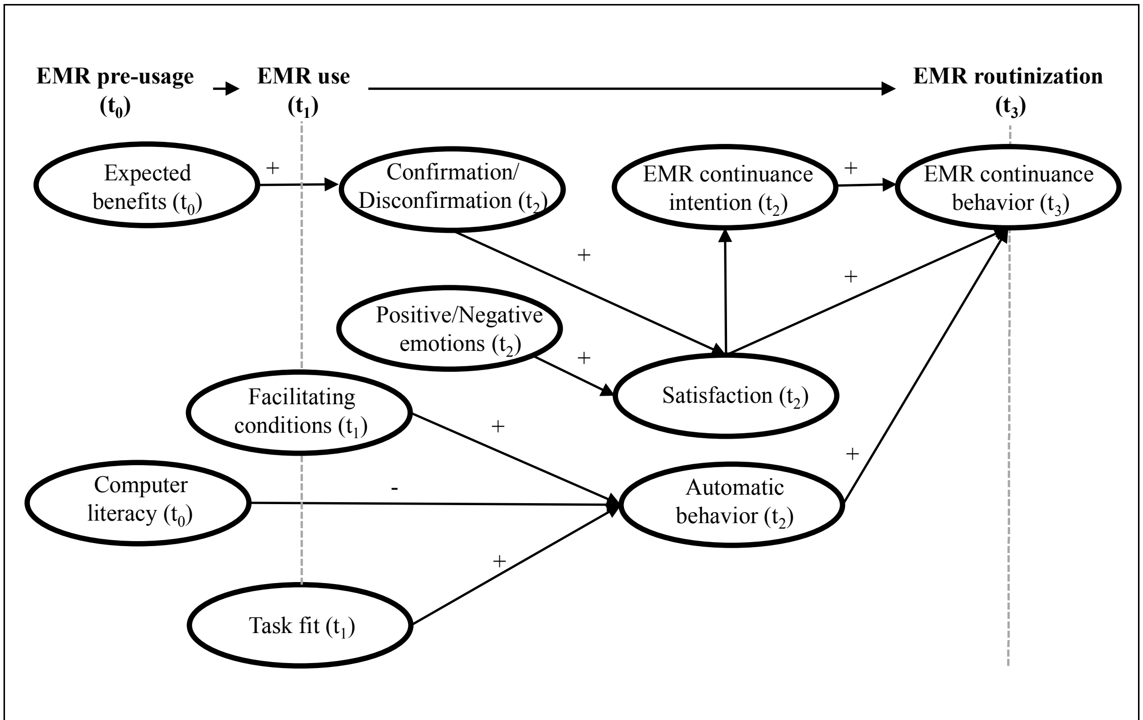

Figure 5. Overall proposed research model

Study Context

The market for EMR is large, consisting of a variety of solutions differing in functionality, connectivity, security, and ease of use (EHR Scope 2012; Health Technology Review 2012). While in the past larger hospitals tended to develop their own EMR, nowadays cost-cutting measures and continuously increasing complexity urge many of these hospitals to implement standardized software, since the IT-department is no longer able or capable to further develop the initial solution. This was also the case in the hospital we analyzed for testing the previously defined hypotheses.

Located in a major metropolitan area and consisting of more than 5,500 internal staff (mostly employees working in nursing and administration) and 1,400 external specialized physicians, the hospital responds to more 73,000 medical treatments a year. Great part of the information exchange between internal staff and the external physicians was accomplished via paper shuffling prior to the implementation of the new EMR. Given that the hospital only has a minimal on-site crew of medical specialists, the clinical documentation process has always played a pivotal role; yet was also the major pain point: An EMR existed that contained some “bits and pieces” of a clinical documentation, but no real summary of a patient’s history. The information quality was low, as non-qualified employees often were in charge of feeding the systems. Clinical and non-clinical information (e.g. customer address, bills etc.) was hosted on different systems and thus somehow “disconnected” from each other.

With the new EMR, six new modules including an electronic patient history (e.g. patient demographics, allergies), clinical documentation (e.g. flow sheets, clinical notes), coding and billing information, diagnostic results from laboratory, radiology or pharmacy, a description of the measures taken (e.g. activity recording, schedule), and a computerized physician order entry (CPOE) were delivered by the IT-department.

The implementation of the EMR resulted in several radical changes in the work routines and responsibilities of physicians and nurses: First, all information (clinical and non-clinical) has to be documented at the "point of action"; for instance, nurses are now requested to document her/his actions directly at the patient's bed instead of posteriorly at the ward's office. Second, all information has to be documented by the person who is in charge of the specific action; for example, the prescription of a drug has to be documented by the treating doctor, not by her/his medical assistant or secretary. Third, *all* information has to be documented; there are no more privileges for certain specialists or occupation groups. This obviously provoked a dislocation of previously "established" usage behavior, but also helped to emerge new work routines and collaboration patterns. Since the use of the EMR is compulsory, a classical acceptance study (e.g. non-electronic vs. electronic) would not have provided much new insights. Instead, we concluded that the study context offered a unique opportunity to better understand routinization of technology (i.e. the long-term effects of confirmation/disconfirmation with a system).

Method

There has been severe criticism that the great part of IS continuance studies applied cross-sectional designs out of convenience, instead of using more complicated and arduous longitudinal designs for truly exploring deviations in the continuance behavior (Bhattacherjee and Barfarm 2011). In order to obtain a better understanding of and insight into the phenomenon of interest, as well as to be able to really detect or explain behavioral deviations, a longitudinal design for the study was chosen. In the following sub-sections, the data collection strategy, sample characteristics, and analysis approach is described in more detail.

Data Collection and Analysis

Our data collection strategy involved a quantitative survey 6 months before and after the implementation of the new EMR, as well as parallel semi-structured interviews (cf. Figure 6). The time interval of 6 months was chosen to provide the hospital's IT-department with enough time for implementing the new system as well as for communicating the potential changes and related vision. In the post-adoption stage, the 6 months period allowed the medical professionals to thoroughly become acquainted with the new EMR. Finally, there was also the request of the hospital management to obtain first results on the EMR continuance behavior no longer than 9 month after implementation.

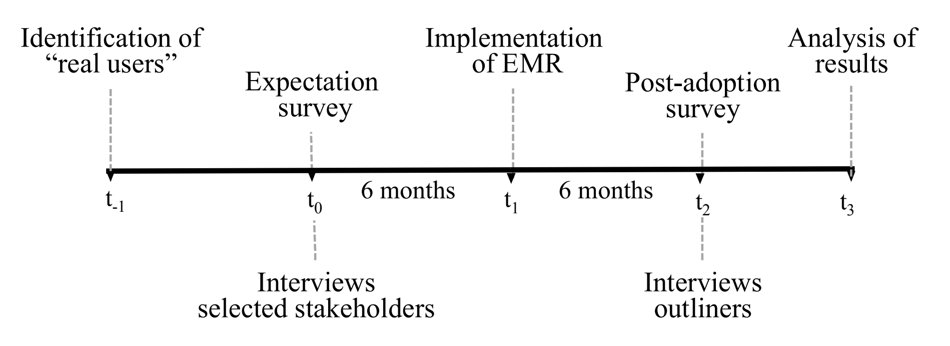

Figure 6. Data collection strategy and timeline

The first survey (t_0), conducted in June 2010, was used to inquire the expectations that healthcare professionals have with regard to the adoption of the new EMR. In order to minimize the bias stated by McLeod and Guynes Clark (2009) that occurs because of asking wrong "users" (i.e. healthcare professionals that actually do not interact with the system or dispose someone else to do so), we first analyzed the user base with the help of the hospital's IT-department and consequently only included individuals in the study sample who had real experiences with the prior system and who attended the introductory course to the new EMR (t_{-1}). An email invitation was sent to this selected group of hospital internal and external staff, asking for the completion of an online questionnaire consisting of eight blocks of questions, including questions related to their expected benefits of the new EMR, computer literacy, task-technology-fit, habits, satisfaction level, emotional affects, as well as EMR usage intention and behavior (cf. Appendix). The participation in this study was voluntary, however, anonymous questionnaires were not allowed. To operationalize the constructs of our research model we used measurement items which either had been applied and validated in prior research (e.g. Bhattacherjee 2001; Bhattacherjee et al. 2008; Fitterer et al. 2011; Gans et al. 2005) or which wording was modified in order to fit the context of this study (e.g. Dishaw and Strong 1999; Goodhue and Thompson 1995; Shaw and Manwani 2011). A 5-point Likert scale anchored with 1= Strongly Agree and 5 = Strongly Disagree was used for ordinal items. The draft version of the questionnaire was checked beforehand by leading nursing and medical staff, with a view to removing any inconsistencies and generally improving the structure. Since evidence exists, that social norms have a strong impact on health workers (Walston and Chadwick 2003), we additionally conducted parallel interviews with "opinion leaders" in order to detect distortions like group behavior or discipline related attitudes and perceptions.

In May 2011 a second survey (t_2) was conducted, questioning the participants of the first survey about their post-adoption cognitive beliefs and affects. For this, a slightly adapted version of the initial questionnaire was designed and likewise given restricted online access to it. After a quick analysis of the received data, additional interviews with participants were conducted who reported considerable differences between the expected and the actual continuance behavior (outliners). In doing so, more detailed data was obtained that helped to get "an insider-view" on the motivations behind the drastic changes in the continuance behavior.

To analyze the quantitative data (t_3) we used partial least squares (PLS), which is a multivariate technique that facilitates testing of psychometric properties of the scales used to measuring a variable as well as estimating the parameters of a structural model (Esposito Vinzi et al. 2010; Wold 1982). PLS is particularly applicable in research fields where theory is not well developed. A major advantage of using PLS as compared to other statistical techniques is the fact that it does not depend on having multivariate normally distributed data and can be used with relatively small sample size (Ringle et al. 2012). Another reason for choosing PLS is the possibility for specifying formative constructs (Petter et al. 2007), although this was not applied in this study. The software package SmartPLS 2.0 was applied for modeling construct dependencies and estimating quality criteria and effect sizes. The supplemental qualitative data from the interviews was coded and analyzed for frequent emerging themes and analyzed for common situated social and distributive factors.

Sample

In order to determine the basic population of this survey we inspected the old EMR system's log files. This resulted in a list of a total of 746 registered users, respectively potential respondents. However, only 200 on this list complied with the requirement to previously having attended the introductory course of the new EMR. From the 200 individuals invited to participate in the initial expectation survey, we received 108 valid and usable responses, yielding a primary response rate of 54%. Respondents of valid questionnaires were asked again to participate in the post-adoption survey. We obtained another 66 valid responses from this last survey, yielding a secondary response rate of 61.1% or a total response rate of 33%. Out of the total sample 43.9% declared themselves as clinicians (i.e. medical specialists at the hospital), 37.9% as nurses, and 18.2% as physicians (i.e. medical specialists with private practice). 57.6% were male. The age of the respondents ranged from 18 to 65 and thus represented the full range of career levels (from beginners to very experienced professionals). At the time of the survey, 23.1% were between 18 and 29 (Generation Y), 20% between 30 and 44 (Generation X), 33.8% between 45 and 54 (late Baby Boomers), and 13.1% between 55 and 65 (early Baby Boomers). Less than 5% of the received questionnaires were outliners. As illustrated in Figure 7, the sample also reproduces the views of a wide range of different medical disciplines. All of the respondents had at least a degree of proficiency and experience in one of the stated medical disciplines.

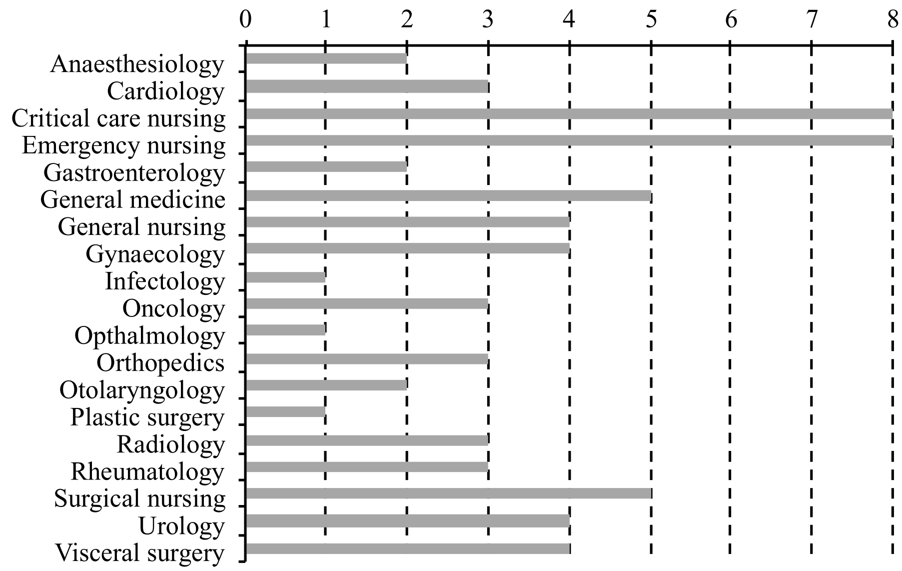

Figure 7. Respondents per discipline (N=66)

Results

Applying PLS means to specify two distinct models, a structural model describing the relationships or paths among structural dimensions, and a measurement model which links the constructs with a set of operational measures. Following this two-step analytical procedure, the measurement model was first examined and then the structural model was tested.

The Measurement Model

To test reliability and validity of the operationalized model, several criteria were used (cf. Table 1). The coefficient Cronbach's Alpha (α) was applied to determine the reliability of the operationalized constructs. Following Cortina (1993) the values for α should be greater or equal to 0.8 for a good scale, 0.7 for an acceptable scale, and 0.6 for a scale which is used for exploratory purposes. All constructs complied with this quality measure. It is interesting to note that the constructs related to habitual and emotional responses, such as automatic behavior (AB), computer literacy (CL), and emotions (EM), had a slightly superior reliability as the rest of the constructs. Only facilitating conditions (FC) with a value of 0.56 did not prove to be reliable and therefore has to be considered with cautious. As α is biased against short scales of two or three items, which typically leads to an underestimation of reliability, composite reliability was used as additional quality criterion. According to Chin (1998), values should be greater than 0.6 in case of exploratory purposes and greater than 0.7 for an adequate confirmatory model. All the measured constructs did comply with this criterion though.

To determine the convergent validity of the operationalized model, a further estimation of the average variance extracted (AVE) was performed. AVE captures the amount of explained variance relative to the total amount of variance and is considered sufficient if it has a value equal to 0.5 or more (Fornell and Larcker 1981). At the lower end of acceptable limits, AVE values of 0.52 for continuance intention (CI), 0.57 for task fit (TF), and 0.58 for satisfaction (ST) were measured. Highest convergent validity was measured for the construct automatic behavior (AB) with a value of 0.90 and computer literacy (CL) with a value of 0.85.

Table 1. Reliability and validity

Constructs	Mean	SD	α	Composite reliability	AVE
AB	2.32	1.18	0.89	0.95	0.90
CB	2.01	1.54	0.63	0.84	0.73
CD	2.43	0.92	0.69	0.86	0.76
CI	2.53	1.23	0.69	0.72	0.52
CL	2.53	1.51	0.82	0.92	0.85
EM	2.01	1.01	0.82	0.87	0.64
EB	2.95	1.20	0.70	0.84	0.65
FC	2.43	1.01	0.56	0.73	0.60
ST	2.34	1.33	0.64	0.73	0.58
TF	2.54	1.23	0.74	0.84	0.57

The correlations between the latent variables are illustrated below in Table 2.

Table 2. Inter-construct correlations

	AB	CB	CD	CI	CL	EM	EB	FC	ST	TF
AB	1.00									
CB	0.46	1.00								
CD	0.32	0.40	1.00							
CI	0.30	0.44	0.34	1.00						
CL	0.29	0.31	0.31	0.51	1.00					
EM	0.19	0.22	0.31	0.15	0.34	1.00				
EB	0.32	0.35	0.36	0.25	0.31	0.24	1.00			
FC	0.36	0.34	0.52	0.29	0.28	0.32	0.51	1.00		
ST	0.39	0.43	0.35	0.38	0.29	0.25	0.38	0.39	1.00	
TF	0.31	0.22	0.46	0.47	0.23	0.17	0.21	0.19	0.33	1.00

Individual item reliability was assessed by examining the loadings of each item on its construct. Following Hulland (1999), high loadings imply that there is more shared variance between the construct and its measures than error variance. Contrary, low loadings mean that the item only provides little additional value to the explanatory power of the measurement model. According to Hulland (1999), loadings greater than 0.7 are seen as acceptable. However, items with loading values greater than 0.5 may also be valid in case the item makes a considerable contribution to better reflect the construct. In this sense, all items are acceptable and are given full consideration (bold values in Table 3). However, some items were found, which loaded higher to another latent construct, such as EB_1 and EB_4 which loaded higher to EM instead of EB. According to Geffen and Straub (2005) this is problematic, since the correlation of the latent variable scores with the measurement items needs to show an appropriate pattern of loadings; as a rule of thumb they propose that measurement item loading on their assigned latent construct should be 0.10 higher than the loadings on any other latent construct. Still we decided not to delete these items since we believe they provide additional value for theory development.

Table 3. Loading and cross-loading of measures

	AB	CB	CD	CI	EB	EM	FC	CL	ST	TF
AB1	**0.95**	0.78	0.54	0.40	0.32	0.31	0.39	0.33	0.64	0.42
AB2	**0.94**	0.64	0.43	0.28	0.32	0.28	0.45	0.26	0.62	0.42
CB1	0.47	**0.80**	0.42	0.40	0.22	0.16	0.27	0.26	0.56	0.22
CB2	0.78	**0.90**	0.53	0.52	0.48	0.34	0.37	0.31	0.61	0.38
CD1	0.37	0.44	**0.67**	0.52	0.33	0.15	0.50	0.47	0.27	0.30
CD2	0.35	0.35	**0.68**	0.21	0.35	0.08	0.12	0.38	0.18	0.16
CD3	-0.02	0.06	**0.65**	0.26	0.06	-0.01	0.25	0.13	0.02	0.03
CD4	0.44	0.46	**0.85**	0.15	0.47	0.42	0.65	0.39	0.57	0.26
CI1	0.33	0.43	0.31	**0.85**	0.19	0.08	0.25	0.26	0.24	0.55
CI2	0.31	0.52	0.32	**0.89**	0.38	0.12	0.30	0.32	0.22	0.69
EB1	0.26	0.38	0.54	0.38	**0.64**	0.20	0.44	0.76	0.08	0.14
EB2	0.19	0.28	0.30	0.20	**0.87**	0.78	0.47	0.28	0.57	0.19
EB3	0.35	0.40	0.39	0.25	**0.88**	0.84	0.61	0.38	0.68	0.26
EB4	0.21	0.23	0.30	0.10	**0.78**	0.84	0.50	0.32	0.63	0.19
EM1	0.41	0.17	0.11	0.04	0.37	**0.59**	0.21	0.14	0.36	0.30
EM2	0.18	0.25	0.27	0.04	0.70	**0.93**	0.48	0.27	0.60	0.06
EM3	0.25	0.32	0.40	0.19	0.75	**0.92**	0.52	0.40	0.57	0.19
EM4	0.04	0.14	0.30	0.25	0.31	**0.75**	0.46	0.53	0.10	0.00
FC1	0.45	0.38	0.64	0.30	0.65	0.53	**0.98**	0.60	0.57	0.35
FC2	0.30	0.31	0.54	0.28	0.58	0.28	**0.87**	0.42	0.13	0.16
CL1	0.29	0.32	0.46	0.34	0.56	0.36	0.68	**0.92**	0.27	0.24
CL2	0.21	0.19	0.27	0.13	0.56	0.55	0.39	**0.77**	0.62	0.23
ST1	0.74	0.66	0.54	0.30	0.41	0.45	0.54	0.15	**0.89**	0.46
ST2	0.20	0.30	0.37	0.53	0.36	0.24	0.39	0.12	**0.76**	0.61
TF1	0.41	0.40	0.34	0.68	0.31	0.13	0.30	0.29	0.27	**0.83**
TF2	0.35	0.34	0.24	0.64	0.21	0.18	0.16	0.23	0.27	**0.88**
TF3	0.33	0.04	0.06	0.31	-0.09	0.09	0.23	-0.02	0.20	**0.66**
TF4	0.25	0.18	0.54	0.40	0.32	0.31	0.39	0.33	0.64	**0.95**

The Structural Model

The results of estimating the structural model using SmartPLS path weighting scheme is illustrated in Figure 8, where * and ** indicate significance at 0.05 and 0.01 levels, respectively. As suggested by Bollen and Stine (1992), we tested the significance of the interrelations between the manifest and latent variables applying the bootstrap procedure with 500 resamples. The t-scores obtained for the indicators ranged from 0.44 to 4.84, indicating that not all paths were significant (also see Table 4).

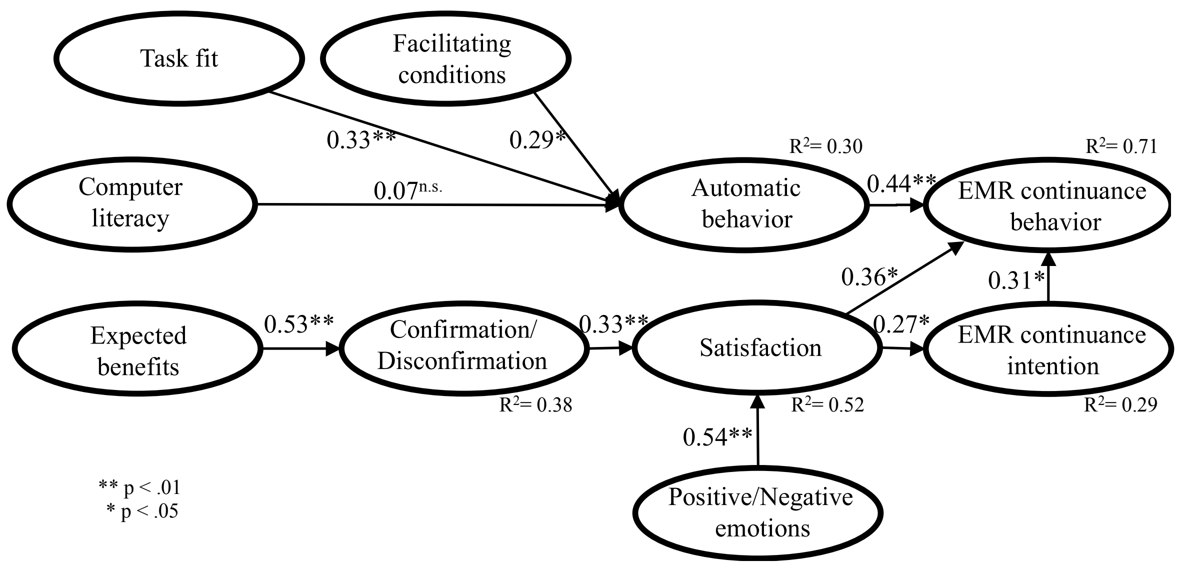

Figure 8. Results of structural model estimation (one-tailed test)

The analysis showed that automatic behavior had a considerable and highly significant effect on the EMR continuance behavior (path-coefficient=0.44 and t-score=4.27). A total of 30 percent of the variance of this construct was explained by the used measures (R^2=0.30). Different results were found for the antecedents of automatic behavior. Whereas task fit (path-coefficient=0.33 and t-score=3.58) and facilitating conditions (path-coefficient=0.29 and t-score=2.32) seem to be meaningful pre-conditions for developing habitual responses, no significant effect was measured for computer literacy (path-coefficient=0.07 and t-score=0.44).

A strong and highly significant effect was found between expected benefits and confirmation/disconfirmation (path-coefficient=0.53 and t-score=4.04). The used measures explained 38 percent of the variance of the construct (R^2=0.38). A meaningful significant effect was also found between confirmation/disconfirmation and satisfaction (path-coefficient=0.33 and t-score=4.19) and between satisfaction and EMR continuance intention (path-coefficient=0.27 and t-score=2.69). The antecedents accounted for 29 percent of the variance (R^2=0.29). The obtained results are therefore in line with "traditional" post-acceptance studies.

The effects of positive/negative emotions also proved to have a strong and highly significant effect on a EMR user's level of satisfaction (path-coefficient=0.54 and t-score=4.84). Together with confirmation/disconfirmation, emotional affects could explain 52 percent of the variance of satisfaction (R^2=0.52).

A significant direct effect between satisfaction and EMR continuance behavior could also be demonstrated (path-coefficient=0.36 and t-score=3.45). Most notably, the antecedents explained 71 percent of the variance of EMR continuance behavior (R^2=0.71).

	Table 4. Results of PLS path analysis			
Hypothesis	Path description	Path- coefficient and significance	t-score	Result
H1	Expected benefits → confirmation/ disconfirmation	0.53**	4.04	Supported
H2	Confirmation/disconfirmation → satisfaction	0.33**	4.19	Supported
H3	Satisfaction → continuance intention	0.27*	2.69	Supported
H4	Continuance intention → continuance behavior	0.31*	4.02	Supported
H5	Positive/negative emotions → satisfaction	0.54**	4.84	Supported
H6	Satisfaction → continuance behavior	0.36*	3.45	Supported
H7	Computer literacy → automatic behavior	$0.07^{n.s.}$	0.44	Not supported
H8	Task fit → automatic behavior	0.33**	3.58	Supported
H9	Facilitating conditions → automatic behavior	0.29*	2.32	Supported
H10	Automatic behavior → continuance behavior	0.44**	4.27	Supported

Discussion and Conclusion

The objective of this study was to develop and empirically validate a theoretical model conceptualizing the key determinants affecting a EMR user's continuance behavior. Unlike "traditional" post-acceptance studies, which underlying premise exclusively is based on conscious and reasoned behavior, we also integrated habitual (i.e. automatic behavior) and emotional (i.e. unintentional or unconscious behavior) responses to explain the phenomenon of interest. Using a longitudinal study design and data collected from 66 "real" EMR users, the proposed model was tested. The model exhibited an adequate fit with the surveyed data supporting the contention that emotions and habits strongly affect EMR continuance behavior. However, we also found that one of the constructs, notably literacy/self-efficacy, did not provide additional explanatory power to the model. The overall results contain a number of interesting research findings to be discussed in the following sub-sections.

Implications for Theory and Research

Our findings presented strong support to the existing theoretical links of "traditional" research models studying IS continuance. In fact, all relations (H1-H4) explaining continuance behavior as a result of reasoned actions showed significant effects and thus reinforced the established perception for conceptualizing post-acceptance (e.g. Bhattacherjee 2001).

While most of the healthcare professionals consciously understand the necessity and utility of an EMR, its usage is often connected to habits and regulations (e.g. for statistical or administrative purposes) and thus may cause strong emotional responses. The study showed that emotions, such as anger (e.g. because of bad systems performance), fear (e.g. panic to making mistakes and entering wrong data), or pleasure (e.g. because of user-friendly design), had an extraordinary lasting effect on a user's satisfaction (H5), which in turn directly affects EMR continuance behavior (H6). However, the impact of emotions on the continuance behavior of voluntary systems' users might be different and has to be explored in future.

Evidence was provided that automatic behavior positively affected EMR continuance behavior (H10). We also confirmed the argument of Ortiz de Guinea and Markus (2009), who postulated a stronger consideration of habitual responses in IS continuance research. The effects of habits on IS continuance is also in line with previous findings on post-acceptance (e.g. Liao et al. 2006; Limayem and Cheung 2008). However, as opposed to these studies, we also conceptualized the environmental cues enabling the faster development of automatic behavior. The study showed that a good task-fit and sufficient facilitating conditions helped EMR users to develop habits (H8-H9) and thus ultimately positively affected continuance behavior. No significant effect emanated from a user's literacy or self-efficacy (H7). This is contrary to the qualitative results of Shaw and Manwani (2011), who reported a strong relation between self-efficacy and usage. Reasons for that may be found in operationalization of used measures or in the environment of the specific context of this investigation. Further research is needed to really demonstrate a causal linkage.

Implications for Healthcare Practice

From a practical perspective, several important recommendations for health information managers, and software vendors can be deduced from this research.

The study results underscored the importance of both reasoned actions, and subliminal effects like habits and emotions. In order to increase the continuance intention and lastly continuance behavior of EMR users, health information managers and software developers must therefore not only emphasize the optimization of "hard factors" (e.g. measurable benefits from the EMR implementation such as cost reduction, efficiency increase, or better medical outcome), but also have a much stronger focus on considerably enhancing underlying "soft factors" (e.g. transition of useful evolved work routines, influencing negative or positive feelings and attitudes towards system usage).

To support the "reasoned rationale", health information managers may implement a formal process to continuously capture, document, and manage the healthcare professionals' performance expectations, as confirmed expectancies proved to have a strong impact on satisfaction and finally on continuance behavior. For instance, this could be realized by organizational benchmarks or self-assessments illustrating the level of achievement (i.e. discrepancy between expected benefits and actual performance perception).

Reinforcing positive and weakening negative emotions may be a good strategy for nourishing the "unreasoned rationale". Positive feelings could be attained by introducing an incentive or reward system, increase co-determination or by directly improving the EMR system's design. The latter could also help to diminish negative feelings, for instance, by providing extended capabilities for customization, or amending the graphical user interface and navigation structures. Indirectly, group or role-specific user manuals, extended trainings, etc. may prevent negative feelings as well. The denoted measures may also aid users to easier develop automatic behavior, which proved to have a substantial impact on the EMR continuance behavior.

Limitations and Future Work

As with any empirical field study, this work has limitations. The primary limitation is the reliance on a single informant. It is possible that users of other hospitals with a congruent EMR instantiation would have provided different responses regarding the continuance intention and behavior. Future research in post-acceptance of EMR should incorporate responses from multiple hospitals to truly assess the nature of continued usage of such systems.

Second, as we already stated, the healthcare industry imposes some obligations to systems usage. Generalizing these results to other industries and types of IS should therefore be handled carefully. Hence, future applications and adaptations of the post-acceptance model of IS continuance may include the voluntariness of system usage as further construct to be assessed.

Third, it is important to note that generally the measurement of expectation is problematic (either direct measurement or calculating of difference scores) as it comprehends several factors for bias (Venkatesh and Goyal 2010). To reduce bias, particular emphasis should be placed to distinguish between expectation and experience component measures in order not to combining them into a single score.

Finally, with the provided findings we hope to encourage other researchers not only to substantiate their work on the broadly proliferated assumption that users behave rationally and are conscious of all their actions, but also to start thinking of effects which habitual and emotional responses could have on a user's long term adoption behavior. This is particularly dependent on the context. Hence, future research related to routinization of IT use may also put more effort in explaining the contextual uniqueness and boundaries of their studies.

Appendix – Measurement Items

Expected benefits (1= Strongly Agree; 5 = Strongly Disagree)
EB1. Using the new EMR will increase information quality (e.g. consistency, completeness, traceability). EB2. Using the new EMR will lead to better medical outcome (e.g. patient safety, adequacy of treatment). EB3. Using the new EMR will make me more efficient (e.g. in daily activities, learning). EB4. Using the new EMR will improve governance and trust (e.g. privacy, security, conformity).
Confirmation/disconfirmation (1= Strongly Agree; 5 = Strongly Disagree)
CD1. The new EMR improved information quality much more than I initially had expected. CD2. The new EMR improved medical outcome much more than I initially had expected. CD3. The new EMR improved efficiency much more than I initially had expected. CD4. The new EMR improved governance and trust much more than I initially had expected.
Positive/negative emotions (1= Strongly Agree; 5 = Strongly Disagree)
EM1. Using the new EMR is annoying. EM2. Using the new EMR causes me fear (e.g. anxiety of making mistakes, not being able to use it). EM3. Using the new EMR causes makes me happy (e.g. playfulness to learn new things). EM4. I enjoy using the new EMR.
Satisfaction (1= Strongly Agree; 5 = Strongly Disagree)
ST1. My emotions with using the EMR are predominantly positive. ST2. Overall, I feel satisfied with the new EMR.
Computer literacy (1= Strongly Agree; 5 = Strongly Disagree)
LS1. My computer skills are excellent and sufficient to handle the new EMR. LS2. I am confident and able to perform my job using the new EMR.
Task fit (1= Strongly Agree; 5 = Strongly Disagree)
TF1. The EMR helps me to perform all my diagnostic activities (e.g. diagnostic tests, anamnesis). TF2. The EMR helps me to perform all my treatment activities (e.g. prescription, medication). TF3. The EMR helps me to perform all my nursing or care activities (e.g. nutrition, patient observation). TF4. The EMR helps me to perform my administrative activities (e.g. patient referral, billing).
Facilitating conditions (1= Strongly Agree; 5 = Strongly Disagree)
FC1. Is the hospital's infrastructure suitable for the new EMR (e.g. computer screens, input devices). FC2. Is the hospital's IT-support capable of helping me with the new EMR (e.g. response to tickets).
Automatic behavior (1= Strongly Agree; 5 = Strongly Disagree)
AB1. Using the new EMR has become automatic to me. AB2. Using the new EMR is natural to me.
Continuance intention (1= Strongly Agree; 5 = Strongly Disagree)
CI1. I willingly intend to continue using the new EMR to perform my assigned job responsibilities. CI2. I am eager to extend my usage of the new EMR for more of my assigned job responsibilities.
Continuance behavior (<20% | 21-40% | 41-60% | 61-80% | >81%)
CB1. Percentage of cases I've documented with the new EMR. CB2. Percentage of working time I'm actually using the new EMR.

References

Ash, J.S., and Bates, D.W. 2005. "Factors and Forces Affecting EHR System Adoption: Report of a 2004 ACMI Discussion," *Journal of the American Medical Informatics Association* (12:1), pp. 8-12.

Astleitner, H., and Leutner, D. 2000. "Designing Instructional Technology from an Emotional Perspective," *Journal of Research on Computing in Eduction* (32:4), pp. 497-510.

Atchariyachanvanich, K., Okada, H., and Sonehara, N. 2006. "What Keeps Online Customers Repurchasing through the Internet?," *ACM SIGecom Exchanges* (6:2), pp. 47-57.

Bhattacherjee, A. 2001. "Understanding Information Systems Continuance: An Expectation-Confirmation Model," *MIS Quarterly* (25:3), pp. 351-370.

Bhattacherjee, A., and Barfarm, A. 2011. "Information Technology Continuance Research: Current State and Future Directions," *Asia Pacific Journal of Information Systems* (21:2), pp. 1-18.

Bhattacherjee, A., Perols, J., and Sanford, C. 2008. "Information Technology Continuance: A Theoretic Extension and Empirical Test," *Journal of Computer Information Systems* (49:1), pp. 17-26.

Bhattacherjee, A., and Premkumar, G. 2004. "Understanding Changes in Belief and Attitude Toward Information Technology Usage: A Theoretical Model and Longitudinal Test," *MIS Quarterly* (28:2), pp. 229-254.

Bollen, K.A., and Stine, R.A. 1992. "Bootstrapping Goodness-of-Fit Measures in Structural Equation Models," *Sociological Methods & Research* (21:2), pp. 205-229.

Chin, W.W. 1998. "The Partial Least Squares Approach for Structural Equation Modeling," in *Modern methods for business research,* G.A. Macoulides (ed.). Mahwah: Lawrence Erlbaum Associates, pp. 295-336.

Cooper, R.B., and Zmud, R.W. 1990. "Information Technology Implementation Research: A Technological Diffusion Approach," *Management Science* (36:2), pp. 123-139.

Cortina, J.M. 1993. "What is Coefficient Alpha? Examination of Theory and Applications," *Journal of Applied Psychology* (78:1), pp. 98-104.

Cronin, J., J. J., and Taylor, S.A. 1994. "SERVPERF Versus SERVQUAL: Reconciling Performance-Based and Perceptions- Minus-Expectations Measurement of Service Quality," *Journal of Marketing* (58:1), pp. 125-131.

Davis, F.D. 1989. "Perceived Usefulness, Perceived Ease of Use, and User Acceptance of Information Technology," *MIS Quarterly* (13:3), pp. 319-339.

DeLone, W.H., and McLean, E.R. 1992. "Information Systems Success: The Quest for the Dependent Variable," *Information Systems Research* (3:1), pp. 60-95.

Dishaw, M.T., and Strong, D.M. 1999. "Extending the Technology Acceptance Model with Task-Technology Fit Constructs," *Information & Management* (36:1), pp. 9-21.

EHR Scope. 2012. "EMR Comparison." Retrieved January 18, 2012, from http://www.ehrscope.com/emr-comparison/

Esposito Vinzi, V., Chin, W.W., Henseler, J., and Wang, H. (eds.). 2010. *Handbook of Partial Least Squares: Concepts, Methods, Applications*. Berlin, Heidelberg: Springer.

Fitterer, R., Mettler, T., Rohner, P., and Winter, R. 2011. "Taxonomy for multi-perspective assessment of the value of health information systems," *International Journal of Healthcare Technology and Management* (12:1), pp. 45-61.

Fornell, C., and Larcker, D.F. 1981. "Evaluating Structural Equition Models with Unobservable Variables and Measurement Error," *Journal of Marketing Research* (18:1), pp. 39-50.

Gans, D., Kraiewski, J., Hammons, T., and Dowd, B. 2005. "Medical Groups' Adoption of Electronic Health Records and Information Systems," *Health Affairs* (24:5), pp. 1323-1333.

Gefen, D., and Straub, D.W. 2005. "A Practical Guide to Factorial Validity Using PLS-Graph: Tutorial and Annotages Example," *Communications of the Association for Information Systems* (16:1), pp. 91-109.

Glouberman, S., and Mintzberg, H. 2001. "Managing the Care of Health and the Cure of Disease - Part 1: Differentation," *Health Care Management Review* (26:1), pp. 56-86.

Goh, J.M., Gao, G., and Agarwal, R. 2011. "Evolving Work Routines: Adaptive Routinization of Information Technology in Healthcare," *Information Systems Research* (22:3), pp. 565-585.

Goodhue, D.L., and Thompson, R.L. 1995. "Task-Technology Fit and Individual Performance," *MIS Quarterly* (19:2), pp. 213-236.

Handy, J., Hunter, I., and Whiddett, R. 2001. "User Acceptance of Inter-organizational Electronic Medical Records," *Health Informatics Journal* (7:2), pp. 103-107.
Hayashi, A., Chen, C., Ryan, T., and Wu, J. 2004. "The Role of Social Presence and Moderating Role of Computer Self Efficacy in Predicting the Continuance Usage of E-Learning Systems," *Journal of Information Systems Education* (15:2), pp. 139-154.
Health Technology Review. 2012. "EMR Software Reviews." Retrieved January 18, 2012, from http://www.healthtechnologyreview.com/products.php?cid=1&pid=7
Hennington, A., and Janz, B. 2007. "Physician Adoption of Electronic Medical Records: Applying the UTAUT Model in a Healthcare Context," *Communications of the Association for Information Systems* (19:1), pp. 60-80.
Hulland, J. 1999. "Use of Partial Least Squares (PLS) in Strategic Management Research: A Review of Four Recent Studies," *Strategic Management Journal* (20:2), pp. 195-204.
Jha, A.K., DesRoches, C.M., Campbell, E.G., Donelan, K., Rao, S.R., Ferris, T.G., Shields, A., Rosenbaum, S., and Blumenthal, D. 2009. "Use of Electronic Health Records in U.S. Hospitals," *New England Journal of Medicine* (360:16), pp. 1628-1638.
Kazley, A., and Ozcan, Y. 2007. "Organizational and Environmental Determinants of Hospital EMR Adoption: A National Study," *Journal of Medical Systems* (31:5), pp. 375-384.
Kopalle, P.K., and Lehmann, D.R. 2001. "Strategic Management of Expectations: The Role of Disconfirmation Sensitivity and Perfectionism," *Journal of Marketing Research* (38:3), pp. 386-394.
Liao, C., Palvia, P., and Lin, H.-N. 2006. "The Roles of Habit and Web Site Quality in E-Commerce," *International Journal of Information Management* (26:6), pp. 469-483.
Limayem, M., and Cheung, C.M.K. 2008. "Understanding Information Systems Continuance: The Case of Internet-based Learning Technologies," *Information & Management* (45:4), pp. 227-232.
Lin, C.S., Wu, S., and Tsai, R.J. 2005. "Integrating Perceived Playfulness into Expectation-Confirmation Model for Web Portal Context," *Information & Management* (42:5), pp. 683-693.
McLeod, A., and Guynes Clark, J. 2009. "Using Stakeholder Anaylsis to Identify Users in Healthcare Information Systems Research: Who is the Real Users?," *International Journal of Healthcare Information Systems and Informatics* (4:3), pp. 1-15.
Mirani, R., and Lederer, A.L. 1998. "An Instrument for Assessing the Organizational Benefits of IS Projects," *Decision Sciences* (29:4), pp. 803-838.
Morton, M., and Wiedenbeck, S. 2009. "A Framework for Predicting EHR Adoption Attitudes: A Physician Survey," *Perspectives in Health Information Management* (6:1a).
Murray, K.B., and Häubl, G. 2007. "Explaining Cognitive Lock-In: The Role of Skill-Based Habits of Use in Consumer Choice," *Journal of Consumer Research* (34:1), pp. 77-88.
Oliver, R.L. 1980. "A Cognitive Model for the Antecedents and Consequences of Satisfaction," *Journal of Marketing Research* (17:4), pp. 460-469.
Ortiz de Guinea, A., and Markus, M.L. 2009. "Why Break the Habit of a Lifetime? Rethinking the Roles of Intention, Habit, and Emotion in Continuing Information Technology Use," *MIS Quarterly* (33:3), pp. 433-444.
Petter, S., Straub, D.W., and Rai, A. 2007. "Specifying Formative Constructs in Information Systems Research," *MIS Quarterly* (31:4), pp. 623-656.
Polites, G.L., and Karahanna, E. 2012. "Stackeled to the Status Quo: The Inhibiting Effects of Incumbent System Habit, Switching Costs, and Inertia on New System Acceptance," *MIS Quarterly* (36:1), pp. 21-42.
Ramanujam, R., and Rousseau, D.M. 2006. "The Challenges are Organizational not just Clinical," *Journal of Organizational Behavior* (27:7), pp. 811-827.
Ringle, C.M., Sarstedt, M., and Straub, D.W. 2012. "A Critical Look at the Use of PLS-SEM in MIS Quarterly," *MIS Quarterly* (36:1), pp. iii-xiv.
Schectman, J.M., Schorling, J.B., Nadkarni, M.M., and Voss, J.D. 2005. "Determinants of Physician Use of an Ambulatory Prescription Expert System," *International Journal of Medical Informatics* (74:9), pp. 711-717.
Shaw, E., and Manwani, S. 2011. "Extending Feature Usage: A Study of the Post-Adoption of Electronic Medical Records," in: *Proceedings of the 19th European Conference on Information Systems*. Helsinki, Finland.
Sherer, S. 2010. "An Institutional Theory Perspective on Physician Adoption of Electronic Health Records," *Communications of the Association for Information Systems* (26:1), pp. 127-140.

Spil, T.A.M., LeRouge, C., Trimmer, K., and Wiggins, C. 2011. "Back to the Future of IT Adoption and Evaluation in Healthcare," *International Journal of Healthcare Technology and Management* (12:1), pp. 85-109.

Susarla, A., Barua, A., and Whinston, A.B. 2003. "Understanding the Service Component of Application Service Provision: An Empirical Analysis of Satisfaction with ASP Services," *MIS Quarterly* (27:1), pp. 91-123.

Van der Heijden, H. 2004. "User Acceptance of Hedonic Information Systems," *MIS Quarterly* (28:4), pp. 695-704.

Venkatesh, V., and Goyal, S. 2010. "Expectation Disconfirmation and Technology Adoption: Polynomial Modeling and Response Surface Analysis," *MIS Quarterly* (34:2), pp. 281-303.

Venkatesh, V., Morris, M., Davis, G., and Davis, F. 2003. "User Acceptance of Information Technology: Toward a Unified View," *MIS Quarterly* (27:3), pp. 425-478.

Venkatesh, V., Zhang, X., and Sykes, T.A. 2011. "“Doctors Do Too Little Technology”: A Longitudinal Field Study of an Electronic Healthcare System Implementation," *Information Systems Research* (22:3), pp. 523-546.

Verplanken, B., and Aarts, H. 1999. "Habit, Attitude, and Planned Behaviour: Is Habit an Empty Construct or an Interesting Case of Goal-directed Automaticity?," *European Review of Social Psychology* (10:1), pp. 101-134.

Walston, S., and Chadwick, C. 2003. "Perceptions and Misperceptions of Major Organizational Changes in Hospitals: Do Change Efforts Fail Because of Inconsistent Organizational Perceptions of Restructuring and Reengineering?," *International Journal of Public Administration* (26:14), pp. 1581-1605.

Wold, H. 1982. "Soft Modeling: The Basic Design and some Extensions," in *Systems under indirect observation,* K.G. Jöreskog and H. Wold (eds.). Amsterdam: North-Holland, pp. 1-54.

World Health Organization. 2005. "eHealth: Report by the Secretariat." Retrieved January 18, 2012, from http://www.who.int/gb/ebwha/pdf_files/WHA58/A58_21-en.pdf