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Chapter XVI
Predicting Patients' Use of Provider-Delivered E-Health: The Role of Facilitating Conditions

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ABSTRACT

This chapter presents a new rational-objective (R-O) model of e-health use that accounts for effects of facilitating conditions as well as patients' behavioral intention. An online questionnaire measured patients' behavioral intention to use a new e-health application as well as proxy measures of facilitating conditions that assess prior use of and structural need for health services. A second questionnaire administered three months later collected patients' self-reported use of e-health during the intervening period. The new model increased predictions of patients' e-health use (measured in R^2) by more than 300% over predictions based upon behavioral intention alone, and all measured factors contributed significantly to prediction of use during the three-month assessment period.

INTRODUCTION

Increasingly, healthcare provider organizations offer provider-delivered e-health[1] to supply patients with health information and advanced capabilities, such as appointment scheduling, prescription refilling, and online communication with physicians and clinical staff (Hsu, Huang, Kinsman, Fireman, Miller, Selby, & Ortiz, 2005; Wilson & Lankton, 2004). Because designing, developing, and deploying e-health represents a substantial investment by providers, it is important that these applications are actually used by patients. If providers can predict levels of patient e-health use at early stages in the design process, this will help them to be more effective in allocating resources and managing risks associated with e-health delivery.

In this chapter, we propose and test a predictive model of e-health use that accounts for both situational factors (facilitating conditions) that are typically outside patients' direct control and behavioral intention that patients form toward using e-health. In the following sections, we review the background literature that motivates and supports this study, present the research model, and develop hypotheses to test relationships within the model.

BACKGROUND

Wilson and Lankton (2004) studied factors that contribute to initial acceptance of e-health among new registrants to a prototype e-health application. That study found patients' behavioral intention (BI) toward e-health use is predicted well by three prominent models of IT acceptance: the technology acceptance model (TAM) (Davis, Bagozzi, & Warshaw, 1989), the motivational model (Davis, Bagozzi, & Warshaw, 1992), and the integrated model (Venkatesh, Speier, & Morris, 2002). All are examples of *rational* models (Ajzen, 2002; Kim & Malhotra, 2005), so named because predictions are based upon individuals' beliefs regarding such factors as ease of use and usefulness of the IT. Within these models, effects of beliefs upon IT use behaviors are theorized to be fully mediated by BI that individuals form through rational processes. Wilson and Lankton (2004) also report that belief factors in the models are significantly predicted by three patient characteristics that are developed prior to use of e-health: satisfaction with the provider, information-seeking preference, and Internet dependence. This finding is important, as it implies that patients' BI toward e-health use can be predicted early in design stages of application development.

Rational models of behavior have performed well in predicting individual behaviors across a wide range of research domains. In the preponderance of published studies, a positive association is reported between BI and behavior (see reviews by Ouellette & Wood, 1998; Sheppard, Hartwick, & Warshaw, 1988). Based on this substantial literature most IT acceptance studies do not

Table 1. Review of associations between BI and self-reported IT use

Reference	IT Type	Variance in IT Use Explained by BI
Davis et al. (1989)	Word processor	12-40 %
Dishaw & Strong (1999)	Software maintenance tool	36%, including direct effect of perceived usefulness
Hartwick & Barki (1994)	Business IS application	35-74%
Horton, Buck, Waterson, & Clegg (2001)	Intranet	11%
Lai (2004)	Short message services	15%
Limayem & Hirt (2003)	Communication application	47%, including direct effects of habit and facilitating conditions
Moon & Kim (2001)	World wide Web	38%
Morris & Dillon (1997)	Netscape Web browser	19%
Shih & Fang (2004)	Internet banking	24%
Stoel & Lee (2003)	Web-based courseware	4%
Suh & Han (2002, 2003)	Internet banking	3%
Szajna (1996)	E-mail	6-32%

assess actual use, under the assumption that IT use is normatively predicted by BI (Lee, Kozar, & Larsen, 2003). Indeed, a recent review of 277 published IT acceptance studies conducted by one of the authors finds just 13 that evaluate effects of BI on self-reported IT use. Results from these 13 studies are summarized in Table 1.

As calculated from the sample sizes and correlations (actual or estimated), the weighted average correlation between BI and IT use in the studies shown in Table 1 is 36% ($R^2 = .13$), with the 95% confidence interval for correlation ranging from 25-46% and for R^2 ranging from .06-.21. At the higher end of this range BI is quite predictive of actual IT use, but predictions at the lower end of the range clearly are of limited value. In the case of the Wilson and Lankton (2004) study, a low association between BI and e-health use would essentially negate the possibility that antecedent factors mediated by BI are significantly related to e-health use.

Research to date has not reported the level of association between BI and use of e-health, but certain characteristics of the e-health context could diminish the size of this association. Patients' access to e-health often is initiated by situational factors that are outside the individual's personal control, including illness, injury, and other medical concerns. Such factors act as *facilitating conditions* which are theorized to influence individual behaviors outside the framework of beliefs and intentions that underlies rational models (Triandis, 1977, 1980). Triandis writes:

"[A]t any level of habit or behavioral intention, the absence or presence of facilitating conditions will affect the likelihood of a behavior. In an extreme case, the person's habits and behavioral intentions have no relevance if the situation does not permit him or her to behave (Triandis, 1977, pp. 206-207).

Facilitating conditions are difficult to incorporate directly into models of behavior, because of the wide range of distinct events that can promote or obstruct any specific action. For this reason, IT researchers have applied proxy measures for the presence or absence of facilitating conditions. For example, Thompson, Higgins, and Howell (1991) applied *perceived availability of guidance in selecting computer hardware and software* as a proxy measure for a facilitating condition related to the number of products that are available for an individual to select from.

Although a number of studies have applied proxy measures of facilitating conditions to model IT use, results are mixed. Some studies find significant predictions of IT use from proxy measures, including subjects' age and experience (Venkatesh, Morris, Davis, & Davis, 2003), but other studies fail to find significant effects (Thompson et al., 1991; Limayem & Hirt, 2003).

Because e-health is frequently used to respond to an unusual medical situation, facilitating conditions may be more important to e-health than to other IT. As illustrated in Table 1, typical studies address forms of IT in which incentives for use are frequent and consistent, e.g., word processing software used by MBA students (Davis et al., 1989), and in which external obstacles to use have been removed (e.g., campus computer labs provided to support student access to course communication software) (Limayem & Hirt, 2003).

Motivational and obstructive effects of facilitating conditions are especially important in the healthcare context, as patients who are willing to use health services will not necessarily have an immediate medical need (Cantor & Fallon, 1997). Although a patient may intend to use e-health in the future for accessing health information or scheduling an appointment for a medical examination, it remains unlikely that he or she will take action unless prompted by some facilitating condition, such as onset of pain. Actual use of e-health at a given moment depends upon its *microrelevance* (i.e., "the degree to which IT-use helps to solve the here-and-now problem of the user in his working process" (Spil, Schuring, & Michel-Verkerke, 2004, pp. 39)), which is predicated to a large degree upon the presence or absence of facilitating conditions. These observations suggest it is important to account for effects of facilitating conditions when modeling e-health use. However, this will require a research perspective that transcends the boundaries of rational models of IT acceptance.

RESEARCH MODEL AND HYPOTHESES

The present study tests a new research model in which the rational factor BI is augmented with objective factors representing patients' prior use of and need for healthcare services. The theoretical justification for this *rational-objective* (R-O) model is grounded in Triandis' (1977, 1980) definition of facilitating conditions as objective factors capable of directly affecting individuals' behaviors, regardless of the state of rational factors, including BI. The behavior of seeking healthcare services clearly reacts to certain facilitating conditions, such as illness or injury. For this reason, it may be anticipated that an individual's prior use of and need for healthcare services will be positively associated with presence of facilitating conditions and that these factors can provide proxy measures representative of facilitating conditions that exist in the prior context. To the extent that facilitating conditions persist across time, prior use of and need for healthcare services can further proxy for contemporaneous measurement of facilitating conditions during a subsequent period. This theorized assessment of proxy factors in predicting e-health use is illustrated in Figure 1.

The R-O research model (shown in Figure 2) posits that prediction of e-health use will be improved by augmenting BI with *offline service utilization, frequency of medical office visits,* and *structural need for medical services*, factors we propose to be associated with presence of facilitating conditions. In the following sections, hypotheses regarding relationships depicted in the research model are presented.

BI Toward Use

As discussed previously, a positive association between BI and behavior is found in a substantial prior literature, both in studies of general behavior

Figure 1. The role of proxy factors in measurement of facilitating conditions

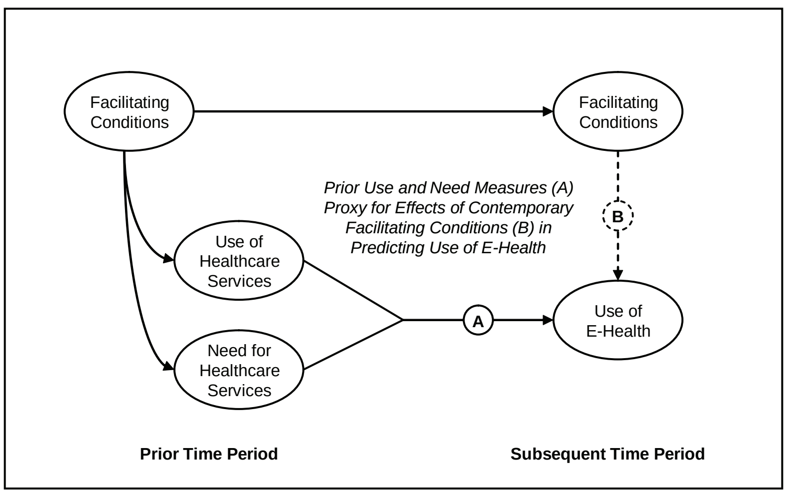
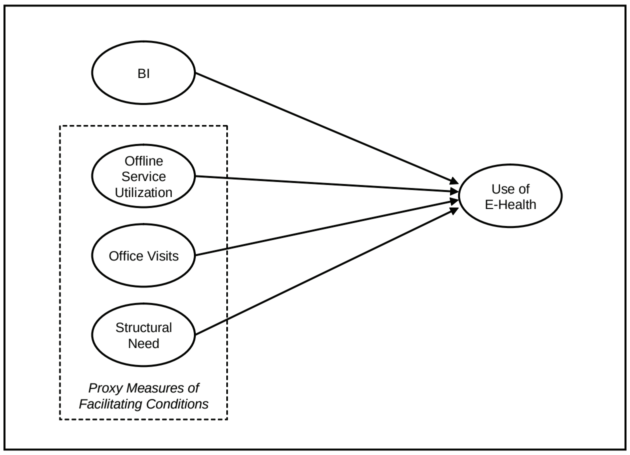


Figure 2. Rational-objective (R-O) research model



(Ouellette & Wood, 1998; Sheppard et al., 1988) and in studies directed toward IT use (Lee et al., 2003). In recognition of this precedent, a similar association is hypothesized between BI and e-health use.

H1: *BI Toward E-Health Use will Predict Use of E-Health.*

Prior Use of Offline Services

Where a certain IT has been used previously, the level of prior use can be more important than BI in predicting subsequent use (Cheung & Limayem, 2005); in some cases, prior IT use can completely subordinate effects of BI (Kim & Malhotra, 2005; Wilson, Mao, & Lankton, 2005). In the present study, participants will not have used e-health previously. However, they will have had the opportunity as patients to use health services at the provider's offline facilities that parallel the services offered via e-health. For example, filling out a prescription refill request form in the e-health application would have many similarities to requesting a prescription refill by phone or in person. Researchers find that prior utilization of an organization's service predicts future service utilization (Naessens, Baird, Jouten, Vanness, & Campbell, 2005). This suggests that e-health use will be influenced by prior use of similar offline health services.

H2: *Prior use of offline health services will predict use of e-health.*

A second way of conceptualizing prior use of health services is to assess overall utilization of provider services beyond the similar services that are offered via e-health. Frequency of office visits exemplifies this type of overall measure, based upon the rationale that patients who visit clinic offices frequently will be externally motivated to use e-health to supplement or replace their visits.

H3: *Prior number of office visits will predict use of e-health.*

Structural Need

Individual need for healthcare is associated with higher rates of healthcare use in general (Ford, Trestman, Steinberg, Tennen, & Alen, 2004; Naessens et al., 2005) and with higher rates of e-health use (Hsu et al., 2005). These observations suggest that use of e-health will increase where need for health services is *structural*, defined herein as need that is statistically associated with observable characteristics of participants. Because the association is statistical across a demographic population, we consider structural need to be a proxy measure of facilitating conditions rather than a direct measure.

H4: *Structural need for health services will predict use of e-health.*

Structural need has not been studied previously as a contributor to IT use (Lee et al., 2003). However, two factors that fit the criteria presented above are age and presence of a chronic health condition, such as diabetes. Both factors are statistically associated with increased need for health services (CDC, 2005, 2007), and Hypotheses 5a and 5b test the individual effects of these factors as contributors to structural need.

H5a: *Age will predict structural need for health services.*

H5b: *Chronic health condition will predict structural need for health services.*

Model Predictiveness

The final hypothesis tests the potency of the full R-O research model in predicting e-health use. This hypothesis contrasts the full model to the rational model—in other words, BI only, and to each alternative nested R-O model (i.e., any model that comprises BI plus a subset of objective factors contained within the full model). In order to assess trade-offs between model predictiveness and parsimony, hypothesis testing will control for differences in the number of factors between models.

H6: *The full research model will be more predictive of e-health use than alternative rational or R-O nested models.*

The following sections describe the research method and present results of hypothesis testing. The chapter concludes with a discussion of implications for practice and research.

RESEARCH METHOD

This research is conducted among patients who registered for access to an e-health application called *MyHealth* (a pseudonym), which was developed by a large Midwest U.S. provider. MyHealth presents encyclopedic health content with both browse and search access, e-mail-style connectivity with the clinic office, prescription refill ordering, and appointment scheduling. Access for patients is unrestricted, but they must first register online and thereafter login using a self-assigned ID and password. The developer of MyHealth is a provider managing approximately 100 clinics. At the time of the study, access to MyHealth was being offered to patients in four of these clinics as a pilot project. Prior to data collection, the research design was reviewed and approved by the lead researcher's Institutional Review Board.

Procedure

An invitation to volunteer for participation was sent to the e-mail addresses of 1,750 individuals who had registered for access to MyHealth following announcement of the Web site in a promotional mailing to clinic patients. On average, registrants received the e-mail invitations approximately two weeks after registration, which provided a short introductory period for them to investigate the site. 163 (9%) of the invitees responded to the invitation and 135 (8%) completed the entire initial online questionnaire. The provider declined to allow the researchers to send follow-up requests to participate. The initial questionnaire measured BI as well as demographic factors and aspects of prior offline health service utilization and need.

Three months later, a second questionnaire was administered to assess use of MyHealth during the intervening period. A request to complete the follow-up questionnaire was e-mailed to the original 135 respondents, and a second request was e-mailed two weeks later to those who had not completed the questionnaire by that time. In total, 83 of the original respondents (61%) completed the follow-up questionnaire. A one-way ANOVA conducted between early and late responders to the follow-up questionnaire showed no significant differences on measures between these groups, suggesting that participants are generally representative of the original respondents.

Responses from the initial questionnaire and the follow-up questionnaire were matched based on the participant's e-mail address. Average age of participants is 52, with a minimum age of 25, and a maximum age of 80, and 75% are women. Following registration, participants accessed MyHealth an average of 1.9 times (s.d. = 3.1 accesses).

RESULTS

Hypothesis testing was conducted using the partial least squares (PLS) approach to structural equation modeling (SEM). PLS simultaneously apportions variance across a structural model and is capable of assessing both reflective and formative latent variables (Chin, 1998; Wold, 1985, 1989), two important capabilities in operationalizing the research model used in this study.

The structural model encompasses four independent variables. BI was measured as a reflective latent variable with two indicator items. Offline service utilization was measured as the total of self-reported offline accesses to five health services, and office visits was measured as the total of self-reported visits to healthcare facilities made during the six months prior to completing the first questionnaire. Structural need was measured as a formative latent variable with two indicator items: age and presence of a chronic health condition, measured as a dichotomous variable. The dependent variable in the model, e-health use, was measured as the total of self-reported accesses to five health services offered by MyHealth during the three-month period following completion of the first questionnaire.

Construct Validation

To assess construct reliability and validity, a confirmatory factor analysis (CFA) was conducted using weighted data generated by PLS-Graph as input and modeling the items as reflective indicators of their corresponding constructs following guidelines presented by Gefen and Straub (2005). Results of the CFA analyses are presented in Table 2.

Table 2. Confirmatory factor analysis

Item \ Factor	BI	OSU	SN	OV	Use
BI: I intend to use MyHealth	**0.979**	0.104	0.134	0.032	0.229
BI: I predict I will use MyHealth	**0.985**	0.104	0.113	0.035	0.267
OSU: Offline Service Utilization	0.106	**1.000**	-0.177	0.340	0.417
SN: Structural need: Age	0.045	0.051	**0.492**	0.030	-0.153
SN: Structural need: Chronic Condition	0.115	0.171	**0.840**	-0.154	-0.260
OV: Office Visits	0.034	0.340	-0.118	**1.000**	-0.030
Use: E-Health Use	0.254	0.417	-0.310	-0.030	**1.000**

Convergent validity and discriminant validity were assessed using criteria developed by Fornell and Larcker (1981). Convergent validity is not assessed for single-item measures or formative latent variables, such as structural need. It is established for reflective latent variables when (1) all indicator loadings are significant and all loadings are above .70, (2) composite construct reliability for each factor is in excess of .80, and (3) average variance extracted (AVE) for each factor is above .50. For the BI reflective latent variable, all indicator items are above .70, composite construct reliability is .982, and AVE is .964, indicated that convergent validity is present in this factor.

Discriminant validity is established when between-construct correlations are less than the square root of AVE for each construct, which is calculated as .982 for BI and .688 for structural need. The between-construct correlations are substantially lower than the AVE figures for all factors, indicating that discriminant validity is present in both multi-item factors.

Hypothesis Tests

All hypotheses are supported. E-health use is predicted by BI (path coeff. = .254, $p < .001$), utilization of offline services (path coeff. = .410, $p < .01$), frequency of prior office visits (path coeff. = .213, $p < .05$), and presence of structural need (path coeff. = .294, $p < .001$). Structural need is predicted as a formative latent variable by age (path coeff. = .562, $p < .01$) and by chronic health condition (path coeff. = .864, $p < .001$). Finally, the full research model (shown in column 8 of Table 2) provides significantly better predictions of e-health use than any nested model ($p < .05$). Significance of R^2 differences was calculated using F-tests that control for differing number of variables in each model, as presented by Subramani (2004). Modeling of e-health use based only upon BI (shown as column 1 of Table 2) is significantly worse than other models except model 2 (BI plus office visits).

DISCUSSION AND CONCLUSION

The findings demonstrate that predictiveness of rational models of IT acceptance, such as TAM, is limited in the context of e-health. Yet these predictions can be dramatically improved by incorporating objective measures that proxy for facilitating conditions, as we did using offline service utilization, prior office visits, and structural need. These are factors that can be assessed at early stages of e-health application development to identify patient populations who are most likely to use e-health and to guide design of e-health to support targeted needs. For example, the findings regarding chronic disease suggest affected patients are disproportionately motivated to try

Table 3. Full and nested models arranged in order of increasing explained variance (R^2)

Relationship / Model	1	2	3	4	5	6	7	8
BI → E-Health Use	.254^3	.255^3	.297^3	.301^3	.212^2	.212^2	.253^3	.254^3
Offline Service Utilization → E-Health Use					.395^2	.460^2	.341^2	.410^2
Office Visits → E-Health Use		.038		.082		.193^1		.213^1
Structural need → E-Health Use			.347^3	.357^3			.281^3	.294^3
E-Health Use Model R^2	.065	.066	.183	.190	.219	.252	.294	.333

^{1} *$p < .05$* ^{2} *$p < .01$* ^{3} *$p < .001$ (one-tailed t-tests)* out e-health and are well-positioned to benefit from targeted services, such as online support for disease management.

The findings also have important implications for research. Although a number of studies have reported that prior IT use is predictive of subsequent use outside the framework of rational models (e.g., Cheung & Limayem, 2005; Kim & Malhotra, 2005; Kim, Malhotra, & Narasimhan, 2006, Limayem & Hirt, 2003), the results here indicate that prior use of offline services has similar effects on subsequent IT use. This finding suggests researchers need to reconsider the mechanisms that influence use of e-health and related IT.

Two mechanisms for explaining the effects of prior IT use are prominent in the current literature. The first mechanism proposes that prior experiences drive development of reasoned beliefs, culminating in the formation of BI toward use (Ajzen, 2002). But in the present study offline service utilization, prior office visits, and structural need factors each show significant direct effects on e-health use beyond any mediating effects of BI. The second mechanism proposes that effects of prior IT use on subsequent use occurs through formation of habits (Kim et al., 2006). However, habits are developed through repetitive action (Ouellette & Wood, 1998), and the opportunity for repetitive use of MyHealth by participants was virtually non-existent prior to administration of the first questionnaire in our study.

Thus, neither mechanism offers a satisfactory explanation of findings in the present study. However, the findings are consistent with the proposition that e-health use is predominantly determined by facilitating conditions that are essentially outside the control of individual patients. As discussed previously, past research finds facilitating conditions to be only equivocal predictors of IT use, however, most of this research has been directed toward IT in which effects of facilitating conditions are limited by the structure of the research domain, such as where external obstacles have been removed. Findings of the present study suggest that there is a class of IT, including e-health, in which facilitating conditions are exceptionally salient. It will be important for future researchers to determine what characteristics these IT share and to consider the potential effects of facilitating conditions when designing research. One idea that has been proposed is that e-health is one example of an emerging class of IT designed to support sporadic uses, and the sporadic nature of the activity reduces the importance of BI in predicting future IT use (Wilson et al., 2005).

FUTURE RESEARCH DIRECTIONS

It is interesting that contrasts among full and nested models reveal that each of the proxy factors for facilitating conditions is a significant predictor of e-health use. This finding affirms both the choice of factors in the study and the practice of implementing multiple measures, yet it also raises questions that may provide direction for future research. First, the findings show that both specific and general service utilization are predictive of use, but there is need for theory development to explain why. We need to understand which aspects of service utilization are key to motivating use of online services and whether these differ between e-health and other IT. Second, the results linking structural need to e-health use deserve additional exploration. The findings that factors of age and chronic health condition contribute to a formative latent factor suggest that e-health is well-received by populations who may benefit the most from services that e-health can readily offer, such as healthcare information and online support communities. It will be important for future researchers to study which services are most beneficial to populations with specific patterns of structural need (e.g., elderly diabetics), and to investigate other factors that may contribute to structural need. Finally, it will be equally important for researchers to study alternative proxy measures of facilitating conditions in order to identify an optimal trade-off between accuracy and parsimony.

CONCLUSION

This study of e-health use builds upon a prior study of initial acceptance (Wilson & Lankton, 2004). The combined research models tested in these two studies give providers a foundational framework for making early predictions about patients' acceptance and use of e-health applications. Joint findings of the two studies also provide researchers with a greater understanding of specific ways in which patients' interactions with e-health vary from other types of IT and demonstrate the importance of considering effects of facilitating conditions when designing e-health research.

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ENDNOTE

[1] For brevity, we refer to "provider-delivered e-health" simply as *e-health* and "health-care provider organizations" as *providers* throughout the remainder of the chapter.