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ABSTRACT

Many IT acceptance models assume a positive association will exist between behavioral intention (BI) toward IT use and actual use of the IT. Yet in some cases this relationship is weak or nonsignificant, and models based on predictions mediated by BI lose their value. In this paper I report findings of a weak relationship between BI and IT use in a study that applies IT acceptance models to predict patients' use of e-health. I theorize this weak relationship arises from effects of facilitating conditions that initiate much of the use of e-health. In a *post hoc* analysis, I propose and test an alternative model that augments TAM with measures of prior use of offline health services and structural need. Results of this test indicate that these measures can dramatically improve predictions of initial e-health use.

Keywords

Technology acceptance model (TAM), health services, healthcare need, IT and healthcare

INTRODUCTION

Most major U.S. healthcare provider organizations now supply e-health services to patients. Through *provider e-health*[1] the patient's own healthcare provider organization uses the Internet to deliver health services including informational content and advanced capabilities, such as appointment scheduling, prescription refilling, and online communication with physicians and clinical staff (Lazarus, 2001). Designing, developing, and deploying e-health represents a substantial investment, and it is important to providers that these services are cost-effective. Yet patients sometimes fail to use the very e-health services that providers think will be most essential (Payton and Brennan, 1999). If providers could predict patients' acceptance and use of e-health at early stages in the design process, this would help them to be more effective in allocating resources and managing risks associated with delivering e-health.

Wilson and Lankton (2004) address the issue of initial acceptance in a study of new registrants for a prototype e-health application. They find acceptance of e-health (measured as BI toward use) is predicted well by three prominent models of IT acceptance: the technology acceptance model (TAM) (Davis, 1989), the motivational model (Davis, Bagozzi, and Warshaw, 1992), and the integrated model (Venkatesh, Speier, and Morris, 2002). In addition, Wilson and Lankton identify three antecedent characteristics (information seeking propensity, prior satisfaction with medical services, and Internet dependence) that can be used to predict constructs within these models even prior to the time that patients are introduced to a specific e-health application.

It should be noted that Wilson and Lankton did not measure e-health use. Instead, their research design assumes the existence of a positive association between BI and behavior based on a substantial literature (see reviews by Ouellette and Wood, 1998 and Sheppard, Hartwick, and Warshaw, 1988). The assumption that BI leads to use has been applied widely in IT acceptance research, however, the degree of association varies substantially among studies which explicitly test this relationship. I reviewed 277 IT acceptance studies and found just 13 that evaluate effects of BI on self-reported IT use[2] (see Table 1). Calculating from the sample sizes and actual or estimated correlations across these studies, the weighted average correlation of BI with use is 36% (R^2 = .13) and the 95% confidence interval ranges from 25-46% (R^2 CI = .06-.21).

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[1] For brevity, I reference "provider e-health" simply as *e-health* and "healthcare provider organizations" as *providers* throughout the remainder of the paper.

[2] There are 9 additional studies that examine the effects of BI on objectively-measured use.

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

Table 1. Review of Studies Testing Association Between Behavioral Intention and Self-Reported IT Use.

Although the reported effects of BI on use are substantial at the higher end of this range, effects at the lower end offer limited practical prediction of use. Researchers have proposed several explanations for weak associations, including the length of time between measurements or instability of intentions due to a lack of experience (Davis, Bagozzi, and Warshaw, 1989; Fishbein and Ajzen, 1975; Szajna, 1996), effects of social desirability on BI responses (Harris, Donaldson, and Campbell, 2001), irrational behaviors (Kim and Malhotra, 2005), and omission of external factors that might influence use (Davis, et al., 1989; Harris et al., 2001).

The overriding objective in studying patients' acceptance of e-health is to provide practical guidance for providers. Therefore, it is important to qualify the assumption that BI does in fact explain variance in e-health use. In the Wilson and Lankton (2004) study, data were drawn from a questionnaire administered during the first two weeks following patients' registration for e-health access. Meaningful usage data were not available at that time, but a follow-up questionnaire was administered later to many of the original participants in order to assess their use of the system. In this paper I begin by describing the initial research method and then present an analysis of the combined data, finding that the association between BI and e-health use is quite low compared to prior studies. This finding prompts a *post hoc* analysis in which an explanation is proposed for the weak association between BI and e-health use and hypothesize and alternative relationships are tested in an attempt to improve predictions of use. The principle intellectual contribution of this study is increased understanding of ways to overcome constraints in modeling IT use in the context of e-health, some of which may be generalizable to similar contexts outside healthcare.

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. healthcare provider. MyHealth presents encyclopedic health content with both browse and search access, email-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 healthcare 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 test.

Procedure

An invitation to volunteer for participation was sent to the email addresses of 1,750 individuals who had registered for access to MyHealth following announcement of the website in a promotional mailing to clinic patients. On average, registrants received the email 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 healthcare 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 health service use and need.

Three months later a new questionnaire was administered to assess use of MyHealth during the intervening period. A request to complete the follow-up questionnaire was emailed to the original 135 respondents, and a second request was emailed 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 email address. Average age of participants is 52, with a minimum age of 25 and a maximum age of 80, and 75% are women. Data screening showed no differences in any of the constructs by age or gender. Following registration, participants accessed MyHealth an average of 1.9 times (s.d. = 3.1 accesses).

Association Between BI and Use of MyHealth

Structural equation modeling (SEM) was used to test the association between BI and MyHealth use. Because of the relatively small sample size, the partial least squares method of SEM was applied using PLS-Graph (Chin, 1998). The independent variable in the model is BI, a latent factor deriving from two indicator measures that are drawn from prior research (Venkatesh et al., 2002). The dependent variable is e-health use, which measures the total number of times participants self-reported having used MyHealth for each of five services (these are referenced hereafter as *health services*): request a prescription refill, request an appointment, get health information, communicate with physician, and communicate with other healthcare staff. A significant relationship is found between BI and use (β = .254, p < .001, use R^2 = .065), however, predictiveness is low relative to the weighted average results of R^2 = .13 in the prior IT literature. This weak association suggests that determinants of BI will have relatively little effect on e-health use, regardless of their relationship with BI. This is especially true for antecedent factors studied by Wilson and Lankton (2004), which are theorized to exert only indirect effects on BI. Clearly these findings call for re-evaluation of the applicability of prominent IT acceptance models to the context of e-health and for the assessment of alternative models.

REANALYSIS: AN EXPLANATION AND NEW HYPOTHESES

Wilson and Lankton (2004) focused their attention on determinants of BI. The reanalysis presented in the present paper focuses on determinants of use, including BI. The first issue I address is to explain how characteristics of the e-health domain may act to weaken the assumed association between BI and use. Following that discussion, I present a new research model and propose hypotheses to test the model.

Explaining a Weak Association

E-health uses the same Internet infrastructure and WWW software conventions as many other online applications. However, predictions of use based on BI vary considerably across studies of online applications. For example, some studies of online communication and banking applications find BI to be highly predictive of use (Limayem and Hirt, 2003; Shih and Fang, 2004) but others find low predictiveness (Suh and Han, 2002, 2003; Szajna, 1996). The equivocal nature of findings among studies of similar technologies suggests the association between BI and use is not due to technology characteristics. Thus, I turn to two other types of factors that have been identified in the literature as influencing use. These are factors relating to individual users and factors relating to the task activities that are performed (Davis, et al., 1989, Hong, Thong, Won, and Tam, 2001; Igbaria, Guimaraes, and Davis, 1995; Keil, Beranek, and Konsynski, 1995). I consider each factor in turn.

Participants in this study are undeniably unique relative to subject populations of most IT acceptance research. They are older and comprise a higher proportion of women than is the case in any of the studies I reviewed in Table 1. Yet despite these demographic characteristics, cognitive measures taken from participants reflect relationships among beliefs and BI that parallel findings throughout the IT acceptance literature. Wilson and Lankton note regarding their test of three prominent IT acceptance models in this population, "it is reassuring to find that they are robust in the previously untested context of e-health and among a subject group primarily composed of middle-aged to elderly female medical patients, a population that has not previously been studied by technology acceptance researchers" (2004, p. 245). It is only in the relationship between BI and use that the results diverge from typical findings. The number of older individuals who use e-health services is disproportionately high relative to younger adults (McKillen, 2001), thus, it seems unlikely that participants in this sample would be especially reluctant to act upon their intentions.

A more likely source for divergence from typical findings arises from the activities e-health is used to support, which center on acquiring health information, diagnosis, or treatment. Access to e-health frequently is initiated by onset of illness, injury, or medical concern. In such circumstances, motivational effects of BI on e-health use are likely to be subordinated to *facilitating conditions* outside an individual's personal control. Triandis writes

> At 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, 1997, pp. 206-207).

I propose that facilitating conditions related to illness, injuries, or medical concerns are more salient to e-health than is the case with facilitating conditions relating to typical IT applications that are addressed in IT acceptance research, such as email and web browsing. As a result, facilitating conditions could play a larger role than BI in determining use of e-health. This proposition has several ramifications for future research designs. First, it cautions against assuming a strong association between BI and use in the context of e-health, so future studies should implement longitudinal designs that allow measurement of e-health use. Second, models of IT acceptance that are based entirely upon rational processes, such as TAM, will be less predictive in the context of e-health and other applications where facilitating conditions subordinate BI. Finally, it will be necessary to evaluate alternative models of acceptance in order to increase predictiveness to levels that can accurately guide providers in designing successful e-health applications.

In the following sections, I present a *post hoc* analysis of data from the two MyHealth questionnaires that begins to address the research ramifications presented above. I first propose a research model that augments the relationship between BI and use with three factors hypothesized to proxy for direct measurement of facilitating conditions. I then test these hypothesized relationships and conclude with a discussion of the overall findings.

Research Model and Hypotheses

The research model I propose for the new analysis augments BI with three factors related to participant's experiences and situation prior to being introduced to e-health. As shown in Figure 1, the model posits that, in addition to BI, offline service use, frequency of medical office visits, and structural need for medical services will jointly determine use of e-health.

Where a specific IT has been used previously, the level of prior use can be a more important predictor of future use than BI (Cheung and Limayem, 2005) or can replace effects of BI altogether (Kim and Malhotra, 2005). In effect, prior use serves as a proxy measure of the presence or absence of facilitating conditions during the prior period. Although participants in the present study did not use MyHealth previously, they did use the same health services that MyHealth supports. Prior utilization of an organization's service is known to predict future service use (Naessens, Baird, Jouten, Vanness, and Campbell, 2005), suggesting that use of MyHealth will be influenced by prior use of the same health services offered by the provider in its offline facilities, e.g., at a healthcare clinic.

H1: Prior use of offline health services will predict use of e-health.

A second aspect of prior use relates to utilization of general services offered by the provider. I hypothesize that interacting with the provider in the form of office visits will offer a measure of general service utilization that is salient to predicting use of MyHealth. The rationale is that patients who visit clinic offices frequently will be more motivated to use MyHealth regardless of the level at which they use the five specific offline health services.

H2: Prior number of office visits will predict use of e-health.

Wilson, Mao, and Lankton (2005) conducted a study of IT continuing use involving applications that are used only sporadically. They consider e-health to be an example of *sporadic use* IT, based upon the irregular and infrequent occurrence of factors that initiate many accesses (e.g., onset of illness). Wilson et al. find that irregular prior use and habit are key predictors of continued use in a setting where subjects had several months of prior use experience. Based on these findings, they call for research to predict initial use from individuals' *need* for services. Healthcare researchers find that need for healthcare is associated with higher rates of healthcare utilization (Ford, Trestman, Steinberg, Tennen, and Allen, 2004; Naessens et al., 2005), and that individuals with a low need for health services are less likely to use e-health services (Hsu, Huang, Kinsman, Fireman, Miller, Selby, and Ortiz, 2005). Thus the third hypothesis tests the predictiveness of prior need for health services that is structural, i.e., where need is statistically associated with observable characteristics of participants. Because the assessment is statistical rather than direct, I consider structural need to be a proxy measure for presence or absence of facilitating conditions.

H3: Structural need for health services will predict use of e-health.

Structural need has not been studied to my knowledge in the context of IT acceptance. 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, and I propose in Hypotheses 4a and 4b to test their individual effects as formative antecedents to structural need within the research model.

H4a: Age will predict structural need for health services.

H4b: Chronic health condition will predict structural need for health services.

The final hypothesis tests the predictiveness of the full research model vs. alternative nested models.

H5: The full research model will be more predictive of e-health use than any nested model.

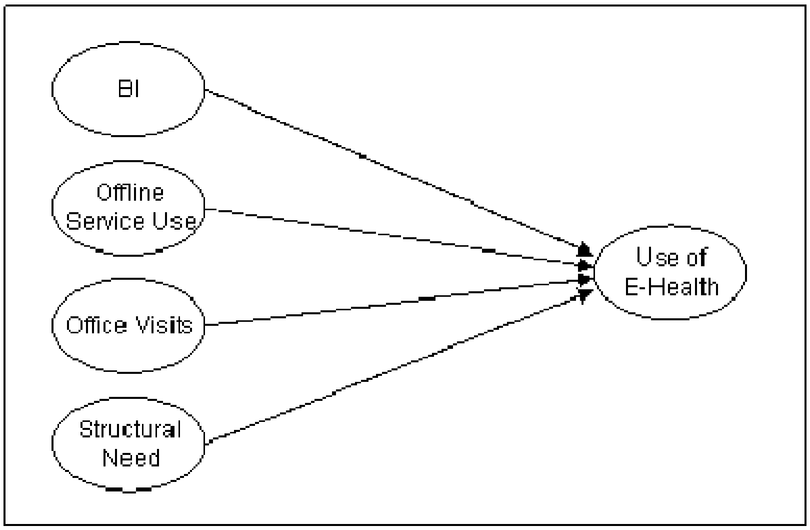

Figure 1. Research Model.

RESULTS

Hypothesis testing was completed using PLS-Graph. BI was measured as a reflective latent variable with two indicator items. Offline service use 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 (Gefen, Straub, and Boudreau, 2001) with two indicator items: age and presence of chronic health condition. E-health use was measured as the total of self-reported access to five health services on MyHealth during the three-month period following completion of the first questionnaire. Confirmatory factor analysis and correlation analysis were conducted but are not reported here because of space constraints. These analyses indicate that the measures are internally reliable and construct-valid.

All hypotheses are supported. E-health use is predicted by use of offline services (path coeff. = .410, $p < .01$), frequency of prior office visits (path coeff. = .213, $p < .05$), and by 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 presence of a chronic health condition (path coeff. = .864, $p < .0001$).

Finally, the full research model (shown in column 8 of Table 2) provides significantly better predictions of e-health use than any other model ($p < .05$)[3]. Modeling of e-health use based upon BI (shown as column 1 of Table 2) is significantly worse than all other models except model 2 (BI plus office visits).

[3] Significance of R^2 differences was calculated using between-model F-tests that account for the differing number of variables in each model.

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 Use → 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 R^2	.065	.066	.183	.190	.219	.252	.294	.335

[1] $p < .05$ [2] $p < .01$ [3] $p < .001$ (one-tailed *t*-tests)

Table 2. Model Comparisons, Arranged in Order of Increasing Explained Variance (R^2)

DISCUSSION

The findings demonstrate that predictiveness of rational models of IT acceptance, such as TAM, can be limited in the context of e-health. Predictions of initial use of e-health can be improved substantially by incorporating measures of offline service utilization and structural need. This finding has important practical implications, as these factors can be assessed early in the design process. Healthcare providers can use this information to identify patient populations who are most likely to use e-health and to guide design of e-health applications that support targeted needs. For example, the findings regarding chronic disease suggest affected patients are disproportionately motivated to try out e-health and are well-positioned, therefore, to benefit from targeted services, e.g., providing support for disease management.

In addition, contrasts among full and nested models show the importance of studying BI, offline service use, and need jointly. Regardless of need, patients sometimes do not use health services due to a wide range of geographic, financial, organizational, social, trust, and personal factors (Ford, Bearman, and Moody, 1999; Forrest and Starfield, 1998; Leisen and Hyman, 2004). For these individuals, prior use can be an essential predictor of future use. In many cases patients who are willing to use health services may not have an immediate, medical need (Cantor and Fallon, 1997).

It would be useful for future research to build upon these findings. First, measurement should be extended beyond the three-month period I assessed in order to understand how well the research model predicts longer-term effects and to explore usage patterns of participants who indicated their intention to use MyHealth but who may not have had a cause to use it during the assessment period. Second, 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 motivate use of online services. Finally, the results linking use to two aspects underlying structural need (age and chronic health condition) suggest that e-health is well-received by populations who may benefit most from e-health services, such as healthcare information and online support communities. This finding should prompt researchers to explore whether additional factors may be important contributors to this construct and to study which services are most beneficial to populations with specific patterns of structural need, e.g., elderly diabetics.

Conclusion

The present research was designed initially to be an application of three well-established IT acceptance models to predict e-health use by incorporating context-specific antecedents into the models. That design was successful at the stage of predicting BI, but subsequent measurement of e-health use revealed an unexpectedly low association between these factors. This finding prompted a *post hoc* analysis of the overall data to determine whether prediction of e-health use could be improved by augmenting BI with factors representing offline health service utilization and structural need for health services, applied as proxy measures for facilitating conditions. These factors offer the benefit of being available for measurement prior to the design of e-health services. The augmented research model greatly improves prediction of e-health use beyond TAM and other prominent IT acceptance models. Although the route was circuitous, this finding does meets the practical objective of providing practical guidance for providers.

The present study also holds interesting ramifications for researchers. Although authors have called for addressing effects of prior behaviors and need in modeling initial stages of IT use, relatively little research has been reported in this area. The findings suggest that exploring *non-rational* characteristics of individual IT users can provide important improvements in predicting initial IT use in cases where effects of BI are subordinated by facilitating conditions, as appears to occur in the context of e-health.

REFERENCES

1. Cantor, C., and Fallon, B. (1997) *Phantom illness: Recognizing, understanding, and overcoming hypochondria,* Houghton Mifflin, Boston.
2. Cheung, C. M. K., and Limayem, M. (2005) The role of habit in information systems continuance: Examining the evolving relationship between intention and usage, in D. Avison, D. Galletta, and J. DeGross (Eds.), *Proceedings of the 26th International Conference on Information Systems,* Las Vegas, NV, USA, University of Minnesota, 471-482.
3. Chin, W. (1998) The partial least squares approach to structural equation modeling. In G. A. Marcoulides (ed.), *Modern Methods for Business Research,* Lawrence Erlbaum Associates, Mahwah, NJ, 295-336.
4. Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1992) Extrinsic and intrinsic motivation to use computers in the workplace, *Journal of Applied Social Psychology,* 22, 1111-1132.
5. Davis, F. D., Bagozzi, R. P., and Warshaw, P. R. (1989) User acceptance of computer technology: A comparison of two theoretical models, *Management Science,* 35, 982-1002.
6. Davis, F. D. (1989) Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly,* 13, 319-329.
7. Dishaw, M. T., and Strong, D.M. (1999) Extending the technology acceptance model with task-technology fit constructs, *Information & Management,* 36, 9-21.
8. Fishbein, M., and Ajzen, I. (1975) *Belief, attitude, intention and behavior: An introduction to theory and research,* Addison-Wesley, Reading, MA.
9. Ford, C. A., Bearman, P. S., and Moody, J. (1999) Foregone health care among adolescents, *Journal of the American Medical Association,* 282, 2227-2234.
10. Ford, J. D., Trestman, R. L., Steinberg, K., Tennen, H., and Allen, S. (2004) Prospective association of anxiety, depressive, and addictive disorders with high utilization of primary, specialty and emergency medical care, *Social Science & Medicine,* 58, 11, 2145–2148.
11. Forrest, C. B., and Starfield, B. (1998) Entry into primary care and continuity: The effects of access, *American Journal of Public Health,* 88, 9, 1330-1337.
12. Gefen, D., Straub, D. W., and Boudreau M-C. (2001) Structural equation modeling and regression: Guidelines for research practice, *Communications of the AIS,* 4, 7.
13. Harris, K. D., Donaldson, J. F., and Campbell, J. D. (2001) Introducing computer-based telemedicine in three rural Missouri counties, *Journal of End User Computing,* 13, 4, 26-35.
14. Hartwick, J., and Barki, H. (1994) Explaining the role of user participation in information system use, *Management Science,* 40, 4, 440-465.
15. Hong, W., Thong, J. Y. L., Wong, W. M., and Tam, K. Y. (2001) Determinants of user acceptance of digital libraries: An empirical examination of individual differences and system characteristics, *Journal of Management Information Systems,* 18, 3, 97-124.
16. Horton, R. P., Buck, T., Waterson, P. E., and Clegg, C.W. (2001) Explaining intranet use with the technology acceptance model, *Journal of Information Technology,* 16, 237-249.
17. Hsu, J., Huang, J., Kinsman, J., Fireman, B., Miller, R., Selby, J., and Ortiz, E. (2005) Use of e-health services between 1999 and 2002: A growing digital divide, *Journal of the American Medical Informatics Association,* 12, 164-171.
18. Igbaria, M., Guimaraes, T., and Davis, G. B. (1995) Testing the determinants of microcomputer usage via a structural equation model., *Journal of Management Information Systems,* 11, 4, 87-114.
19. Keil, M., Beranek, P. M., and Konsynski, B. R. (1995) Usefulness and ease of use: Field study evidence regarding task considerations, *Decision Support Systems,* 13, 1, 75-91.
20. Kim, S. S., and Malhotra, N. K. (2005) A longitudinal model of continued IS use: An integrative view of four mechanisms underlying postadoption phenomena, *Management Science*, 51, 5, 741-755.

21. Lai, T. L. (2004) Service quality and perceived value's impact on satisfaction, intention and usage of short message service (SMS), *Information Systems Frontiers,* 6, 4, 353-368.

22. Lazarus, I. R. (2001) Separating myth from reality in e-health initiatives, *Managed Healthcare Executive*, June, 33-36.

23. Leisen, B., and Hyman, M. R. (2004) Antecedents and consequences of trust in a service provider: The case of primary care physicians, *Journal of Business Research*, 57, 9, 990-999.

24. Limayem, M., and Hirt, S. G. (2003) Force of habit and information systems usage: Theory and initial validation, *Journal of the AIS,* 4, 65-97.

25. McKillen, D. (2001) E-health traffic—slow but steady growth, *Marketing and Media,* 36, 9,10-12.

26. Moon, J., and Kim, Y. (2001) Extending the TAM for a World-Wide-Web context, *Information & Management,* 38, 217-230.

27. Morris, M. G., and Dillon, A. How user perceptions influence software use, *IEEE Software*, 4, 58-65.

28. Naessens, J. M., Baird, M. A., Jouten, H. K. V., Vanness, D. J., and Campbell, C. R. (2005) Predicting persistently high primary care use, *Annals of Family Medicine,* 3, 4, 324-330.

29. Ouellette, J. A., and Wood, W. (1998) Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior, *Psychological Bulletin,* 12, 54-74.

30. Payton, F. C., and Brennan, P. F. (1999) How a community health information network is really used, *Communications of the ACM,* 42, 85-89.

31. Sheppard, B. H., Hartwick, J., and Warshaw, P. R. (1988) The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research, *Journal of Consumer Research,* 15, 325-343.

32. Shih, Y., and Fang, K. (2004) The use of a decomposed theory of planned behavior to study Internet banking in Taiwan, *Internet Research,* 14, 3, 213-223.

33. Stoel, L., and Lee, K. H. (2003) Modeling the effect of experience on student acceptance of web-based courseware, *Internet Research,* 13, 5, 364-374.

34. Suh, B., and Han, I. (2002) Effect of trust on customer acceptance of Internet banking, *Electronic Commerce Research and Applications,* 1, 247-263.

35. Suh, B., and Han, I. (2003)The impact of customer trust and perception of security control on the acceptance of electronic commerce, *International Journal of Electronic Commerce,* 7, 3, 135-161.

36. Szajna, B. (1996) Empirical evaluation of the revised technology acceptance model, *Management Science,* 42, 1, 85-92.

37. Triandis, H. C. (1997) *Interpersonal behavior,* Brooks/Cole Publishing, Monterey, CA.

38. Venkatesh, V., Speier, C., and Morris, M. G. (2002) User acceptance enablers in individual decision making about technology: Toward an integrated model, *Decision Sciences,* 22, 297-316.

39. Wilson, E. V., and Lankton, N. K. (2004) Modeling patients' acceptance of provider-delivered e-health, *Journal of the American Medical Informatics Association*, 11, 4, 241-248

40. Wilson, E. V., Mao, E., and Lankton, N. K. (2005). Predicting continuing acceptance of IT in conditions of sporadic use. In N. C. Romano, Jr. (Ed.), *Proceedings of the Eleventh Americas Conference on Information Systems,* Omaha, NE, USA.