Taking Charge of Your Health: The Drivers of Enrollment and Continued Participation in Online Health Intervention Programs

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Abstract

Information technology (IT) is fundamentally altering the way in which healthcare is delivered to consumers, and offers the promise of improving patient safety, reducing medical errors, improving efficiency, and increasing the reach of health delivery programs. The aim of this research is to examine the factors affecting the adoption and post-adoption of a significant IT innovation in healthcare: online health intervention programs that provide technology-mediated guidance and aid individuals in self-managing their health care. A key challenge confronting health program providers is that of motivating initial enrollment and subsequent continued participation in these interventions. Limited prior work in the information systems and health informatics literature has examined the uptake of technology-mediated health intervention programs. Using data from an online healthcare portal site, this study proposes and empirically tests relationships between the determinants and participation in online health intervention programs.

1. Introduction

Information technology (IT) has recently become the focus of attention in the healthcare sector as key stakeholders view it as an important means to address persistent problems of quality and cost in healthcare delivery [4,31]. A number of important innovations are being introduced, including electronic health records, telemedicine, and electronic prescribing [5]. In this context, one remarkable transformation is the extent to which the online availability of health-related information via the Internet has created a significantly more well-informed consumer population [15]. In 2006, a Pew Internet and American Life Project revealed that approximately 10 million individuals in America use the Internet daily to obtain health or medical information [14]. Given the extent to which consumers are using the Internet for accessing health information, it is not surprising to witness the emergence and rapid growth of online health intervention programs in health and insurance portal sites.

Technology offers several advantages as a channel for health intervention programs. Online healthcare intervention programs offer a cost-effective means for both healthcare organizations and individuals to administer and monitor lifestyle changes that promote wellbeing. Unlike offline programs, online health programs allow healthcare organizations to lower their long-term labor costs for monitoring clients. Technology mediation supports easy and less labor intensive capture of crucial patient interactions. These data can then used to provide additional value-added services to patients through data mining and personalization. Individuals can also lower resources in terms of time and money. This is due to the increased accessibility and flexibility technology provides in terms of location and schedule. Simply put, with online health intervention programs, individuals can access these programs with no geographic or temporal boundaries.

However, in spite of the many advantages of online health interventions, their uptake has been slow [1]. In fact two major issues identified across 15 National Institutes of Health-funded behavior change projects were engagement and maintenance of participation in health intervention programs. Another 2005 survey conducted by Forrester Consumer Technographics showed that 28% of people who completed an online health risk assessment (HRA) enrolled in a structured health program. For online health programs to be effective, it is important to understand how to facilitate user enrollment in the recommended programs, and to prevent user disengagement before program completion. The purpose of this study is to examine the factors affecting users' initial and continued participation in these programs.

A review of the literature indicates that research examining online health programs is limited. The handful of existing studies provides some insights into the effectiveness of such programs and the types of patients who are likely to see benefits from participation. For instance, in an empirical study on automated mental health interventions, Lieberman et al. [24] found that patients with higher motivation to change their behavior are more likely to find online intervention programs helpful. However, this study did not explore whether higher motivation has any impact on enrollment and subsequent participation. Another study by Hill et al. [18], provides some evidence of the usefulness of online health intervention programs. Their results reveal greater improvements in self-esteem, social support and empowerment in chronically ill rural women when they participated in an online health intervention program as compared to those who did not participate. To the extent that online health intervention is a relatively nascent phenomenon but one that has the potential to be of significant value, further research on understanding how such programs may be successfully implemented is clearly warranted.

As with many offline programs related to health maintenance, online health intervention programs are user initiated, directed, and controlled. Thus, their success is critically contingent on the capability of individuals to self-regulate. Self-regulation is the ability to remain focused on a goal and maintain this ability until goal attainment [3]. Continued usage or post adoptive behavior in the context of IT requires enforcement of self-regulatory behavior. Similar to other self-regulatory processes, continued usage requires individuals to operate through a personal standard which causes them to continuously evaluate the system and react accordingly to this standard, such as deciding whether to use the system or terminate its use. Ultimately, the health and wellness benefits of online health intervention programs can only be ensured through continued use by users. While literature in health informatics sheds some light on the characteristics of individuals engaging in online health programs, relying solely on this perspective is limiting as this literature does not explicitly incorporate the role of technology when applying the theories in an online context. The uptake of online health intervention programs typically involves the interplay between the determinants of health prevention behavior and technology but the current literature does not offer much guidance on this interplay. Thus understanding the determinants by considering both aspects can help to sharpen existing theory. We provide a theoretical framework that integrates both information systems literature on technology acceptance and health informatics literature in order to propose a model for initial and continued participation of individuals in online health intervention programs.

Motivated by the growing prevalence of online health intervention programs and their social and economic value potential, we focus on three research questions: 1) what factors affect an individual's initial enrollment in an online health intervention program, 2) what factors affect continued participation in the program, and 3) how do the drivers of initial participation differ from those of continued involvement? We use data from an online health portal related to an online exercise and nutrition program that includes 925 initial enrollees and over 404 participants who continued the program. Results reveal that the drivers of initial participation are distinct from those of continued participation and provide insights for health-related organizations in implementing similar technology-mediated health programs and guidelines for normative health behavior change.

2. Theoretical Background

Two streams of literature, information systems and health informatics, constitute the foundation for the theoretical framework underlying our study. We provide a brief review of the relevant literature and key findings from it.

2.1. Information Technology Adoption and Post-adoption

There is a robust body of IS literature grounded in theories from social psychology that examines various phenomena related to IT adoption and usage, including intentions to use, actual use behavior, and post-adoptive use. A recently formulated Unified Theory of Acceptance and Use of Technology (UTAUT) [43] synthesizes the dominant theoretical models proposed in prior work as conceptualizations of IT use and adoption behavior. Drivers of acceptance behaviors include attitudes, subjective norm, and various beliefs about the outcomes associated with technology use. Most relevant to our conceptualization is the key finding in UTAUT of the moderating influence of individual level factors on technology adoption and use. These factors include demographics, user experience, and organizational context. The impact of individual differences is especially important in online health programs because previous studies in the health informatics literature have found significant relationships between demographics and participation in offline health programs. UTAUT provides insight into an initial set of individual characteristics such as age and gender that are likely to influence participation in online health programs using a technology adoption perspective. Next, we extend this set of individual differences to include others that are particularly salient in previous literature on health behavior.

2.2. Health Behavior

Moorman and Matulich [28] developed a model of health behavior where consumer characteristics are conceptualized as health motivation or health ability. Their theory emphasizes the importance of interaction effects among these characteristics to explain a wide range of actual preventive behaviors in the daily lives of the consumers ranging from health information seeking to stress management. Three types of individual characteristics were examined: health motivation, perceived health status, and health ability.

First, health motivation is defined as an individual's "goal-directed arousal to engage in preventive health behaviors" [25,32]. This characteristic focuses on individual willingness to perform or interest in performing heath behaviors. Thus, an individual who has higher health motivation is more likely to perform certain types of health enhancing behaviors such as exercising regularly, not smoking, and eating a balanced diet.

The second individual characteristic, "perceived health status", refers to the consumers' perceived physical and mental well-being. In previous literature, results related to the effects of perceived health status on the adoption of health behaviors have been inconclusive [28]. On one hand, research has found that consumers who have low perceived health status increase their uncertainty about their ability to achieve a better health status, which in turn has a negative effect on health promotion behavior. Other research finds lower perceived health status to be beneficial for consumers as it increases the adoption of health prevention behaviors such as engaging counseling services in hospitals [34].

Finally, health ability is defined as the consumers' resources, skills, or proficiencies for performing preventive health behaviors. Seven types of consumers' ability were examined in their study: health knowledge, health locus of control, health behavioral control, education, age and income. The findings from this study suggest that different types of determinants are important for different types of health enhancing behaviors.

To develop a comprehensive framework which can explain the behaviors of users who participate in online health intervention programs, we adopt two lenses: health behavior adoption and technology adoption. The UTAUT model provides a theoretical framework for understanding the role of individual characteristics in technology adoption and use, and the consumers' health behavior perspective [28] identifies the factors driving individual health prevention behavior. Juxtaposing the insights from the two literatures, we propose a model for examining the initial and continuous participation of online health programs as shown in Figure 1. The theoretical rationale for the proposed relationships is developed below.

3. Research Hypotheses

As shown in Figure 1, three classes of individual characteristics are proposed to be salient drivers of initial participation: demographics, socio-psychological variables, and individual motivation. Among demographic variables, two characteristics dominantly found to be important determinant in previous work which will be used in this study are age and gender.

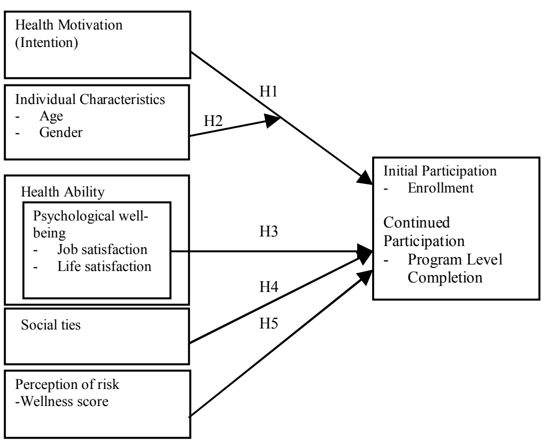

Figure 1: Research Model

3.1 Intention

Intention is the "forethought" for behavior to occur and has been conceptualized as the commitment to take action in order to change [3]. It is a psychological state that encapsulates the "willingness, or behavioral readiness, to initiate behavior change". However, the relationship between intention and adoption is not clear. In examining intention and participation in health programs, Davis and his colleagues found intention to be weakly related to actual behavior and participation [10]. Opportunity, resource availability and limitations, beliefs and cost-benefit analysis are some mediating factors that may influence this relationship. However, these factors are not the focus of this study.

Although previous results are equivocal for finding an effect on adoption of offline health programs, we argue that in considering the participation intention in online health intervention programs, there are two aspects that are germane – health motivation and adoption intention of the information system. First, health motivation [39] has been found to have a direct effect on offline health enhancing behaviors. Second, adoption intention may be directly influenced by performance expectancy [43]. In user acceptance studies, intention has been found to be a significant predictor of actual behavior [38]. Since health motivation and technology adoption intention both constitute the participation in online health intervention programs and have a positive effect, we suggest that participation intention will have a positive effect on participation in online health intervention programs.

> H1: Initial participation intention in an online health intervention program is positively associated with initial and continued participation.

3.2. Individual Characteristics

Demographic characteristics are important influences on health prevention behavior. In the health informatics literature, age, income, gender and education have been examined in previous research where mixed results were found. On the other hand, in the technology adoption and use literature, age and gender have been found to moderate the influence of behavioral intention on adoption [42]. We juxtapose the findings across disciplines and discuss how each of these demographic characteristics is likely to affect the participation in online health intervention programs.

3.3. Age

The effect of age on participation in online health programs is likely to be somewhat complex. The health informatics literature finds that older people are more likely to participate in health intervention programs as compared to younger people. This finding has been explained on the basis of one's: (1) perceived susceptibility (or vulnerability) to a negative outcome and (2) perceived benefits of taking a certain action. Health belief theorists argue that older individuals will exhibit positive health behavior because of the increased perceived vulnerability of self to poor health status [23, 34]. To the extent that age is significantly associated with an increasing number of health related issues and heightened chances of co-morbidity and mortality, one would expect to find older users to be more likely to participate in online health intervention programs to reduce their perceived vulnerability. Similarly, for continuous participation, there is empirical evidence that older users are more likely to continue participating in online health programs as compared to younger users [44]. However, there is also reason to believe that the findings in most of the studies in offline health programs may not carry over to the online health programs context. Although several of the health studies suggest that older individuals are usually more likely to participate in offline health programs, younger consumers have been found to perform certain health behaviors more frequently and with greater persistence than older consumers when their health motivation is low [27].

The difference in the delivery platform for the health program is likely to affect participation. In this study, the health programs are technology-mediated. Age has been found to be an influential driver of technology acceptance and use: previous studies in the technology use and acceptance literature find that younger users are more strongly influenced by attitude toward using the technology whereas older workers are more strongly influenced by subjective norm [28,29]. In fact, age has been shown to be a moderating influence on the effect of intention on enrollment such that younger users are more likely to have a stronger effect of intention on enrollment as compared to older users [41].

Based on these findings, we posit that younger users will be more likely to participate in online health programs. There are two reasons underlying this expectation. First, since the channel that the health program is delivered on is fully technology mediated, it involves significant cognitive and information processing. Older users may experience greater difficulty in using electronic information due to increased stress on physical ability such as their eyesight. Studies have also found older users to be less receptive to technology as compared to younger users [2,21]. Second, there is a higher likelihood that older users may already have enrolled in other health programs. This competition reduces the likelihood that older users will enroll in online health programs. We therefore test:

> H2a: The influence of participation intention on initial and continued participation in an online health intervention program is moderated by age, such that the effect is stronger for younger users.

3.4. Sex

Many individual behaviors have been attributed to sex. In general, sex is associated with systematic variations in the traits possessed by men and women. Although there could be many sex traits which could influence the effect of intention on participation in online health intervention programs, risk avoidance behavior is likely to exhibit a strong influence in the health care context.

Studies have found that women typically have a higher occurrence of illnesses and disabilities as compared to men. It has been suggested that differentials due to the frequency of illness and pace of death lead to differences in the adoption of health care services and self management among females and males [7, 43]. This claim has been supported in the health informatics literature as studies find the effect of sex to be significant for participation in both online and offline health programs where females are more likely to participate as compared to males. Therefore, extending this line of reasoning, sex is likely affect participation in online health programs.

In IS research, previous studies have found significant moderating effects of sex on technology use [42]. Women are influenced by the extent to which they believe that people who are important to them think they should perform the behavior, i.e., subjective norms are highly influential for women [42]. It follows that women are more likely to participate in an online health intervention program because it will be perceived as a beneficial activity. This is also consistent with the risk-avoidance behavior exhibited by women discussed in the health literature. The convergence of the results from these two streams of literatures leads us to posit that sex has an effect on both initial and continued participation in online health intervention programs.

> H2b: The influence of participation intention on initial and continued participation in an online health intervention program is moderated by sex, such that females are more likely to participate as compared to males.

3.5. Psychological Well-Being

Psychological well-being refers to an individual's affective state of mind. In this study it is conceptualized as an individual's satisfaction in two major domains: their job and their overall life. Psychological well-being can be viewed as an important trigger to a person's intention to change. The notion of health ability [27] reflects psychological well-being because studies have shown that an individual with better psychological well-being can engage in health enhancing behaviors more effectively because s/he is able to have better "thought-action" skills and the ability to deploy resources for achieving better health [15]. Furthermore, a higher level of psychological well-being is likely to invoke positive emotions and lead to an optimistic attitude in an individual. Higher satisfaction with life can become a motivator creating a higher level of readiness to change which causes one to take positive actions to further improve general well-being [36]. In fact, gratitude oriented people have been found to have better well-being and take more positive health actions such as spending more time exercising [13]. Moorman and Matulich [27] found that under certain conditions (e.g. health knowledge, perceived health status, health locus of control, health behavioral control, education, age and income) individuals with higher perceived health status are more likely to perform certain health behaviors. To the extent that individuals are satisfied with their work and life domains, they are likely to perceive a more positive health status and take action to maintain the positive state of their existence. Based on this logic we test:

> H3: An individual's level of psychological well-being is positively associated with initial and continuous participation in an online health intervention program.

3.6. Social Ties

The preceding discussion has identified several individual-level factors that affect participation in online health intervention programs. However, individuals fundamentally exist within a social context. As suggested in both health informatics and information systems literature, it is also important to consider the complex interplay arising from the interactions between individuals and their collective as the latter is likely to have a major influence on individuals' decision to participate in health promotion behavior. Stronger social ties with friends and family lead to greater emotional and informational provide a source of relevant information.

Such social support has been posited to promote general mental and physical well being [8,35], and act as an environmental stimulus for a person to take positive actions in maintaining good health [16,39]. A supportive social environment is created with the availability of supportive social ties and reinforces positive beliefs about participation in health programs. Previous studies have found evidence that social support is associated with healthy lifestyle behavior. Some studies have argued that social support has a major role to play in smoking cessation behavior, although there is mixed support for this finding [19,6,11,12]. In addition, previous studies have found that the perceived relationship strength of an individual with their colleagues has a positive effect on participation in offline health program. For instance, Scheier and Carver [37] found a positive relationship between organizational support and participation in offline health programs. This is because a positive work climate is associated with less stress, which essentially leads to a greater intention to take positive action. Based on a similar logic, social influence has been found to have an effect on use intention in the technology adoption literature [42]. The degree to which an individual perceives his or her important "others" regard the use of the system as an essential behavior, he or she is more likely to use a technology. Extending this line of reasoning to the online health intervention programs, since the participation in online health programs will be deemed as a beneficial activity, it is likely that an individual who has strong ties with his family and peers will perceive that these important referents believe that he should participate in an online health program. Hence he is more likely to enroll and participate in the program. We therefore test:

> H4: The strength of an individual's social ties is positively associated with initial and continued participation in an online health intervention program.

3.7. Perception of Risk

The final influence on initial and continued participation, perception of risk is conceptually identical to perceived health status. Wang and Etter [45] argue that the concept of "health vulnerability" plays an important role in causing behavioral change. Those with a lower perceived health status are likely to be more motivated as compared to an individual who perceives himself or herself as healthy. If one perceives himself as more prone to a disease, the desire to take positive action by enrolling in a health program which prevents the disease is strengthened. Hill et al. [18] found that the belief that one is more vulnerable to tuberculosis actually led people to take preventive action. Similarly, there are many other studies which support this relationship [20,22,25]. Therefore, if one perceives himself as more prone to a disease, he is likely to persist in the program to improve his health.

> H5: An individual's perception of risk is positively associated with initial and continued participation in an online health intervention program.

4. Research Method, Data Collection and Analysis

4.1. Research Context

Our empirical analysis is based on archival data from a health-program provider company that hosts its programs on a popular online health portal site. The sampling period is one year, from 24 May 2005 to 30 Jun 2006. In addition to providing online health intervention programs, this portal also offers online health information for its users. The potential user is anyone who registers at the web site. This data source was provided as a snapshot from the company's database. The information that serves as the input for this analysis is drawn from the users' responses to health risk appraisal (HRA), users' activity log and users' enrollment and participation in the health intervention programs. To ensure privacy of the users, we obtained the data in de-identified form with a unique userid associated with each user.

At the portal site, a registered user of the portal can choose to provide responses to a health risk appraisal (HRA) form. Registration is open and available to anyone. A health risk appraisal form consists of a set of demographics, lifestyle, health, and behavior questions to evaluate a person's health risk. Based on the user's responses to these questions, the site generates a wellness score for the user. Users can choose to enroll in any of the online health coaching programs provided for weight loss, nutrition, exercise, quitting smoking, managing diabetes, heart disease, and stress. Each program consists of several levels, with a quiz provided at the end of every level. The quiz tests the knowledge of the users based on the information provided at each level. For testing of research hypotheses, we focus on users who have enrolled in an exercise and nutrition program that is a general wellness program and does not cater to any specific health condition.

4.2. Measures

4.2.1. Dependent variables. For initial participation, we use a binary dependent variable "enroll", to capture the initial participation outcome. This measure reflects whether the user enrolls in the exercise and nutrition online health coach program. For continued participation, we employ the program level that the user is currently at, reflecting persistence in the program after initial enrollment.

4.2.2. Independent variables. There are four independent variables for the initial participation and continued participation models: psychological well-being, perception of risk, initial participation intention and individual characteristics (age and sex). For each of these variables, responses from the health risk appraisal forms are used. Except for psychological well-being and perception of risk, all other variables are measured using single-item indicators.

Table 1 lists all constructs and their corresponding measures. We performed a factor analysis for psychological well being and obtained factor loadings greater than 0.65 for two items as shown in Table 1, suggesting that they represent a single latent construct. We operationalized the perception of risk based on the wellness score. This wellness score is generated by the HRA vendor using three key areas of the health and lifestyle of an individual. The first area is behavioral health risks measured by 10 separate items including smoking status, physical activity, body weight, blood pressure, total cholesterol, HDL cholesterol, alcohol consumption, seat belt usage, illness days and self-assessment of health. Mortality risks relating to heart disease, past stroke, cancer, diabetes, emphysema and chronic bronchitis comprise the second area. Finally, prevention practices such as blood pressure and cholesterol management are also included in the generation of the wellness score. The range of the wellness score is from 50 to 100.

Table 1: Variable Operationalization

Construct	Item(s)
Enroll or not	Enrollment in online health program
Age	Age (at last birthday)
Sex	Female /Male [1=Male, 2=Female]
Perception of Risk	Wellness score (Range: 50-100)
Intention	In the next 6 months, would you participate in a program that would help you to enhance your overall health? *Yes, No, Not sure*
Psychological Well-being	Would you agree you are satisfied with your job? In general, how satisfied are you with your life? (include personal and professional aspects) *Completely satisfied, mostly satisfied, partly satisfied, not satisfied*
Social Ties	In general, how strong are your social ties with your family and / or friends? *Very strong, About average, Weaker than average, Not sure*

4.2.3. Sample. A total of 19,033 HRA responses were obtained during the one year sampling period, of which 925 were from users enrolled in at least one health intervention program. Of these enrolled users, 404 users actually went through at least the first level in the exercise and nutrition program. The demographic profile of users who responded to the HRA is summarized in Table 2. The respondent group has an average age of 42, and is comprised of 36% male and 64% female. 87% of the respondents are Caucasian, 7% were Black, 3% were Hispanic, 1% were Asian or Pacific Islander, less than 1% were American Indian and less than 1% belonged to any other races. The sample is generally well-educated, with approximately 33% of the registered users being college graduates. Only 1.8% of the registered users attended high school, 16.9% were high school graduates, 28.9% attended college, 32.4% were college graduates and about 20% had post-graduate or professional degree. The mean income is in the range 40,000 to 74,999. Descriptive statistics for all research variables are presented in Tables 3. We note that a majority (67%) of the users has a health profile in the "excellent" category and none of the respondents belong to the "poor" health category. As observed from the data, the range of wellness score is from 50 to 100 and the average wellness score is high at 83.5, suggesting that the sample is reasonably healthy.

5. Empirical Results

We use regression analyses to test the research hypotheses. For enrollment, we use logistic regression because of the binary nature of this dependent variable. Ordinary least squares regression is used for the continued participation model. Results of the logistic and OLS regression are presented in Table 3. For each dependent variable, we estimate two models: one with only direct effects (Model 1), and a second that includes the interaction terms (Model 2).

5.2.1. Findings for Initial Participation

We proposed direct effects from psychological well-being, social ties, perception of risk, and participation intention on initial enrollment. In addition, we posited moderating effects for age and sex on the relationship between initial participation intention and enrollment. Participation intention has a significant and positive effect on enrollment ($\beta=0.854$, $p<0.01$) therefore H1 is supported. As proposed in H2a, age has a significant moderating influence on the effect of participation intention on enrollment. Sex does not moderate this relationship, therefore H2b is not supported. However, we observe that sex has a significant main effect on enrollment. In the case of H3, contrary to our prediction that psychological well-being is positively associated with enrollment, we find the effects of psychological well-being ($\beta=-0.100$, $p<0.01$) to be significant and negative. Both social ties (H4) and perception of risk (H5) are not significantly related to enrollment.

5.2.2 Findings for Continued Participation

The results for continued participation (Table 4) indicate that the drivers of persistence are distinct from the factors found to affect initial participation. H1 which proposed a positive influence of participation intention on continued participation ($\beta=-1.186$, $p<0.001$) is not supported. Age does not significantly moderate the effects of participation intention on persistence, therefore H2a is not supported. Although we find a significant moderating effect for sex, but in contrary to H2b, the results did not indicate that females were more likely to enroll or continue to participate in the programs. Perception of risk (H5) has a positive and significant effect ($\beta=0.016$, $p<0.01$) on continued participation, while psychological well-being (H3) is not significantly related to continued participation. As in the case of enrollment, the extent of an individual's social ties do not significantly influence their continued participation in the online health intervention program (H4).

Table 2: Health Profile of Respondents

Health Status	Wellness Score	Percentage
Fair	51-60	4.2
Good	61-70	12.2
Very Good	71-80	16.2
Excellent	80-100	67.4

Table 3: Regression Results for Initial and Continued Participation

Independent Variable	Mean	S.D.	Enrollment Model 1	Enrollment Model 2	Continued Participation Model 1	Continued Participation Model 2
INTENTION	1.223	0.975	0.854*	0.472	-0.212+	-1.186**
			(0.104)	(0.434)	(0.119)	(0.488)
AGE	42.39	11.57	-0.011*	-0.016*	0.002	0.003
			(0.004)	(0.004)	(0.004)	(0.005)
SEX	N.A.	N.A.	0.763*	0.724*	0.086	0.028
			(0.107)	(0.112)	(0.123)	(0.126)
PSYCHOLOGICAL WELL-BEING	6.099	1.089	-0.100**	-0.100**	-0.063	-0.058
			(0.041)	(0.041)	(0.052)	(0.052)
SOCIAL TIES	1.567	0.592	-0.092	-0.095	0.024	0.017
			(0.073)	(0.073)	(0.087)	(0.087)
PERCEPTION OF RISK	83.89	10.75	0.004	0.004	0.017*	0.016*
			(0.004)	(0.004)	(0.005)	(0.005)
AGE*INTENTION	51.88	45.105		0.024*		-0.012
				(0.009)		(0.010)
SEX*INTENTION	2.05	1.788		-0.256		-0.533**
				(0.241)		(0.271)
Constant			-4.515*	-4.030*	0.234	0.857
			(0.453)	(0.545)	(0.505)	(0.602)
Observations			19016	19016	404	404
R^2					0.040	0.053

* p <0.05; ** p<0.01

6. Discussion

Our research was motivated by the increasing prevalence of technology as a vehicle for improving the quality and accessibility of health and wellness programs. While prior studies have examined various aspects of off-line programs, we focused on a new and emerging type of intervention – online health programs that allow users to take charge and self-manage their health. The uptake of these programs has been slow and thus we sought to understand what factors explain the slow uptake. Broadly, our research has examined different outcomes in the context of such health intervention programs: initial enrollment and continued participation. We discuss each of these dependent variables in turn.

6.1.Initial Participation

For initial enrollment, consistent with prior studies, the results from this study provide some indication that individual characteristics such as age and sex play an essential role in users' enrollment in an online health intervention program. Our finding on age suggests that younger users with low intention are more likely to enroll in online health programs as compared to older users (Figure 2). On the other hand, older users are more likely to enroll in online health programs as compared to young users when the intention is high. Post hoc tests of the slopes reveal that the effects remained significant when intention is both high and low. Health programs may be suitable for specific user groups (e.g. young and old) and the interaction result suggest that depending on the goals of the site owners, site owners can focus their marketing efforts on specific programs targeted at a specific group of users such as the young users with low intention or older users with high intention. However, not all the hypothesized relationships were supported for enrollment. Contrary to the hypothesized relationship for psychological well-being, we found a negative and significant effect. This result indicates that individuals who are less satisfied with their life and work are more likely to enroll in the program. One plausible explanation for this contrary finding is that these individuals use the lack of satisfaction in life as a means to justify the action to increase their quality of life. In other words, the negative life situation motivates these individuals to seek ways to induce positive states in some other aspects of their life such as health. Another alternative explanation is in line with the locus of control theory. This theory suggests that individuals will seek something they can control and in this case, participating in online health intervention programs to improve their health, when other aspects of their life and work may not be under their control.

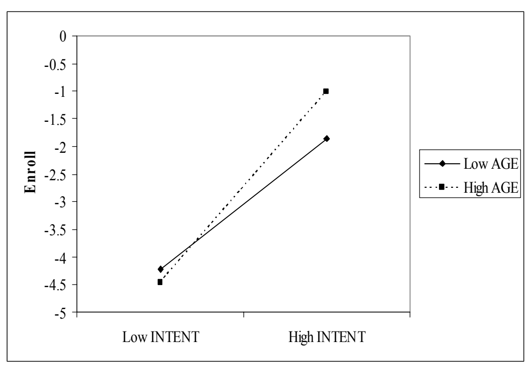

Figure 2: Moderating Effect of Age

We also find that social ties are not significant in predicting enrollment, indicating that the logic of social influence from friends and family does not apply in this setting. However, we believe that this finding may be an artifact of the way in which this construct was operationalized – a more granular measurement scale may have revealed relationships that our somewhat coarse measure was unable to pick up. This could also explain why we did not find any effect of perceived risk on initial enrollment.

6.2. Continued Participation

There is a striking difference in the results obtained for continued participation. The wellness score, a proxy measure for perception of risk, has a positive and significant effect ($p<0.05$), corroborating some of the earlier findings in the health informatics literature. We find a strong moderating effect of sex suggesting that sex play a central role in sustaining participation. This effect is negative and significant ($p<0.01$): the interaction plot (Figure 3) suggests that males are more likely to continue participation compared to females and this difference is greater with higher intention and this was supported by two-way ANOVA.

In addition, continuing intention has a negative effect. This is contrary to our hypothesized relation. One plausible explanation could be that individuals who are likely to sustain their participation are individuals who are already enrolled in similar programs such as offline health intervention programs and continued participation allows them to assess the viability of the program offered by the site. Although we did not find significant effects for psychological well-being and social ties, future research with fine grained measures could help to shed light on these relationships.

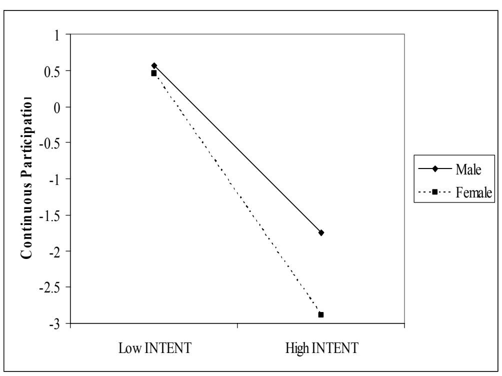

Figure 3: Moderating Effect of Sex

6.3. Theoretical Contributions and Implications

This study is an effort to provide an integrative lens toward studying the adoption of online health programs, a relatively new phenomenon. We demonstrate the value of integrating studies from technology adoption and health studies. In considering the adoption of health programs administered over a technology mediated channel, factors that affect technology adoption is likely to have an impact on online health program adoption. The present research demonstrates the value of the integrative lens to have a more comprehensive understanding in this area which we do not see in current studies. However, we acknowledge that to a large extent, the results did not do justice to the model as we were limited by the data.

These findings for initial participation have some important practical implications for health portal sites that offer online health intervention programs and for health professionals and site owners who manage them. Our results demonstrate the importance of distinguishing between initial and continued participation. Besides the need to distinguish the antecedents of initial and continued participation, future research needs to acknowledge the differences between antecedents of online and traditional health programs. From a practical view point, online site owners need to note the tendencies and try to balance demographics profile among their users. The interaction results for the continued participation model suggest that site owners need to consider increasing their efforts in sustaining the participation for females more than males. Site owners can also decide on the type of programs to focus their efforts on based on the different users which can be derived from their database. To save costs, the results also suggest that site owners can decide on targeting marketing messages to specific groups of users. Finally, results from this study suggest that site owners can influence participation in the range of programs by altering users' perception of risk. Since previous studies have found that a higher perceived risk is likely to increase participation, online health program providers can consider incorporating messages that create a heightened perception of risk by providing information on the adverse outcomes of not engaging in health promotion behaviors.

7. Limitations and Future Research

The results from this study should be interpreted with caution in light of its limitations. This study uses secondary data that inevitably suffers from some shortcomings. First, measures used may not be adequate in capturing some constructs. We acknowledge that single item measures and proxy measures may prove to be a threat to validity. This can be complemented by future research that solicits survey responses from users and health program providers. Second, the low R-square values for the models suggest that other factors that could be salient are not captured in the model. Furthermore, this is exacerbated by the use of secondary data where we derive the gross measures for our constructs. However, our goal in this research was to theorize and empirically test for the presence of significant relationships as opposed to explaining substantial variance in the dependent variables. Our data and measures allow us to adequately investigate the factors affecting initial and continued participation in technology mediated health intervention programs. Although a few hypotheses were not supported, this study provides a starting ground for further work in this area by illuminating some important determinants derived from integrating technology use literature and health literature which may be considered in future work. Finally, the study is limited to the context of online health intervention programs from a single portal site. Future work could examine other similar sites to corroborate the findings from this study.

8. Conclusion

This study sought to examine the determinants of users' adoption and post-adoption behavior in online health intervention programs. It elucidates the factors affecting initial participation and continued participation in online health intervention programs. Previous research on health intervention programs has largely been conducted in off-line settings and may be inadequate to identify the factors affecting participation in online health intervention programs. In order to fill this gap, we theorized using different streams of literature to provide an integrated perspective. Two theoretical models for initial enrollment and continued participation were proposed and empirically tested. A noteworthy strength of the study is that, in contrast to much research on technology acceptance that uses intentions as an outcome, our data includes actual behavior on initial participation and continued persistence in the program. The findings underscore the role of individual differences, psychological well-being, and perception of risk in enrollment, and maintenance of participation. Moderating influences of age and sex were found for initial and continued participation respectively. A comparison between antecedents found in previous literature on traditional health intervention programs and the findings from this study revealed a few differences. This highlights the importance of considering the role of technology and integrating factors found in the IS literature when studying the adoption and use of online health intervention programs.

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