The Use of Online Health-Management Tools and Health Care Utilization among Older Americans

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Abstract

Background and Objectives. The digital divide, or differences in access to technology, can have far-reaching consequences. This study identified disparities in access to online health-related technology. It then investigated associations between online health-related technology use and health care utilization among older adults in the U.S.

Research Design and Methods. The study used a cross-sectional data set of 1,497 adults aged 51 and older from the 2014 Health and Retirement Study (HRS)'s supplemental module (Health Behaviors), and the RAND version of the HRS fat file.

Results. Older age, being a racial/ethnic minority, married, uninsured, and having lower educational attainment, lower-income, and reporting poorer health were each associated with lower levels of use of online health-management tools. The use of online health-management tools was associated with a 34% greater mean number of doctor visits (IRR = 1.34, S.E. = 0.10, $p < 0.05$) than non-use. However, such use was not associated with the number nor type of hospitalizations. Indeed, only health care needs as measured by self-rated health status (OR = 0.58, S.E. = 0.18, $p < 0.05$) and the number of chronic conditions were associated with hospitalizations (OR = 1.68, S.E. = 0.07, $p < 0.05$).

Discussion and Implications. While more research is needed to clarify the purposes (e.g., prevention vs. treatment) and outcomes of health care service utilization as a function of technology use, it may be wise to proactively tackle the digital divide as one upstream strategy for improving various health and health care outcomes among older adults.

Keywords: Inequities, Race/ethnicity, Social determinants of health, information and communication technology

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Background and Objectives

The objectives of this study are to identify differentials in accessing health-related technology, and to investigate associations between health-related technology use and health care utilization among older adults in the U.S. The concept of social determinants of health has received growing attention in the last decades by researchers from multiple disciplines including public health, healthcare administration, and social epidemiology in order to uncover potential underlying causes of existing health disparities (Braveman & Gottlieb, 2014). More recently, the concept of the "commercial" determinants of health has emerged in the literature. Although the theoretical proposition of the commercial determinants of health is still evolving, it often entails the potential impacts of commercial products, interests, and activities on public health (Maani et al., 2020). These two frameworks emphasize the importance of interactions and linkages between societal- and community-level health resources, and individual health decision-making and behaviors (Breland, Wong, & McAndrew, 2020; Kaplan, Spittel, & David, 2015; Revenson & Gurung, 2019).

The growing availability of web-based or online health-management tools has amplified opportunities to advance self-efficacy and self-management within the context of health maintenance and promotion. Solomon (2008) discusses the potential use of information technology as a self-management tool for health. Moreover, the use of online technology has diffused so widely that it addresses virtually every area of health care prevention and treatment ranging from sickle cell disease (Saulsberry et al, 2020) to breast cancer (Kim et al, 2020). However, as a result of the rapid advancement and adaptation of technology in health care industries, older populations may have poorer access to online health-related self-management tools than their younger counterparts. The entire concept of self-management as an act of individuals' choice behaviors in health care is increasingly determined by external factors (e.g., access to web-based health self-management tools). Therefore, these tools, which are generally defined as information and communication technology (ICT), are in need of investigation. Specifically, individuals' access to health technology and the potential health consequences require more empirical inquiries that address the well-established challenges of the digital divide. With less access and use of ICT, older adults can become one of the most disadvantaged subpopulations.

Theoretical Framework

Having skills and knowledge of ICT connects individuals' access to health information with their actual usage. That is, individuals' ICT access may be limited by both the individual- and societal-level resources available to them. Yet, the level of digital skills may also be a barrier to individuals' actual usage. At the same time, given that the majority of U.S. households (80 to 86%) have internet access through computers and/or mobile devices that are becoming increasingly user-friendly, the absence or presence of individuals' motivation to use technology may be a function of initial experience and/or simple choice behavior (Kaplan et al., 2015; Smith, 2014).

The concept of the digital divide has been continually acknowledged as a part of social inequality in the social science literature (van Dijk, 2012). Moreover, older age has been empirically linked to lower access to and usage of ICT (Fang et al., 2018). Limited exposure to ICT in earlier life not only delays technical skill development but also reduces interest and motivation for ICT usage among some adults over the life course. Although some research on the digital divide has focused on older adults, other sub-populations as defined by gender, race/ethnicity (Mitchell, Chebli, Ruggiero, & Muramatsu, 2018), and socioeconomic status (e.g., education and income; Choi & DiNitto, 2013; Yamashita et al., 2019) have been more widely researched.

Extending the digital divide as a framework for scientific inquiry in the area of public health, the thesis herein is that basic digital skills and previous experiences are linked to the use of health-related ICT such as online health information and health-management websites (Hall, Bernhardt, Dodd, & Vollrath, 2015). Despite improvements in the availability and accessibility of health-related ICT, the digital divide persists. However, it may be the case that individuals' motivation, resources, and digital skills jointly explain the health-related ICT usage. Because these questions have been left unanswered, it is critical to empirically address the health-related ICT divide as it affects the health outcomes of older adults – a group who may be at a disadvantage.

Despite the importance of such an exploration, a major gap exists in the current literature regarding whether an association exists between the use of health-related ICT and specific health behavior outcomes including health care service utilization in later life (Schulz et al., 2014). Indeed, health care and health outcomes as well as the digital divide are progressively salient in later life. Cumulative disadvantages in digital access and use over the life course creates inequality in access to health information and resources and, as a result, can exacerbate health inequalities among older people (see Latulippe, Hamel, & Giroux, 2017; Montague & Perchonok, 2012). The evidence on the health-related digital divide is quickly growing (Fang et al., 2018; Mitchell et al., 2018). Yet, a lack of empirical research linking health-related ICT to health care service utilization in later life leaves the relationship unsettled and undefined.

Although limited, existing literature suggests the existence of several possible pathways between use of health-related ICT and health behaviors. Using health-related ICT is linked to individuals' immediate access to health information which may enhance their health knowledge (Delello & McWhorter, 2017). Importantly, using health-related ICT could improve health literacy which is "the degree to which individuals have the capacity to obtain, process, and understand basic health information and services needed to make appropriate health decisions" (Ratzan & Parker, 2000, p. vi). Health literacy is negatively associated with certain types of health care utilization (e.g., hospitalization, emergency room visits) among older adults (Cho, Lee, Arozullah, & Crittenden, 2008). At the same time, health literacy may be a determinant of health-rated ICT use (Levy, Janke, & Langa, 2015). Additionally, using ICT is associated with health care service utilization through social ties with family, friends and health professionals (Czaja, 2018; Delello & McWhorter, 2017; Gerst-Emerson & Jayawardhana, 2015).

Given the relative scarcity of literature on online health-related ICT and specific health care behavior outcomes, this study was framed using Ronald Andersen's health care utilization model (Andersen, 2008). In Andersen's model, the predisposing (e.g., age, gender, race/ethnicity, educational background), enabling (e.g., income, health insurance, health resources) and need (e.g., health status, disease) factors are specified as the distal, intermediate and proximate determinants of personal health care utilization, respectively. Health-related ICT was considered as an enabling factor in this study given Andersen's model and Van Dijk's (2012) theoretical framework. In previous work, need factors (e.g., poor health status, comorbidity) have been conceptualized as the proximate and, arguably, the most important predictor of health care service utilization (Bähler, Huber, Brüngger, & Reich, 2015; Evashwick, Rowe, Diehr, & Branch, 1984; Ilinca & Calciolari, 2015; von Lengerke, Gohl, & Babitsch, 2014).

Research Questions and Hypotheses

Considering previous findings on the health-related digital divide and existing health disparities, the current study extended the scope of inquiry to individuals' use of online health-related ICT and health care utilization patterns. Taken together, we addressed the following primary research questions.

(1) What predicts online health-related information and communication technology use among older adults?

(2) Is the use of online health-related information and communication technology associated with health care utilization?

We hypothesized that predisposing and enabling factors are predictors of online health-related ICT use in older adults. However, we expected that the direction of the associations would vary for predisposing factors (e.g., older age would have a negative effect; higher educational attainment would have a positive effect on ICT use). At the same time, we expected that the enabling factors would be consistently positively associated with ICT use. Finally, given previous empirical studies explaining the pathways between ICT use and health-related outcomes, and its role as an enabling factor, we hypothesized that use of online health-related ICT would be associated with lower use of health care services.

Methods

To address the research questions, cross-sectional data set were obtained from the 2014 Health and Retirement Study (HRS)'s supplemental module (Health behaviors), as well as the RAND version of the HRS fat file. This latter source includes all original variables as well as derived variables from all available years. This allowed our study to utilize the relevant information that was not available in the 2014 supplemental module. The HRS was first established in 1992 and is an ongoing and biennial data collection of nationally representative samples of cohorts of older adults (age 51 years and older). In addition to the core modules that are consistent across waves of data collection, each wave includes special/supplemental modules on specific themes such as the module on health behaviors that was collected in 2014. The 2014 supplemental module on health behaviors was conducted using a sample of 1,497 participants. Of those, 1,385 participants or 93%, provided sufficient information on the variables of interest for the present study.

Measures

Variables

Dependent variables. Personal health care service utilization was the dependent variable for this study and was measured using the reported number of doctor visits and hospitalizations. Doctor visits were based on the self-reported count of how many times a respondent had seen or talked with a medical doctor in the last two years. To account for possible outliers at the upper end of the distribution, doctor visits were top-coded at 50 based on a visual examination of the data distribution. Hospitalizations were coded as a dichotomous variable indicating whether or not a respondent reported having been hospitalized in the last two years. These two indicators of general health care service utilization are consistent with measures used in other recent research (Gerst-Emerson & Jayawardhana, 2015; Wherry & Miller, 2016).

Independent variables. The use of online health-management tools and websites was the primary independent variable for this study and was coded as a dichotomous variable based on whether or not a participant used such a website in the past month. The definition of online health-management tools and websites included … "those connected with doctor's office, health care agency, the insurance company, pharmacy, or other health-related websites such as Patient Portals or Weight Watcher Online" (Institute for Social Research, 2019). Relatedly, the use of a health-related mobile application was also examined in our preliminary data analysis. Health-related mobile applications were defined as "…downloadable health-related mobile applications for a smartphone or tablet computer such as an iPad, Android, or Kindle Fire" (Institute for Social Research, 2019). However, due to the low reported usage of these devices (less than 4%) among respondents, we decided not to include it in the analysis. In short, we selected only the use of online health-management tools because they are indicative of the behaviors specific to individual health care, while other platforms may be for purposes unrelated to health care or for multiple purposes.

Covariates

Based upon the Anderson model and survey items available in the HRS data, the researchers identified several predisposing factors including age (in years), gender (women vs. men), race/ethnicity (Black or Hispanic vs. White & Others), nativity (born in the U.S. vs. not), marital status (married vs. not married), and educational attainment (college or higher vs. less than college). Similarly, total household income and health insurance status (insured vs. uninsured) were identified as enabling factors. Finally, need factors included in the analysis were self-rated health (poor & fair vs. good, very good & excellent) and the number of chronic conditions (0 -7). This latter variable was computed based on self-reported hypertension, diabetes, cancer, lung disease, heart disease, mental health issues, and arthritis.

Statistical Analysis

All analyses were conducted using SAS version 9.4 (SAS Institute Inc., 2002-2012). The unweighted descriptive summary based on the use of health-management websites and mobile applications was computed in order to generate descriptive statistics. A series of bivariate tests (*t*-test or *chi-square* test) were conducted for each variable of interest. As a part of the descriptive summary and to address the first research question, weighted logistic regression analysis was used to model the use of online health-management websites as a function of the relevant factors (i.e., the covariates in the main analysis).

For the analysis of the number of doctor visits, a negative binomial regression was estimated (DeMaris, 2005). Since the number of doctor visits was a count variable, as part of the preliminary analysis, we fitted a Poisson regression. However, the equidispersion assumption of a Poisson regression model was violated (Allison, 2012). The SAS macro program, SURVEYGENMOD (da Silva, 2017), was used to incorporate the complex sampling design (i.e., sampling, cluster and stratification weights) of the HRS (Heeringa, West, & Berglund, 2017). The unconditional model with one independent variable was first evaluated. The covariates were then added to the model to construct the fully conditional model. The model quality was assessed based on the likelihood ratio test (null model vs. unconditional model) and the Akaike Information Criteria (AIC) with the 10-point difference as the cut-point. The fully conditional model was considered the final model as it showed a significant improvement from the unconditional model.

We used binary logistic regression for the analysis of hospitalizations (Allison, 2012). The PROC SURVEYLOGISTIC, command was used to model the dichotomous outcome as a function of the independent variable and the covariates (SAS Institute Inc., 2019). The complex sampling weights included with the HRS were incorporated into the model estimation (Heeringa et al., 2017). The model was built in the same manner as the analysis of doctor visits. Model quality was assessed using the likelihood ratio test (null model vs. unconditional model) and the area under the receiver operating characteristics (ROC) curve (> 0.70 = acceptable; > 0.80 = excellent; and > 0.90 = outstanding; Hosmer & Lemeshow, 2013). The area under the ROC curve was greater than 0.70 in the conditional models. Therefore, our final models were considered to have acceptable predictive accuracy.

Several sensitivity analyses were conducted. For the SUREYGENMOD macro program, the SURVEY LOGISTIC command was used with the dichotomized doctor visits (0 vs. at least 1). Statistical significance and the direction of the associations, when verified, were consistent. The final model was tested using a few different measurements (e.g., years of education instead of educational attainment) as well as a slightly different specification (e.g., with and without nativity). Overall, the results were consistent. Additionally, possible interaction effects were tested. Since health care utilization is often driven by specific needs (i.e., poor health, (Andersen, 2008), interaction effects between health status and use of health-related technology variables were explored. However, none of these were statistically significant and were excluded from the final models. Finally, multicollinearity was examined based on the variation inflation factor (VIF) for each predictor variable. None of these exceeded the suggested threshold (VIF > 10) (DeMaris, 2005).

Results

Descriptive and Bivariate Analyses

Table 1 shows the unweighted descriptive summary of the HRS health behavior supplemental module for respondents in the analytic sample. Approximately 14% of respondents used online health-management websites. Overall, those who used online health-management websites used health care services more frequently but were less likely to be hospitalized compared to their counterparts. Also, users of online health-management websites were more likely to be younger, white, born in the U.S., highly educated, insured, and healthier than non-users.

Predictors of Health-Management Website Use

To describe the relationship between the use of online health-management websites and the covariates, and to address the first research question, Table 2 summarizes the results from the weighted logistic. Older age, racial/ethnic minorities (e.g., Black and Hispanic vs. Whites & Other), being married, lower educational attainment, lower-income, being uninsured, and reporting poorer health were each associated with lower utilization of online health-management websites. These statistically significant predictors of demographic, socioeconomic, and health-related characteristics can be considered indicators of the digital divide, and in turn, predictors of differences in health outcomes in later life. Importantly, the area under the ROC curve of the logistic regression model was 0.80. This value indicates excellent predictive accuracy.

The Use of ICT and Doctor Visits vs. Hospitalization

Table 3 addresses the second research question and presents the results from the weighted negative binomial regression models addressing the number of doctor visits (as a measure of health services use) in the last two years. In both the unconditional and conditional models (Model 1 & Model 2), the use of online health-management websites was positively associated with the number of doctor visits. Specifically, online health-management website users had a 34% greater mean number of doctor visits (Incidence rate ratio = 1.34, Standard-error = 0.10, $p < 0.05$) than the non-users after adjusting for the covariates.

Table 4 addresses the second research question and presents the results from the weighted binary logistic regression models on hospitalization in the last two years. Results indicate that using online health-management websites was not associated with hospitalizations. It should be noted that the respondents' hospitalizations were most likely determined by their health status. Indeed, self-rated health and the number of chronic conditions were significantly associated with hospitalizations ($p < .05$). A one-unit increase in self-rated health (better health) was associated with a 0.58 times odds of being hospitalized after adjusting for the covariates. Also, an additional number of chronic conditions was associated with a 1.68 times odds of being hospitalized after accounting for the covariates.

Discussion and Implications

This study was designed to address a gap in the research literature by investigating associations between the use of online health-management websites and health care service utilization in later life. Results from the regression analyses showed that the use of online health-management websites was positively associated with the number of doctor visits. That is, older adults who used online health-management tools utilized health care services more frequently than those who did not. However, as would be expected, the use of online health-management sites was associated with fewer hospitalizations.

Previous review studies suggest that the use of online health resources provides more advantages than disadvantages. That is, the potential benefits (e.g., enhanced communication in health care settings, better understanding of health and/health care information; successful chronic disease management) of using online health resources appear to outweigh negative outcomes (e.g., biased/misleading medical treatment information, privacy concerns) (Chinn, 2011; Tan & Goonawardene, 2017). As such, unequal access to and use of web-based health care resources potentially exacerbates differentials in health outcomes. It is important to point out that this finding does not negate the possibility of negative outcomes from health-related ICT use.

Descriptive statistics (Table 2) identified the specific demographic characteristics (i.e., age, marital status, and race/ethnicity), socioeconomic status (i.e., educational attainment and income), and health status variables that were predictive of the use of online health-management websites. Given the known benefits of online health resources and unequal access/usage by the individuals' characteristics, the disproportionate utilization of online health-management websites is arguably another representation of the operation of the digital divide as manifested within a health care context.

While the findings about the sociodemographic and socioeconomic characteristics are useful in identifying at-risk populations in terms of health care outcome differentials, more detailed analysis is required in future research studies in order to rigorously determine whether within-group variabilities and complex interactions with other risk factors are operative. For example, older age is generally considered a key predictor of a health care-related digital divide. However, age does not solely determine access to or usage of health-related ICT (Fang et al., 2018). Recent studies clearly revealed that a variety of factors can be considered given that predisposing (e.g., gender, race/ethnicity, education) and enabling factors (e.g., income) jointly contribute to the digital divide in older populations (Fang et al., 2018; Mitchell et al., 2018). In this respect, future research is needed that disentangles complex interactions between the known risk factors of access to, and usage of, health-related ICT.

This is important given that needs factors such as poorer health status and greater comorbidities were associated with a greater number of doctor visits as well as with more hospitalizations. In view of the health care service utilization model (Andersen, 2008), health status indicators should be the proximate determinants of health outcome. In this respect, it is possible that the use of online health-management websites may be linked to different types of doctor visits. That is, using online health-related tools may be associated with preventive health care service utilization as well as a quicker response (e.g., treatment-seeking) to any urgent health issues among older adults. In other words, older adults who use health-related ICT may tend to act more proactively and efficiently in health care systems when compared with their counterparts (Hall et al., 2015). In the same vein, more empirical evidence is needed to clarify associations between health-related ICT use and detailed health care quality and service utilization outcomes by sub-populations. This research need is demonstrated by the fact that the benefits (e.g., health outcomes, health care utilization patterns) from health-related ICT among racial/ethnic minorities are still unclear due to generally poorer access and lower usage than the average populations, (Mitchell et al., 2018). Additional research is needed that investigates relationships between the use of health-related ICT and other specific types of health behaviors, in order to identify potential pathways through the digital divide that may be related to motivations, ICT access, and individuals' digital skills (van Dijk, 2012).

Limitations of the Study

This study had several limitations. First, health care utilization behaviors are complex and we should not rule out possible reverse causal relationships. For example, health status (a needs factor) may have impacted the enabling factors such as income. Also, being able to have access to online health-related ICT may indicate access to other resources (e.g., health care services). In this study, we used the health care utilization model by Andersen to guide the model specifications. Second, the measurement of internet use needs refinement (Schulz et al., 2014). In its current form and measurement, the underlying purpose of online health-management website use is unclear. Future research is required that enhances the measurement of online health-management websites as a function of variables such as preventive health, medical treatment, or general information inquiry. Third, possible omitted variable bias cannot be ruled out. In particular, health beliefs, personality, and social networks may explain some of the relationships between the variables of interest in this study (Schomerus et al., 2013). Also, HRS data do not provide possibly important measures of individuals' technology access as a function of the tools required to use online resources. Accordingly, more detailed measures of enabling factors such as health literacy and specific pathways to ICT access (e.g., personal computer, tablet device) should also be considered in future research. Finally, although the HRS provides longitudinal data, the health behavior module was included only in the 2014 module. Therefore, our findings and discussions are limited to the scope of a cross-sectional rather than longitudinal data analysis.

Contributions of the Study

Despite these limitations, this study makes several important contributions. The analysis is one of the first in the literature to specifically examine associations between the use of online health-related ICT and specific health behavior outcomes as measured by health care service utilization using a nationally representative data. This study provides empirical evidence to link the digital divide to health care service utilization in later life. Also, the digital divide and health disparities among older populations remains an underexplored area. The findings from this study add new insights to the existing literature and provides suggestions for areas of future study (Mitchell et al., 2018). Finally, in view of Andersen's model (2008), the findings suggest that the role of online health-management websites are important above and beyond the need factors in health care utilization.

Preliminary implications based on the findings from this study are worth noting. Given the positive association between the use of online health-management websites and doctor visits, health-related ICT has the potential to improve preventive health care, early interventions, and serious health problems among older adults. Timely interventions can reduce costly health care services such as hospitalization and emergency room visits. Specific strategies to promote preventive health care service use should be designed when more research evidence investigating the pathways (e.g., social ties, knowledge, health literacy) becomes available. On a related note, the empirical evidence from this study can justify the use of more resources and policy changes to address the existing digital divide. Specifically, two areas - use of online tools among older adults, and the usability of these tools for older adults - should be simultaneously addressed. For example, in view of the commercial determinants of health, increasing access to health-related ICT and providing health-related ICT for diverse populations with different levels of digital skills/knowledge is a simple, yet, sound strategy for systematically improving health outcomes (Maani et al., 2020). This may also result in improvements in overall health outcomes while also addressing other social issues (e.g., social isolation). In this sense, targeting the digital divide may be an upstream approach which addresses multiple domains of public health issues that include, yet, extend beyond the often-discussed social determinants of health (Braveman, Egerter, & Williams, 2011).

In conclusion, the use of online health-management websites is positively associated with utilization of specific health care service as measured by doctor visits among older adults in the U.S. While more research is needed to clarify the purposes and outcomes of health care service utilization within this context, it may be a wise investment to proactively address the digital divide as one upstream strategy for augmenting a variety of health and health care outcomes.

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Conflict of Interest

None.

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Table 1: Unweighted Descriptive Summary by the Online Health-related Technology Use

Variables	Use of Online health-management websites		
	TOTAL (n = 1,385) Mean (SD) or %	YES (n = 192) Mean (SD) or %	NO (n = 1,193) Mean (SD) or %
Number of doctor visits [a]	7.90 (8.91)	10.54 (10.32)*	7.43 (8.56)
Hospitalization (YES)	24.02%	16.67%*	25.21%
Predisposing factors			
Age (years)	68.25 (9.69)	64.04 (7.87)*	68.92 (9.78)
Gender (women)	59.86%	62.00%	59.51%
Race/ethnicity		*	
White	62.33%	82.29%	59.10%
Black	21.20%	11.98%	22.69%
Hispanic	13.53%	2.60%	14.29%
Others	2.89%	3.13%	2.85%
Marital status (married)	52.64%	57.29%	51.89%
Educational attainment (college or higher)	21.37%	41.15%*	18.19%
Nativity (born in the U.S. vs. not)	87.08%	95.83%*	85.67%
Enabling factors			
Total household income (logged)	10.43 (1.60)	11.07 (1.42)	10.32 (1.60)*
Health insurance (insured)	68.25%	64.04%*	68.93%
Need factors			
Self-rated health (Good, very good & excellent)	71.11%	82.81%*	69.24%
Number of chronic conditions (1 – 7)	2.18 (1.38)	1.84 (1.29)*	2.23 (1.39)

* $p < 0.05$ based on the bivariate significance tests (YES vs. NO); Due to the small sample size, the Fisher's exact test was also used to verify the bivariate test results; SD = standard deviation

a. top-coded at 50

Table 2: Estimated Odds Ratios from the Binary Logistic Regression Models on the Use of Online Health-management Websites

Variables	Model 1 OR (SE)
Predisposing factors	
Age (years)	0.93 (0.02)*
Gender (women vs. men)	1.16 (0.25)
Race/ethnicity	
Black (vs. white & others)	0.24 (0.33)*
Hispanic (vs. white & others)	0.11 (0.73)*
Marital status (married vs. not married)	0.46 (0.28)*
Educational attainment (college or higher vs. less than college)	2.49 (0.26)*
Nativity (born in the U.S. vs. not)	2.05 (0.37)
Enabling factors	
Total household income (logged)	1.41 (0.14)*
Health insurance (insured vs. uninsured)	3.23 (1.17)*
Need factors	
Self-rated health (Good, very good, excellent vs. fair, poor)	1.73 (0.27)*
Number of chronic conditions (1 – 7)	1.09 (0.09)
Area under the ROC curve	0.80

* $p < 0.05$; OR = Odds ratio; SE = Standard error

The sampling weights were applied in the SAS –SURVEYLOGISTIC command

Table 3: Estimated Incidence Rate Ratios from the Negative Binomial Regression Models on the Number of Doctor Visit

Variables	Model 1 IIR (SE)	Model 2 IIR (SE)
Predisposing factors		
Age (years)		1.01 (0.01)
Gender (women vs. men)		1.03 (0.07)
Race/ethnicity		
Black (vs. white & others)		0.94 (0.08)
Hispanic (vs. white & others)		0.79 (0.19)
Marital status (married vs. not married)		0.89 (0.07)
Educational attainment (college or higher vs. less than college)		1.22 (0.09)*
Nativity (born in the U.S. vs. not)		1.19 (0.13)
Enabling factors		
Use of online health-management websites (Yes vs. No)	1.34 (0.11)*	1.34 (0.10)*
Total household income (logged)		1.06 (0.03)*
Health insurance (insured vs. uninsured)		1.18 (0.20)
Need factors		
Self-rated health (Good, very good, excellent vs. fair, poor)		0.65 (0.11)*
Number of chronic conditions (1 – 7)		1.23 (0.03)*

* $p < 0.05$; IRR = Incidence rate ratio; SE = Standard error; ROC curve = receiver operating characteristics curve
The sampling weights were applied in the SAS macro program - SURVEYGENMOD

Table 4: Estimated Odds Ratios from the Binary Logistic Regression Models on the Hospitalization

Variables	Model 1 OR (SE)	Model 2 OR (SE)
Predisposing factors		
Age (years)		1.02 (0.01)
Gender (women vs. men)		0.82 (0.21)
Race/ethnicity		
Black (vs. white & others)		1.03 (0.28)
Hispanic (vs. white & others)		0.74 (0.36)
Marital status (married vs. not married)		0.90 (0.20)
Educational attainment (college or higher vs. less than college)		1.17 (0.21)
Nativity (born in the U.S. vs. not)		1.50 (0.36)
Enabling factors		
Use of online health-management websites (Yes vs. No)	0.65 (0.26)	0.81 (0.32)
Total household income (logged)		0.95 (0.07)
Health insurance (insured vs. uninsured)		2.45 (0.46)
Need factors		
Self-rated health (Good, very good, excellent vs. fair, poor)		0.58 (0.18)*
Number of chronic conditions (1 – 7)		1.68 (0.07)*
Area under the ROC curve	0.53	0.74

* $p < 0.05$; OR = Odds ratio; SE = Standard error

The sampling weights were applied in the SAS –SURVEYLOGISTIC command