The Long-Term Effect of Health-Related Online Use on Healthcare Utilization and Expenditures Among Older Adults

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Abstract. The study objective is to assess the long-term effect of registering for an online-based wellness program on healthcare utilization and expenditures among the elderly. The associational relationship was measured using a combined propensity score matching (PSM) and interrupted time series (ITS) method. We utilized expansive data—online activity data of the wellness program, administrative claims data, and consumer data—of 332,911 adults aged 65 and older with Medicare Advantage coverage from a health plan, who had one year of data from the pre-registration period (2016) and two years of data from the post-registration period (2017–2018). After using PSM to control for demographic and health characteristics, and insurance type between registered persons and persons without online access (reference group), we found lower costs of $86 per member per month (PMPM) among registered seniors in the second year of online registration, compared to seniors without online access ($p < 0.001$). We also observed fewer emergency room visits among the registered group ($p < 0.001$), but no significant difference in hospital admission rates.

Keywords: Online wellness program · Elderly · Healthcare utilization · Healthcare expenditure · Propensity score matching · Interrupted time series

1 Introduction

Over the past few decades, the internet has become an indispensable part of daily life. In America, 89% of households owned computers and 82% used internet in 2016. Older adults were not far behind: 75% of elderly households (65 years and older) had desktop, laptop, or smart phone and 68% had an internet subscription [1]. Among internet/online users who are US Medicare beneficiaries aged 65 years and older, 45% conducted health-related tasks: searching information on health conditions, ordering or refilling prescriptions, contacting medical providers, and handling health insurance matters. Also, 51% used internet to manage everyday life such as online bills, online banking, and online shopping; and 86% sent emails or texts in 2011, based on a nationally representative sample from the National Health and Aging Trends Study [2].

The objective of this study is to estimate the long-term effect of health-related internet use among elderly on their healthcare utilization and expenditures, using a rigorous method, a combined PSM and ITS as the strongest, quasi-experimental design to evaluate such effect over time.

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2 Methods

2.1 Program Description

A health plan offered its Medicare Advantage (MA) members access to wellbeing resources through CaféWell, an interactive web and mobile tool developed by Welltok. A centralized, digital platform was launched in 2016 for this study population, providing personalized resources that support physical, emotional, financial, and social health. To receive personalized health and wellbeing services, as well as rewards, eligible MA members were asked to register online.

2.2 Data Sources

Segmented regression analysis requires data to be collected regularly over time and organized at equally spaced intervals. Monthly or annual health care records of utilization and/or expenditures are commonly used sources of time series data. A sufficient number of time points before and after the intervention is needed to conduct ITS analysis. A general recommendation is for 12 data points before and 12 data points after the intervention. A minimum of 100 observations is also desirable at each time point to achieve an acceptable level of variability of the estimate [3].

We linked three different data sets at an individual level: administrative claims data, online registration data from the CaféWell program, and consumer data. We used 4 years of administrative claims and enrollment data of all adults enrolled in an MA plan, covering the period 1/1/2015 to 12/31/2018. One year from January to December 2016 was considered the pre-intervention period and the two years between January 2017 and December 2018 were considered the post-intervention period. We also integrated online registration records for the CaféWell program from January 2017 to December 2018. We determined who had no online access using Welltok's proprietary consumer database.

2.3 Definition of Internet Use

We defined two different measures of internet use: active health-related internet use and non-online access. The intervention group is defined as aged adults who actively use internet for health-related activities, specifically the CaféWell program. The control group is defined as aged adults who did not have online access using the consumer data.

2.4 Healthcare Utilization and Expenditures

To measure the effect of internet use, we used healthcare utilization and expenditures as outcome measures. Monthly emergency department (ED) visit rates and hospitalization rates, and healthcare expenditures, allowed amount, per member per month (PMPM) were calculated on a rolling 12-month basis. For example, PMPM of rolling year at the data point of January 2016 is calculated as the aggregated healthcare expenditures for the period 2/1/2015 to 1/31/2016, divided by 12 months.

2.5 Study Sample

Inclusion criteria for the study sample are listed:

1. Continuous enrollment for 48 months during pre- and post-intervention periods;
2. Age 65 years and older in 2016;
3. Annual healthcare expenditures, allowed amount, less than $56,000 (98 percentile) in 2016, to reduce the influence of outliers.

The intervention group then required continuous registration in the CaféWell program during the post-intervention period for assessment of the program effect, while the control group who met the inclusion criteria but did not have online access, was identified (see Fig. 1).

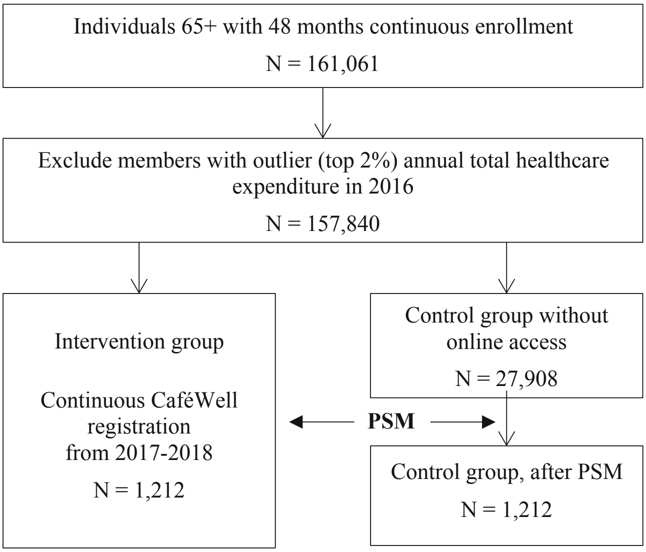

Fig. 1. Sample selection step

2.6 Propensity Score Matching (PSM)

Assessing the effect of health-related internet use on health care utilization and expenditures requires controlling for factors that influence a user's decision to use the internet. Such decision can reflect both observed and unobservable differences in characteristics between online users and non-online users. Studies that examined determinants of internet use found that older adults who were younger, non-Hispanic white, and of higher socioeconomic status were more likely to use the internet [5, 6].

Using a logistic regression model, we estimated the propensity score of registering in the CaféWell program for all individuals based on a set of observed covariates, without interactions or nonlinear terms. On the premise that the expenditures and utilization trends would be similar between the intervention and control group during the pre-intervention period, the control group were then matched to the intervention group. PSM was used to control for cost and utilization during the pre-intervention period; age; gender; number of chronic conditions; co-morbidities including diabetes, hypertension, mental disorder, chronic kidney disease (CKD), and cancer; and insurance type (HMO vs. PPO). Specifically, the Greedy matching algorithm was used.

All persons who registered in the CaféWell program were then matched to persons who did not have internet access, based on their propensity scores, using caliper of 0.2 standard deviations. To examine the quality of the match, we used either the Mann-Whitney-Wilcoxon rank sum tests due to non-normal distribution for continuous variables or $\chi 2$ tests for categorical variables.

2.7 Interrupted Time Series (ITS)

When random assignment is not feasible, ITS analysis is considered a powerful quasi-experimental design for evaluating effects of interventions, primarily because of its control over the effects of regression to the mean. Nevertheless, without a comparison group, the treatment effect of a single study group may still be biased because of selection issues or secular trends. Therefore, an ITS can be much strengthened with the addition of a control group [4].

In a basic ITS, the time-period is divided into pre- and post-intervention segments, and two parameters (level and trend) are estimated in each segment. The level is the value of the series at the beginning of a given time interval (i.e., the *y*-intercept of the first segment), which measures immediate change of outcomes due to the intervention. The trend is the rate of change of outcome measure (in other words, the slope) over time after the intervention [3]. Statistical tests of difference-in-difference in intercepts and slopes over time (from the pre- to the post-intervention period) are then carried out.

3 Results

Out of 332,911 adults, a total of 29,120 persons met all inclusion criteria. Their characteristics are shown in the first three columns of Table 1 (labeled before matching). On average, aged adults without online access were older and female, compared to health-related online users. Those without online access were more likely to have HMO coverage, more likely to have heart disease and mental disorders. They had higher PMPM ($), as well as higher rates of ED visits and admission.

Table 1. Characteristics of the study sample before & after propensity score matching

N	All	Before matching[a]		After matching[a]	
		Control group	Intervention group	Control group	Intervention group
	29,120	27,908	1,212	1,212	1,212
Demographic characteristics					
Age[b]	80.51	80.69	76.37***	77.07	76.37
Female[c]	62%	62%	53%***	54%	53%
HMO[c]	44%	44%	37%***	37%	37%
Health characteristics					
Diabetes[c]	21%	21%	25%***	24%	25%
Heart disease[c]	22%	23%	18%***	17%	18%
Hypertension[c]	72%	73%	71%	72%	71%
Mental disorder[c]	21%	21%	19%*	19%	19%
Cancer[c]	17%	17%	17%	18%	17%
CKD[c]	8%	8%	7%	7%	7%
Healthcare utilization and expenditures					
PMPM ($)[b]	661.32	662.76	628.29***	628.24	628.29
Having admission[c]	11%	11%	8%***	8%	8%
Having ED visits[c]	21%	22%	15%***	17%	15%

Note: [a]Statistical tests examine the null hypothesis that the intervention group had same characteristics as the control group; [b]Mann-Whitney-Wilcoxon rank sum test due to non-normal distribution; [c]Chi-square test; the symbols ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

The final study sample consisted of 1,212 health-related online users and 1,212 persons without online access who were successfully matched using PSM. Because residual differences in demographics, health characteristics, and healthcare utilization and expenditures between the two groups were not statistically significant, adequate balance was attained (labeled after matching of Table 1).

One of the greatest strengths of interrupted time series studies is the intuitive graphical presentation of results, and a visual inspection of the series over time is the first step when analyzing time series data [3]. Using the matched sample, we conducted two-group interrupted time series analysis (ITSA) for annual ED rates. Looking at the data points during the pre-intervention period in Fig. 2, we found similar ED rates between online users and non-online users, as expected.

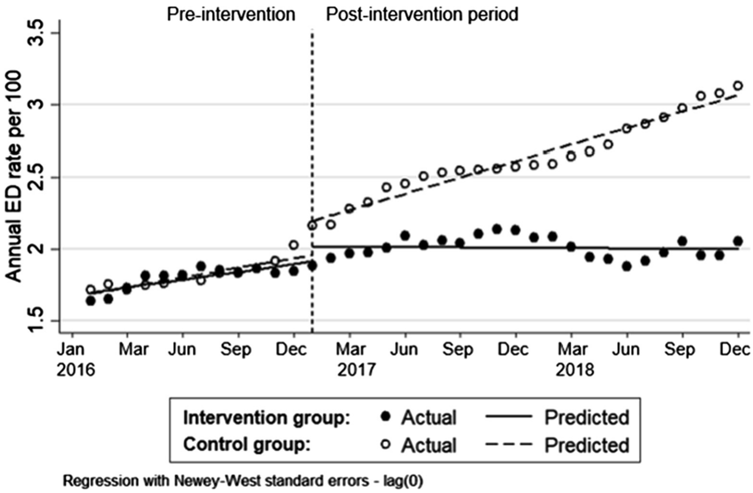

Fig. 2. Two-group ITSA of annual mean ED rates per 100

After the online registration, the average annual ED rates of the intervention group were expected to be changed in its level and/or trend, compared to the control group. Before the intervention, initial ED rates were on average 1.687 per 100 annually and had an increasing trend of 0.023 per year.

Table 2. Parameter estimates, standard errors from the segmented regression models

Parameter	Coef.	S.E.	*t*-stat	*p*-value
Annual mean ED rate per 100				
Difference-in-difference of level	−0.135	0.059	−2.31	0.024
Difference-in-difference of trend	−0.034	0.007	−5.18	<0.001
Average PMPM ($)				
Difference-in-difference of level	−65.9	14.87	−4.43	<0.001
Difference-in-difference of trend	−8.7	1.49	−5.83	<0.001
Annual mean admission rate per 100				
Difference-in-difference of level	−0.361	0.06	−6.02	<0.001
Difference-in-difference of trend	−0.001	0.007	−0.22	0.83

The parameter estimates from the linear segmented regression model confirmed that annual ED rates of online-users (intervention group) decreased from the pre- to the post-intervention period, compared to the control group, in level by 0.135 (difference-in-difference of level in Table 2, p = 0.024), as well as in trend by 0.034 (difference-in-difference of trend in Table 2, $p < 0.001$).

When expressing the results of segmented regression modelling, we can either report level and trend changes like those in Table 2, or we can express the intervention effect as the absolute difference in values. Using the coefficients of the ITS model [7],

Table 3 shows the estimated effect of health-related online use on ED rates. In December of 2017 and 2018, one year and two years after the intervention, annual ED rates decreased by 0.515 ($p < 0.001$) and 0.977 ($p < 0.001$), respectively.

Table 3. Intervention effects 1 year and 2 years after the intervention.

	Annual ED rate/100	PMPM	Annual admission rate/100
Dec., 2017	−0.515***	−$22.47***	−0.023
Dec., 2018	−0.977***	−$85.91***	−0.043

Note: ***, **, and * indicate a significance level of 1%, 5%, and 10%, respectively.

The second panel of Table 2 shows parameter estimates measuring the effect of health-related online use on annual average PMPM ($). We found a significant decrease in level of $65.90 ($p < 0.001$) and in trend of $8.70 per year ($p < 0.001$) among online users, compared to aged adults without online access. Visual inspection of annual mean PMPM over time clearly suggests lower cost among online users for health-related activities, compared to non-online users (Fig. 3).

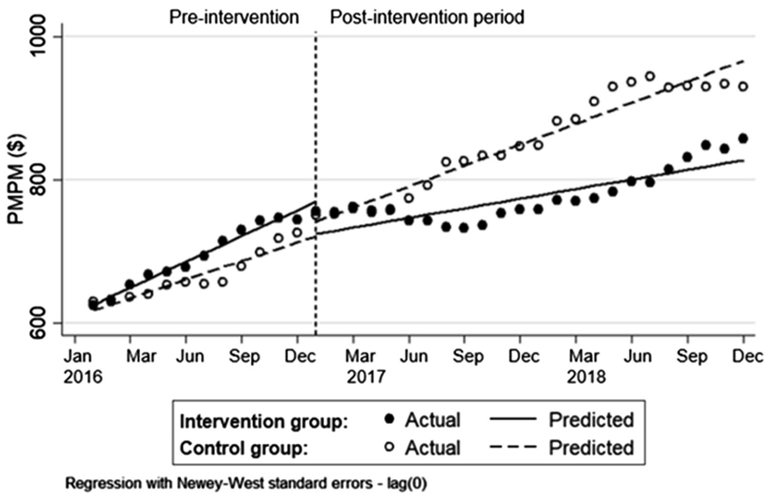

Fig. 3. Two-group ITSA of annual mean PMPM ($)

The estimated intervention effect on PMPM one year and two years after CaféWell registration was a healthcare cost savings of $22.47 and $85.91, respectively (Table 3). Considering the initial mean PMPM of $617.31 before the intervention, healthcare expenditures decreased by 4% and 14%, respectively. However, there was no statistically significant change in annual hospital admission rates (Table 3).

4 Conclusion

We estimated the long-term effect of health-related online use among aged adults on healthcare expenditures and utilization over time, using a rigorous method. To our best knowledge, this is the first published evidence of such effect using this novel study design and time series data. We found reduction in healthcare expenditures one year after the intervention. Cost savings were driven possibly by reductions in ER visits. We have not observed any significant changes in hospital admission rates. In other words, utilization of online health resources among older adults was associated with lower healthcare utilization and expenditures. Our findings also highlight the importance of long-term evaluations to measure such effect, as well as the need for payers to take a long-term investment view when considering an online-based program.

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