Understanding the Link between Patient Portal Use and Health System Utilization

Emergent Research Forum Paper

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Abstract

Identifying the effects of patient portal use on patient engagement with the healthcare delivery system is an active research area. This study aims to understand the link between overall patient portal use (portal activity) and overall health system utilization (encounters) through the analyses of data logs from the patient portal and Electronic Health Record (EHR) system in a large multi-specialty group practice. Analyses of our data revealed correlations between the level of specific portal activity and encounter type. They also show portal use is clustered around other health system utilization activities. Furthermore, total encounters in a given month are predictive of future patient portal activity. Understanding such links can help health care managers plan resources to support patient needs and engagement.

Keywords

Patient portal, Time series analysis, Granger causality, Frequency analysis, Healthcare system use

Introduction

Patients are increasingly interested in engaging with their providers through digital platforms, and healthcare organizations are increasingly facilitating such engagement through patient portals (Braunstein 2015). Patient portals, now widely available in the U.S., are a type of personal health record (PHR) that provides patients with access to their medical record and healthcare team through a web site. This study aims to understand the link between overall patient portal use (portal activity) and overall health system utilization (encounters) by analyzing data logs from the patient portal and Electronic Health Record (EHR) system in a large multi-specialty group practice in the U.S. While this link is important for discovering the opportunities afforded by patient portals, as well as the consequences for resource use, it is still unclear from the literature. We examine how use of a patient portal is affected by utilization of specific healthcare services, and whether use of the portal affects usage of the healthcare system. This ERF paper presents our analyses and preliminary results.

Literature Review

The literature has provided inconclusive results regarding the relationship between patient portal use and utilization of the general health system. For example, patient use of secure email (through secure messaging feature of patient portals) to communicate with providers failed to produce significant differences in clinical services utilization in the initial years of use (Meng et al. 2015). For some patients, such as those with coronary artery disease, the impact of PHR use on patient engagement is minimal (Toscos et al. 2016). On the other hand, patients continue to use email to communicate with their providers. Furthermore, patients with higher out-of-pocket expenses are more likely to use email to
initiated contact with their providers, and use of email reduces other types of encounters with the health system, and improves overall health (Reed et al. 2015). Given the conflicting findings in the literature, this study aims to understand the link between overall patient portal use and overall health system utilization.

**Methodology**

*Data Collection and Preparation*

Study invitations were sent to 10,000 patients of the group practice randomly selected from the 40,000 patients who were patient portal users. Among the invitees, 632 patient portal users agreed to participate in the study. Each participant was assigned a study ID. For all study IDs, encounter and portal utilization data was collected by the group practice on a daily granularity for a 25-month period from January 1st 2011 to February 1st 2013. Portal activity data consisted of all clicked menu items (label and time stamp) and contained 44 different types of actions a user could take on the patient portal. The encounter data consisted of 38 different types of billable activities in the EHR.

*Data Analysis*

Multiple data analysis techniques were utilized to characterize the links between encounter and portal activity data sets. First, two-tail linear regression t-tests were used to analyze the correlation between the amount of portal activity and encounters per user, providing a simple hypothesis test to yield preliminary results. Second, a Granger causality test was used to explore potential temporal relationships between encounters and portal activity at an aggregate level. Third, the frequency with which particular portal activity occurred near specific encounters was analyzed to examine temporal effects associated with individual users, to supplement the aggregate approach used in the Granger test. Analyses were conducted using a combination of Excel and Python scripts. In Python, the statsmodels, scipy, and pandas packages were primarily utilized to analyze the data, and matplotlib to produce graphs.

*Linear Regression t-Test*

After calculating the total number of occurrences of each type of portal utilization and encounter per user, (1) each type of portal activity was regressed against each type of encounter, (2) each type of portal activity was regressed against every other type of portal activity, and (3) each type of encounter was regressed against every other type of encounter, using two-tailed linear regression t-tests to analyze whether the slope of these regressions significantly differed from zero. Because we were most interested in analyzing the volume and type of communication in the context of overall portal activity (in the form of portal logins) to explore engagement, we also performed additional two-tail linear regression t-tests between each combination of normalized total logins, normalized telephone calls, and normalized emails per user. This normalization was performed by dividing each form of communication by the total number of encounters for each given user (removing telephone calls and emails from the encounter category).

Granger Causality Test

The Granger causality test is a type of econometric analysis developed to overcome the limitations of spurious regression in time series data (Granger 1969). This test determines whether the past values of a given time series add predictive power to another time series. In this sense, the null hypothesis is that past values of an exogenous time series \( x \) contain no predictive power for future values of the endogenous time series \( y \), while the alternative hypothesis is that these past values of \( x \) do contain predictive power. We utilized this technique to determine whether, on the aggregate level across all portal users, a relationship existed between the number of encounters over time and number of logins over time. We started our analysis with monthly granularity. We further increased specificity, testing the relationship between logins and no-shows, no-shows and phone calls, and phone calls and logins, for both the weekly and daily granularity. For each of these tests, we tested both \( x \) as the exogenous variable and \( y \) as the endogenous variable, as well as vice versa.

We first fit an exogenous autoregressive model (ARX) to the endogenous variable \( y \), given by the form:

\[ y_t = \alpha_1 y_{t-1} + \alpha_2 y_{t-2} + \alpha_3 y_{t-3} + \cdots + \alpha_n y_{t-n} + \beta_1 x_{t-1} + \beta_2 x_{t-2} + \beta_3 x_{t-3} + \cdots + \beta_n x_{t-n} + \epsilon_t \]
where $y_t$ is the value of variable $y$ at time $t$, $y_{t-1}$ is the value of $y$ in the period directly before $t$, etc., with coefficients $\alpha$ and residual $\epsilon_t$. In this case, $x_{t-i}$ is the value of the exogenous variable $x$ at period directly before $t$, and the $\beta$ are the coefficients of each $x$ variable. Each $y_{t-i}$ and $x_{t-i}$ term is denoted as the “lagged” value of $y$ or $x$ respectively, where $n$ is the maximum lag.

To determine whether the variable $x$ is useful in predicting the variable $y$, we first determined the appropriate maximum lag, and then fit an ARX model via the method of least squares. To determine the optimal maximum lag, we began with an approximate expected maximum lag and from there minimized both Aaik's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) of each additional lag, selecting the smaller number of lags produced by either method. We then performed an F-test on the lagged values of $x$ to determine if any $\beta$ coefficients differed significantly from zero. If so, we then rejected the null hypothesis, instead concluding that the past values of the series $x$ are useful in predicting the future values of the series $y$.

**Frequency Analysis**

To gain a better understanding of the relationship between portal sessions and different encounter types, while still retaining individual relationships between the data, we calculated the probability of a given portal action occurring within ±1 day of a given encounter event. To calculate this for a given portal action and encounter event pair, we summed the number of portal actions occurring within ±1 day of the given type of encounter, by user. We then divided the sum of these values across all users by the total number of occurrences of the given session type for all users. We also plotted the distribution of several of the more intriguing session and encounter pairs with a ±30 day timespan. In particular, we examined different forms of communication (patient emails and telephone calls) and logins that occurred near office visits.

**Results**

**Linear Regression t-Test**

For many of the data we rejected the null hypothesis, instead asserting that there exists a nonzero slope between the data. We calculated 1,406 tests regressing each type of encounter against every other type of encounter, 1,672 tests regressing each type of encounter against each type of session activity, and 1,892 tests regressing each type of session against every other type of session activity. Among the tests ran, 46.4% were significant at the $\alpha=0.05$ level and 39.7% at the $\alpha=0.01$ level. These were almost entirely positive relationships, with 99.8% of those regressions significant at the $\alpha=0.01$ level being positive.

Almost all of the portal activities were positively correlated with other types of portal activities. In general, portal activities were also correlated with the more common encounter events (e.g., no-shows, refill, office visit, orders). In general, the number of encounters was also positively correlated with different types of encounters, these again being the more common encounter types.

As Table 1 shows, positive relationships were again detected when normalized communication variables were explored, but not all of them were significant. Between normed logins and user telephone calls (Row 1 and Figure 1), we failed to reject the null hypothesis that the slope is nonzero (p=0.185). Between normed logins and patient emails (Row 2 and Figure 2), a strong positive relationship existed at the $\alpha=0.01$ level (p=7.04x10⁻⁴⁰) with a correlation coefficient of 0.496. Between normed telephone calls and patient emails (Row 3 and Figure 3), a positive relationship existed at the $\alpha=0.05$ level (p=0.0355) with a correlation coefficient of 0.0843. The high number of hypothesis tests in this approach does create the risk of a Type I error.

<table>
<thead>
<tr>
<th>Variables</th>
<th>Slope</th>
<th>Intercept</th>
<th>R</th>
<th>p value</th>
<th>St. dev.</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. Logins, Telephone Calls</td>
<td>0.006</td>
<td>0.193</td>
<td>0.053</td>
<td>0.185</td>
<td>0.004</td>
</tr>
<tr>
<td>2. Logins, Patient Emails</td>
<td>0.051</td>
<td>0.034</td>
<td>0.496</td>
<td>7.04x10⁻⁴⁰</td>
<td>0.004</td>
</tr>
<tr>
<td>3. Telephone Calls, Patient Emails</td>
<td>0.084</td>
<td>0.085</td>
<td>0.084</td>
<td>0.035</td>
<td>0.040</td>
</tr>
</tbody>
</table>

**Table 1. Regression Results between Normalized Communication Variables and Logins**
Granger Causality Test

As illustrated in Table 2, total encounters helped to predict total portal activity on a monthly scale. As illustrated in Table 3, logins helped to predict no-shows and phone calls on a weekly scale. All three time series were useful in predicting each other on a daily scale, probably due to high weekly seasonality.

<table>
<thead>
<tr>
<th>Endog. Var. (y)</th>
<th>Exog. Var (x)</th>
<th>No. Lags</th>
<th>F value</th>
<th>p value</th>
<th>df denom</th>
<th>df num</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total portal activity</td>
<td>Total encounters</td>
<td>4</td>
<td>3.687</td>
<td>0.0386</td>
<td>11</td>
<td>4</td>
</tr>
<tr>
<td>Model: (y_t = 0.574y_{t-1} + 0.371y_{t-2} - 0.169y_{t-3} + 0.399y_{t-4} - 0.265x_{t-1} - 0.0487x_{t-2} + 0.134x_{t-3} - 0.140x_{t-4} + 661.406)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2. Significant Granger Tests between Monthly Aggregate Encounters and Sessions

<table>
<thead>
<tr>
<th>Endog. Var. (y)</th>
<th>Exog. Var (x)</th>
<th>No. Lags</th>
<th>F value</th>
<th>p value</th>
<th>df denom</th>
<th>df num</th>
</tr>
</thead>
<tbody>
<tr>
<td>Phone calls</td>
<td>Logins</td>
<td>2</td>
<td>11.294</td>
<td>0</td>
<td>102</td>
<td>2</td>
</tr>
<tr>
<td>Model: (y_t = -0.0322y_{t-1} - 0.155y_{t-2} + 0.0753x_{t-1} + 0.0217x_{t-2} + 75.244)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Endog. Var. (y)</th>
<th>Exog. Var (x)</th>
<th>No. Lags</th>
<th>F value</th>
<th>p value</th>
<th>df denom</th>
<th>df num</th>
</tr>
</thead>
<tbody>
<tr>
<td>No-shows</td>
<td>Logins</td>
<td>2</td>
<td>3.213</td>
<td>0.0443</td>
<td>102</td>
<td>2</td>
</tr>
<tr>
<td>Model: (y_t = 0.0677y_{t-1} + 0.0511y_{t-2} + 0.0465x_{t-1} - 0.0238x_{t-2} + 36.632)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 3. Significant Granger Tests between Weekly Aggregate Logins and Phone calls and No-shows

Frequency Analysis

Each of the 38 different types of encounters was matched with each of the 44 different session actions, yielding 1,672 different probabilities. Most probabilities remained below 0.10 likelihood of the given session action occurring within ±1 day of the given encounter type. The probabilities of greater value tended to occur around specific types of encounters, i.e., no-shows, office visits, orders only, patient email, and telephone. From the analysis, it is apparent that the differences in percentage are mostly explained by the type of encounter rather than the type of portal activity. That is, the variance holding portal activity type constant and measuring across different types of encounters is typically two orders of magnitude greater than the variance when holding encounter type constant and analyzing portal activity type.

Some session actions occurred with unusually high probability around specific encounters. For patient email, the following session activities occurred with high probability: appointment autoschedule (0.469), appointment schedule (0.327), evisit (0.825), health maintenance schedule (0.702), medical advice request (0.618), and questionnaire (0.851). Both medication (0.231) and medication renewal request (0.655) occur with high probability near refill.
While telephone and patient email are listed as types of encounters, it is useful to analyze their probability distribution around office visits, and compare this to the distribution of logins around office visits (Figures 4, 5, and 6). Telephone calls, emails, and logins all have similar patterns, spiking both before, after, and on the same day as an office visit. They also each exhibit some form of weekly-recurring pattern. Logins differ in that there is also another spike 3 days after an office visit, possibly checking lab results.

Conclusion

In our data, portal use and health system utilization are correlated at the level of specific portal activity and encounter type; that is, people who utilize the healthcare system for one type of service tend to utilize other services as well. Similarly, the level of use of each portal feature is also correlated with the use of other features. When portal use is examined as a service of the health system, our results show portal use is clustered around other health system utilization activities such as office visits. Our aggregate analysis that total encounters in a given month are predictive of future patient portal activity can provide practical value for planners in healthcare systems. For researchers, these results demonstrate that autoregressive models and econometric methods can be successfully applied to healthcare data, providing an alternative method for analysis.

Our results corroborate the notion that patient portal use is linked to healthcare system utilization. For example, spikes in patient portal usage occur temporally around office visits and other forms of healthcare utilization, suggesting that one may affect the utilization of the other, or perhaps a third confounding variable affects both. Because we did not investigate causal models to explain such relationships, future research should investigate the true causality between patient portal use and health services use. Understanding the links uncovered in this research, as well as the results of future research on their causality, can help patient portal administrators understand and predict the periods of greatest usage of their services, as well as allow healthcare managers to more effectively plan resource allocation. In addition, understanding use may help managers develop more effective communication and patient engagement strategies. In future work, we plan to extend our study to different visit types to further analyze the links between portal use and health system utilization.

REFERENCES