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Using Claims Data to Generate Clinical Flags Predicting Short-term Risk of Continued Psychiatric Hospitalizations

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Abstract

Objective—As health information technology advances, efforts to use administrative data to inform real-time treatment planning for individuals are increasing, despite few empirical studies demonstrating that such administrative data predict subsequent clinical events. Medicaid claims for individuals with frequent psychiatric hospitalizations were examined to test how well patterns of service use predict subsequent high short-term risk of continued psychiatric hospitalizations.

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Methods—Medicaid claims files from New York and Pennsylvania were used to identify Medicaid recipients aged 18-64 with two or more inpatient psychiatric admissions during a target year ending March 31, 2009. Definitions from a quality-improvement initiative were used to identify patterns of inpatient and outpatient service use and prescription fills suggestive of clinical concerns. Generalized estimating equations and Markov models were applied to examine claims through March, 2011, to see what patterns of service use were sufficiently predictive of additional hospitalizations to be clinically useful.

Results—11,801 unique individuals in New York and 1,859 in Pennsylvania identified met the cohort definition. In both Pennsylvania and New York, multiple recent hospitalizations, but not failure to use outpatient services or failure to fill medication prescriptions, were significant predictors of high risk of continued frequent hospitalizations, with odds ratios greater than 4.0.

Conclusions—Administrative data can be used to identify individuals at high risk of continued frequent hospitalizations. Such information could be used by payers and system administrators to authorize special services (e.g., mobile outreach) for such individuals as part of efforts to promote service engagement and prevent rapid rehospitalizations.

Keywords

Medicaid; hospitalization; serious mental illness; administrative data; clinical indicators; performance measures

Mental health policymakers and services researchers routinely use administrative data to describe population characteristics and make inferences about service costs, quality, and treatment outcomes.(1-6) Typically, these are retrospective efforts, sometimes with time lags of years between events and subsequent analytic findings. However, as health information technology advances, service providers have begun using administrative data to inform real-time treatment planning.(7) This report uses Medicaid data from New York and Pennsylvania to model the extent to which various “clinical flags” raised by timely use of claims data may be helpful in identifying individuals at unusual risk of poor outcomes, enabling services providers to use this information to help avert psychiatric hospitalizations.

In any given year, a small subset of people with serious mental illness (SMI) experiences multiple psychiatric hospitalizations. Many initiatives to improve client outcomes while reducing costs focus on these individuals, hence the desirability of using claims data to identify patterns of service use (and non-use) to help identify individuals at imminent risk of hospitalization. If timely and of high enough predictive value to be clinically useful, such information could identify who should receive mobile outreach or other services to help avert another hospitalization. Services such as mobile outreach are expensive, hence timely use of administrative data may help make wise triage decisions.

We used measures from the New York City Mental Health Care Monitoring Initiative (CMI),(7, 8) a quality improvement initiative for frequently hospitalized Medicaid-enrolled individuals with SMI, to examine to what extent Medicaid claims data may be used to predict subsequent psychiatric hospitalizations. The CMI focused on individuals who had been acutely ill enough to have been hospitalized in a psychiatric unit at least twice in the prior year and whose pattern of service use continued to raise significant clinical concerns.

The CMI leadership committee deemed the following patterns of service use as raising clinical concerns significant enough to warrant intervention: Continued frequent psychiatric hospitalizations (defined as 2 or more psychiatric unit admissions within the previous 4 months) -- while many individuals are re-admitted once within a 6-month period, the CMI leadership deemed 2 or more admissions a strong signal suggesting that current treatment needed improvement); lack of engagement in outpatient services (defined as no outpatient services for a mental health or substance use disorder in the previous 4 months); and not taking psychotropic medication (defined as no filling of a psychotropic medication prescription in the previous 2 months). Other mental health service systems, as well as accrediting bodies such as NCQA, have begun using similar flags to identify clinical concerns, prompt interventions, or make inferences about quality of care.

In this manuscript we examine the extent to which these clinical flags are, in fact, predictive of continued psychiatric hospitalizations.

Methods

We used New York and Pennsylvania Medicaid claims to identify Medicaid-enrollees age 18 to 64 with two or more inpatient psychiatric hospitalizations during the year ending March 31, 2009. We defined inpatient psychiatric hospitalizations as an inpatient claim with a mental health or substance use primary diagnosis. We tracked the cohort's service utilization for 24 months to see what patterns of service use were sufficiently predictive of additional hospitalizations to be clinically useful.

We used CMI definitions to identify patterns of service use that were of clinical concern. These flags were: 2 or more psychiatric admissions within the previous 4 months, no outpatient visit for mental health or substance use disorder in the previous 4 months, no filling of a prescription of a psychotropic medication in the previous 2 months. These flags were computed as of the first day of each of the 24 months from April 1, 2009 through March 1, 2011. We included those individuals who had Medicaid eligibility for at least 90% of the previous 4 months as of the first day of the focal month. The New York State Psychiatric Institute's IRB and University of Pittsburgh's IRBs approved the project.

Statistical Analysis

We conducted two complementary analyses (described below) to provide a more robust understanding of the extent to which the clinical flags are predictive of psychiatric hospitalizations. For each month, we calculated the presence/absence of each of the three flags for each individual. Analyses of Medicaid claims indicated that about 90% of mental health inpatient and outpatient services were paid within 4 months of the service date with prescription claims typically generated at the time of fill.

Our overall goal was to better understand what predicted continuing to be a heavy user of inpatient services, operationalized as having two or more hospitalizations in the coming 4 months for individuals with SMI and a history of recent hospitalizations. We used 'lagged' (i.e., previous) occurrences of the various flags to predict the value (present/absent) of a current hospitalization flag. We incorporated variables for patient characteristics, including

age, gender, the number of inpatient admissions during the time period that determined cohort membership, membership in a Medicaid managed care plan, and receipt of Supplemental Security Income (SSI) to control for their association in predicting continued hospitalizations.

We used generalized estimating equations (GEE) models to describe longitudinal trajectories over time. These models allowed us to examine what happened over the entire time period being examined with respect to the outcomes of interest, and let us identify whether there were trends that occurred over the entire time frame (such as a plateauing of the rate of hospitalization). Recognizing that some decision makers must emphasize data from the recent past and ask how those data predict the near term future, we also ran Markov models. The Markov models ask what events (e.g. recent service use) predict the future (e.g., continued frequent hospitalizations) from *this* particular timepoint, and may potentially provide more relevant information regarding what factors may affect the near term future than the GEE analyses.

We used GEE models with a binomial distribution and logit link function to account for correlation of repeated observations over time (SAS PROC GENMOD). We used a GEE approach to examine longitudinal, population-averaged effects of prior flags in predicting future hospitalization flags. The most recent look-back period for a flag was 4 months prior to the 4-month period containing the index hospitalization flag; the second most recent look-back period was the period 4-8 months prior to the index hospitalization flag, and so on in lagged 4-month intervals.

To determine the extent to which, at specific timepoints, prior flags predict future hospitalization flags, we applied Markov chain models (9) using logistic regression (SAS PROC LOGISTIC). At 4-month intervals during the observation period (months 1-4, 5-8, 9-12, 13-16, 17-20), we examined the extent to which presence of hospitalization flag was predicted by previous flags, where the number of previous 4-month intervals, n , defined the Markov model of order n .

In the Markov model of order 1, each four-month period defined a transition, where the flag value (0 or 1) at end of the transition was used to predict the value of the hospitalization flag at the end of the next transition. In Markov model of order 2, two successive 4-month periods defined a transition (months 1-4 and 5-8 comprised the first transition, months 5-8 and 9-12 comprised the second transition, etc.; see Figure 1). Values of the hospitalization flags at the end of two consecutive four-month periods were used to predict the value of the flag at the end of the next 4-month period. Higher-order Markov models were constructed similarly.

Results

Descriptive Statistics

The selection criteria resulted in 11,801 unique individuals in New York and 1,859 in Pennsylvania, with 11,150 New York individuals (94%) and 1,680 in Pennsylvania (90%) meeting the Medicaid eligibility criterion of at least 90% of days in each relevant look back

period. Individuals' service utilization data was used to compute monthly rates of generating flags. Sixty percent of the New York cohort and 54% of Pennsylvania were men. The mean age was 38 ± 11.5 years in New York and 37 ± 11.9 years in Pennsylvania. In New York, the racial mix was 42% white and 37% black, with other races completing the cohort. In Pennsylvania, the racial mix was 63% white and 29% black, with other races completing the cohort. Individuals in New York were classified as residing either in the greater New York City region (62% of the cohort) or elsewhere (38% of the cohort).

Individuals were assigned to one of 5 large diagnostic categories (mood disorders, schizophrenia disorders, alcohol dependence disorders, substance dependence disorders and other mental health or substance use disorders) based on the most common primary diagnoses for hospitalizations determining the analytic cohort. In case of ties, we assigned individuals the most recent of those diagnoses. In New York, schizophrenia disorders (31%), mood disorders (30%) and other mental health or substance use disorders (19%) were most common. In Pennsylvania, mood disorders (62%), schizophrenia disorders (21%), and other mental health and substance use disorder diagnoses (13%) were most common.

Table 1 shows the percentage of individuals for each month with patterns of service use that generated flags suggesting clinical concerns. Because no new members were added to this cohort, the number of those meeting the 90% Medicaid eligibility criteria decreased over time (Table 1).

Over 24-months, the likelihood of generating hospitalization flags fell from 28% to 8% in New York and from 7% to 3% in Pennsylvania (Figure 2), indicating that those remaining in the cohort experienced ever fewer psychiatric hospitalizations over time. In contrast, rates of generating flags indicating no outpatient service use increased from 24% to 30% in New York and from 20% to 35% in Pennsylvania. Rates of generating flags indicating no filling of a prescription for a psychotropic medication in the previous 2 months fluctuated around 37% in New York over time and increased from approximately 25% to 40% in Pennsylvania.

Predicting Hospitalization Flags from Previous Hospitalization Flags

When the GEE model "looked back" from the index interval, the value of the flag for the most recent lagged interval (i.e., the value of a flag for the interval with a lag of 1, representing 2 or more hospitalizations in months 1-4 prior to the index interval) was a significant predictor of the presence of a hospitalization flag in the index interval (New York: OR=4.6, $p<.001$; Pennsylvania: OR=8.7, $p<.001$). In New York, but not in Pennsylvania, values of the two prior hospitalization flags also each significantly predicted future hospitalization flags (flag lagged 4 months: OR=4.7, $p<.001$, flag lagged 8 months: OR=2.2, $p<.001$), and this pattern also held for three, four, and five lagged intervals. Number of inpatient admissions during the time period determining membership in the cohort was a significant predictor of future inpatient flags in all models (in New York, OR=1.2, $p<.001$; in Pennsylvania, OR=1.3, $p<.001$, each with one lagged hospitalization flag).

In New York, Markov models 1-4 consistently showed that generation of hospitalization flags in the most recent prior interval was the strongest predictor of subsequent hospitalization flags, with diminishing associations for relatively distant intervals. Markov model 1 showed that the odds that an individual who had generated a hospitalization flag at month 17 also would generate a hospitalization flag at month 21 was 7.2 ($p<.001$) times that of an individual who had not generated a hospitalization flag. In Pennsylvania the odds ratio of 8.5 was similarly high ($p<.001$). At earlier transition periods, the association was attenuated. Compared to individuals who hadn't set hospitalization flags at the end of transition period 1 (months 1-4), individuals in New York who generated hospitalization flags were 1.8 times more likely to generate additional hospitalization flags at the end of transition period 2 (months 5-8) ($p<.001$). In Pennsylvania, such individuals were 1.7 as likely (n.s., $p=.14$).

When we included Age, Region of residence, Gender, Race, Managed Care status, Diagnosis (New York only), and SSI status in the Markov logistic regression analyses, age reached statistical significance in later transitions, but its odds ratio ranged only from .98 to .99. In New York Markov models, Region was consistently significant, with individuals in New York City showing greater likelihood of generating hospitalization flags over time, with modest odds ratios (e.g., in Markov (1), transition 1, region OR=1.20, $p=.006$).

Using the algorithm described above to assign an individual to a diagnostic category, we examined the utility of diagnosis in predicting inpatient hospitalization flags in New York. Using mood disorders as the referent, GEE models indicated that individuals with a substance use disorder were less likely to generate an inpatient flag (OR=.62, $p<.001$) and individuals with schizophrenia were more likely to generate an inpatient flag (OR=1.18, $p=.009$). Markov models yielded similar results.

To test the predictive models precision, we calculated the area under the receiver operating curve (AUC) for each GEE and Markov model and computed sensitivity, specificity, and predictive values. For the GEE models, the AUC ranged in values from .73 to .78, and from .70 to .78 for the Markov models for one to five predictor intervals, respectively. AUC did not change significantly with the addition of diagnosis to the GEE or Markov models.

Outpatient and Medication Flags as Predictors of Hospitalization Flags

The presence of previous outpatient flags was associated with a lower likelihood of generating a hospitalization flag (OR=.62, $p<.0001$). Similarly, the presence of previous medication flags also was associated with a lower likelihood of generating a hospitalization flag, also with an OR suggesting little clinical utility for this information (OR=.94, $p<.001$).

Discussion

States and other entities that contract with managed care organizations increasingly build claims-based performance measures into contracts to incentivize engaging people in services post-hospitalization and preventing rapid rehospitalizations. Our analyses demonstrated that claims data on prior psychiatric hospitalizations can identify Medicaid-enrollees at unusual risk of continued frequent behavioral health hospitalizations, and that as few as 4 months of

recent claims data are sufficient for this purpose. Managed behavioral health organizations and system administrators could use such information to authorize special services (e.g., mobile outreach, assertive community treatment teams). Studies examining claims for all types of hospitalizations similarly have shown that prior inpatient admissions are among the strongest predictors of future admissions.(10-12)

We found that recent hospitalizations are a greater predictor of continued frequent hospitalizations than more distant hospitalizations, suggesting a triage policy whereby individuals with multiple recent hospitalizations receive additional supports in order to avert a cascade of subsequent hospitalizations. Yet even recent hospitalizations are only fair predictors of continued frequent hospitalizations, and should be considered cautionary flags that a person is unusually at-risk for further hospitalizations, rather than a predictor of the certainty of continued frequent hospitalizations. Our analyses indicate that having access to more than one year's data yields modest, if any, increases in predictive power of who is at greatest risk for continued frequent hospitalizations. Hence, efforts to identify individuals eligible for special services to avert hospitalizations would do well to weight the recent past most heavily and to have such special services in place at the time of discharge.

The finding that lack of participation in outpatient services and lack of filling psychotropic medication prescriptions predict a modest decrease in the likelihood of continued frequent hospitalizations is surprising. We speculate that the project's bar for "participating in outpatient services" was set very low (at least one service in the previous 4 months), hence failed to identify individuals participating sufficiently in outpatient services for these services to have a protective effect. This also may be an instance of individuals who are the most ill receiving services. Alternatively, not using services may indicate that someone is doing well. Over 1/3 of the cohort did not fill a prescription for a psychotropic medication in the prior 2 months, and individuals who met this criterion were slightly less likely to continue to be hospitalized frequently than those who did (odds ratio .94).

The study has noteworthy limitations: Analytic files indicated whether outpatient services and medication fills occurred during 4-month look back periods but not the exact date of these services, thereby introducing more noise than if we could have modeled using precise dates. The CMI focused on individuals with frequent psychiatric hospitalizations, and we do not know how findings would generalize to frequent hospitalizations for other populations. We used data from states with relatively generous Medicaid mental health benefits and robust mental health provider systems and don't know how our findings would generalize to other regions or systems. Medicaid claims data don't provide information about non-Medicaid reimbursed services individuals may have been receiving, nor about the quality or appropriateness of services provided.

In this initiative, the bar for what constituted participating in outpatient services was set very low, while the bar for generating a hospitalization flag (2 or more admissions for mental health or substance use disorder within the previous 4 months) may have been set relatively high. Setting the outpatient bar higher and the hospitalization bar lower would have increased the numbers of individuals in the Care Monitoring Initiative dramatically, overwhelming the system's ability to provide enhanced outreach services.(8) Indeed, in part

because of the large number of individuals generating one or more flags, in its subsequent refinement of CMI, New York State elected to focus on the subset of individuals who continued to be hospitalized frequently and were had received fewer than four outpatient services in six months. Such a shift acknowledges that if someone isn't using outpatient services, isn't filling medication prescriptions, and staying out of the hospital, perhaps systems' resources should focus elsewhere even if that individual had multiple hospitalizations in the past year. Simultaneously, further research is needed to understand how the presence (and absence) of outpatient services and psychotropic medication claims can inform efforts to target services to individuals with mental health disorders at greater risk for negative outcomes, such as hospitalization.

Conclusions

Administrative data can identify individuals at high risk of continued frequent hospitalizations. Our findings suggest emphasizing recent service-use data to identify individuals most in need of services to help break a cycle of continuing rapid psychiatric readmissions. Our findings also have implications for designing algorithms to identify individuals eligible for specialized services, providing a cautionary tale regarding attempts to determine service eligibility based solely on past service use.

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Figure 1.
Markov model for predicting future hospitalization by observing previous hospitalization of Medicaid enrollees during four-month intervals

Figure 2.

Likelihood that prior hospitalization, lack of service use, and lack of prescription fill lead to future hospitalization of Medicaid enrollees over 24 months

Table 1
Service Utilization Based on Medicaid Eligibility (Initial Cohort, New York N=11,801 and Pennsylvania N=1,886)

Month of Observation	Look-Back Period Start	Look-Back Period End	Date of Service Count Calculation	Number With 90% Medicaid-Eligibility During Look-Back Period		Percent Acute Mental Health Inpatient Utilization		Percent No Outpatient Visits		Percent No Psychotropic Drug Fill (%)	
				NY	PA	NY	PA	NY	PA	NY	PA
1	12/1/2008	3/31/2009	4/1/2009	10205	1680	28.3	6.9	23.6	20.2	36.4	24.6
2	1/1/2009	4/30/2009	5/1/2009	10145	1619	24.9	6.3	23.8	21.9	36.3	25.3
3	2/1/2009	5/31/2009	6/1/2009	10000	1567	20.8	5.4	25.2	23.6	37.4	27.2
4	3/1/2009	6/30/2009	7/1/2009	9884	1514	17.7	5.7	26.1	24.9	37.8	27.3
5	4/1/2009	7/31/2009	8/1/2009	9730	1484	14.2	4.3	27.4	27.9	38.2	27.4
6	5/1/2009	8/31/2009	9/1/2009	9604	1449	13.4	3.4	28.2	28.8	38.2	29.3
7	6/1/2009	9/30/2009	10/1/2009	9511	1420	13.0	3.0	28.6	28.5	39.0	28.7
+8	7/1/2009	10/31/2009	11/1/2009	9405	1386	12.5	3.2	29.1	30.5	38.0	28.4
9	8/1/2009	11/30/2009	12/1/2009	9313	1375	11.9	3.2	29.4	30.8	37.7	29.5
10	9/1/2009	12/31/2009	1/1/2010	9206	1361	11.3	2.5	29.6	32.0	38.0	30.4
11	10/1/2009	1/31/2010	2/1/2010	9172	1353	10.9	2.7	29.1	32.6	37.2	30.7
12	11/1/2009	2/28/2010	3/1/2010	9111	1330	10.0	2.3	30.2	33.4	37.4	32.2
13	12/1/2009	3/31/2010	4/1/2010	9048	1323	10.3	2.9	29.3	33.1	36.8	31.1
14	1/1/2010	4/30/2010	5/1/2010	9019	1302	10.3	2.8	29.0	32.9	35.4	31.3
15	2/1/2010	5/31/2010	6/1/2010	8985	1295	10.1	2.8	29.3	32.3	36.4	34.4
16	3/1/2010	6/30/2010	7/1/2010	8957	1292	10.8	2.6	28.9	30.3	36.4	34.2
17	4/1/2010	7/31/2010	8/1/2010	8926	1298	10.2	2.8	29.1	32.4	36.7	34.1
18	5/1/2010	8/31/2010	9/1/2010	8856	1298	10.1	2.8	28.8	33.6	36.1	35.7
19	6/1/2010	9/30/2010	10/1/2010	8811	1286	10.3	2.9	28.5	32.6	36.2	36.0
20	7/1/2010	10/31/2010	11/1/2010	8779	1281	10.0	3.0	28.8	33.3	35.7	37.4
21	8/1/2010	11/30/2010	12/1/2010	8744	1274	9.5	2.1	29.8	34.0	36.2	37.2
22	9/1/2010	12/31/2010	1/1/2011	8703	1267	9.2	2.1	29.4	34.6	36.1	37.8
23	10/1/2010	1/31/2011	2/1/2011	8658	1252	9.0	2.8	29.6	34.6	35.0	39.5
24	11/1/2010	2/28/2011	3/1/2011	8651	1245	8.4	2.7	29.9	35.3	35.9	40.3

(*) The Look Back period for filling a prescription for a psychotropic medication is the previous two months.

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