12-27-2015

System-Wide Prediction of General, All-Cause, Preventable Hospital Readmissions

Ken Musselman
Purdue University, kenmus@purdue.edu

Brandon Pope
Baylor Health Care System, Brandon.Pope@baylorhealth.edu

Steve Witz
Purdue University, switz@purdue.edu

Zhiyi Tian
Purdue University, tianz@purdue.edu

Lingsong Zhang
Purdue University, lingsong@purdue.edu

See next page for additional authors

Authors
Ken Musselman, Brandon Pope, Steve Witz, Zhiyi Tian, Lingsong Zhang, Linda Leon, and Ann Davis

System-wide prediction of general, all-cause, preventable hospital readmissions

Brandon Pope, Ph.D.

Baylor Health Care System

Ken Musselman, Ph.D. Zhiyi Tian Steve Witz, Ph.D. Lingsong Zhang, Ph.D.

Regenstrief Center for Healthcare Engineering, Purdue University

Linda Leon Ann Davis

BayCare Health System

Abstract

Existing studies of hospital readmissions typically focus on specific diagnoses, age groups, discharge dispositions, payer classes, or hospitals, and often use small samples. It is not clear how predictive models generated from such studies generalize across diseases, hospitals, or time periods. In this study, a logistic regression model of readmission risk within 30 days based on hospital administrative data was constructed and validated across hospitals and time periods. The hospitals included both general and specialty hospitals such as long-term care, women's, and children's hospitals. The administrative data included information on patient's demographics, diagnoses, procedures, and discharge disposition. Derivation and validation samples for the cross-hospital analysis yielded C-statistics of 0.722 and 0.706, respectively. The cross-time period analysis yielded C-statistics from 0.736 to 0.755 for five derivation samples, and from 0.681 to 0.701 for fifteen validation samples. The findings indicate that a prediction model can be used with relative success to extrapolate beyond the estimation sample both in terms of hospital and time period. Such risk estimates can be used to inform discharge intervention decisions and increase care coordination.

Keywords: 30-day all-cause hospital readmissions, preventable readmission risk, predictive analytics, derivation and external validation of a prediction model, logistic regression

Introduction

Hospital readmission rates in the U.S. healthcare system are a concern because of the quality of care being received by patients as well as the cost of utilization to those who pay for healthcare. Increased research on readmissions in the last several years has been driven by legislation in the Affordable Care Act articulating increasingly strong financial penalties for hospitals that have relatively high risk-adjusted readmission rates. There is significant debate in the literature as to the extent to which readmissions rates provide a signal of hospital quality (Stefan et al., 2013). Related to this question are findings that hospitals' environments (Joynt & Jha, 2013) and patients' social factors (Calvillo–King et al., 2013) are significantly associated with readmission rates, and that readmission rates are negatively (albeit weakly) associated with mortality rates for some conditions (Krumholz, Lin, Keenan, & et al., 2013). Regardless of how true a signal of hospital quality overall readmission rates provide, preventable hospital readmissions are a significant source of unnecessary utilization and an undesirable outcome for patients.

To this end, considerable effort has gone into developing predictive models of readmission risk and identifying interventions that reduce readmission rates. Statistical and data mining classification methodologies such as logistic regression, decision trees, random forests and support vector machines are being used to develop sophisticated predictive models of readmission risk (Cholleti et al., 2012; Natale, Wang, & Taylor, 2013). However, much of the work being done is focused on specific populations: pediatric (Berry, Toomey, Zaslavsky, & et al., 2013), Medicare patients, veterans (Kaboli et al., 2012), or specific diseases, such as acute myocardial infarction (Dunlay et al., 2012), heart failure (Keenan et al., 2008), and total hip arthoplasty (Cram, Lu, Kaboli, & et al., 2011). General readmission models do exist (Hasan et al., 2010), but the majority of existing studies have limited data, and often do not provide evidence for their model's ability to generalize outside the study data (e.g., across extended time periods, multiple hospitals, or related diseases). Understanding the generalizability of models would significantly inform the ability of discharge planners and nurses to make confident decisions regarding interventions to reduce readmissions. See Kansagara et al. (2011) and Wan et al. (2012) for reviews of predictive models for readmission risk. In this paper, the focus is on general (all admission diagnoses), all-cause (all readmission diagnoses), preventable 30-day readmissions, identifying factors associated with risk of readmission and studying the ability of predictive models to extrapolate to non-derivation hospitals and future time periods.

Data

The study used a retrospective observational design to examine readmission risk. The data set was comprised of hospital records from an administrative database in the BayCare Health System, the largest community-based health system in the Tampa Bay, Florida, area. The six-and-a-half years of data used in the study spanned from 2005 to 2011, during which time BayCare's hospital network expanded from 10 to 11 hospitals (with St. Joseph's Hospital – North becoming operational in 2010). The hospitals included 8 general hospitals (including a Level II trauma center) with bed sizes ranging from 108 to 687 with a mean bed size of 308 and median bed size of 227, and 3 specialty hospitals (women's, children's, and long-term care).

Except for cases of missing or misreported data, the elements for each record included data on the patient (e.g., name, age, gender, payer class, race, language, marital status), admission (e.g., date, hospital, type, diagnoses), stay (e.g., procedures performed, use of ventilator), and discharge (e.g., date, disposition, diagnoses, disease severity index [based on the 3M All Patient Refined DRG (APR DRG) Classification System]). From these data elements, computed variables such as length of stay, days since last discharge, number of prior admissions and Charlson comorbidity index (Charlson, Pompei, Ales, & MacKenzie, 1987) were derived as well as whether or not an unplanned readmission occurred within 30 days. Maintenance chemotherapy and planned procedures not for acute diagnoses or complications of care were considered planned admissions (Horwitz et al., 2012). Although only unplanned admissions were identified as readmissions, both planned and unplanned admissions were included as index admissions.

Cleaning Process

To clean the data, patients and records reflective of unpreventable admissions were removed. This cleaning process was executed in three stages, as depicted in Figure 1. The motivation and the cleaning process are discussed at a high level below, and more specific details regarding ICD-9 codes, MS-DRG codes, etc., are given in the appendix.

In the first stage, patients (meaning all records associated with those patients) for which all or most of their admissions were likely to be unpreventable were removed from the data set. This subset of patients included those with diagnoses of cancer or undergoing chemotherapy, patients with end-stage renal disease (ESRD), patients on hospice care, and patients whose first admission resulted in death.

In the second stage, specific admissions were removed when the reason for that admission could be identified as unpreventable. This subset of admissions included mothers giving birth, deaths and organ donations, rehabilitation visits, and major or significant trauma. A significant number of patients were transferred. These transfers fell into one of two categories: external and internal. External transfers, meaning outside the BayCare Health System, were out of scope, for no transfer hospital information was available. Internal transfers were either to the same hospital or to another BayCare hospital, resulting in multiple records. In both cases, the hospitalizations were combined and the resulting record was assigned to the receiving hospital. Transfers to the same hospital usually arose due to billing, not clinical, needs. Transfers to another BayCare hospital were assumed done for clinical purposes and, thus, were not considered preventable readmissions.

In the third stage, the largest group of admissions removed was observation-only visits, for they did not result in a typical discharge process. While this decision is debatable, it was made for two reasons. First, it was consistent with past Center for Medicare and Medicaid Services' conventions (Bhat et al., 2012), and second, inpatient visits were deemed to be more resource-intensive and amenable to intervention. Other removals at this stage included the first six months and the last 30 days of admissions. This was done to accommodate various calculations associated with patients' historical utilization and to avoid data truncation at the end of the time period. Admissions in the last 30 days, while not included as index admissions, were

used to count readmissions. Finally, admissions with either coding errors (e.g., patients older than 1 admitted as newborns) or incomplete records (e.g., missing race) were removed.

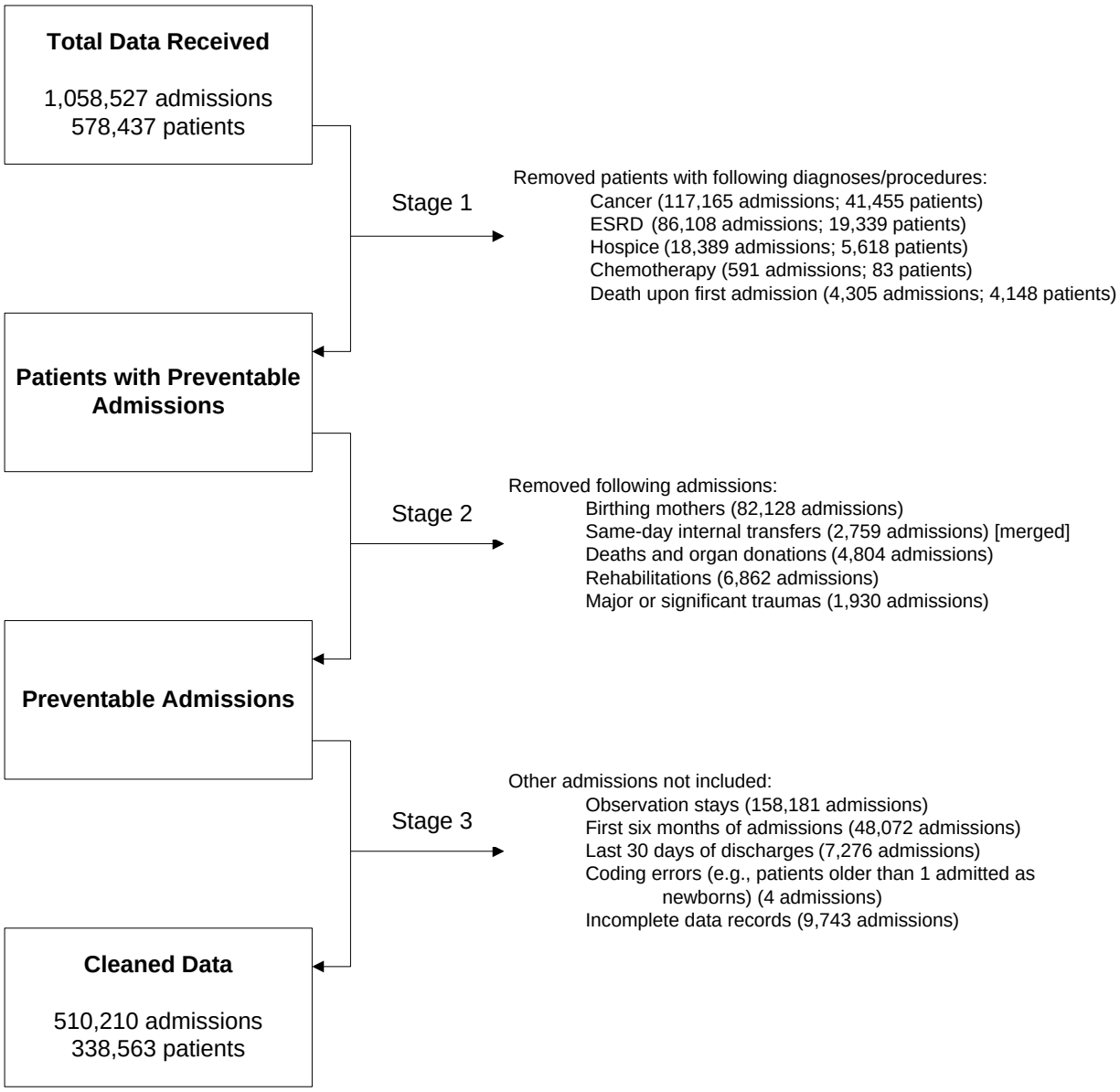

Figure 1. Data cleaning process, showing removal counts at each stage

In the process of removing admissions in the second and third stages, patients could be, in effect, removed from the data set. This was only done in these latter two stages if all of a patient's admissions were removed.

The above exclusion process, with a few exceptions, aligns with CMS' 30-day readmission measure (National Quality Forum, 2012). However, instead of CCS codes, ICD-9 and MS-DRG codes were used to map to essentially the same admission set. Beyond that, the most

significant differences were in the areas of hospice care, cancer disease, renal disease, and major trauma. For hospice care, the patient was assumed to be receiving end-of-life care and any readmission for this patient was thus deemed non-preventable. When cancer patients were examined longitudinally, the vast majority of them had repeated (not necessarily within 30 days), cancer-dominated admissions. As a result, these admissions were also judged to be non-preventable, and the associated patients were then subsequently removed from consideration. The same logic held true for patients with renal disease. Finally, admissions for major or significant trauma were assumed to be unavoidable. Accordingly, these particular admissions, but not the associated patients, were removed from consideration as well.

At the conclusion of the cleaning process, 510,210 admissions across 338,563 patients could be used to study all-cause readmission factors for a general population. Table 1 summarizes the resultant clean data set, in which 8.52% of admissions result in a preventable readmission within 30 days and 11.98% within 60 days. The clean data admissions represent a range of age

Characteristic	Clean Data		Characteristic	Clean Data	
Unplanned 30-day Readmissions, n (%)	43,457	(8.52)	Payer Class, n (%)		
Unplanned 60-day Readmissions, n (%)	61,117	(11.98)	Commercial	168,151	(32.96)
Gender, n (%)			Medicaid	119,930	(23.51)
Female	282,275	(55.33)	Medicare	187,839	(36.82)
Male	227,935	(44.67)	Self-Pay	8,590	(1.68)
Age, mean (SD)	44.24	(29.63)	Pending Assistance	25,700	(5.04)
Race, n (%)			Marital Status, n (%)		
Asian	4,664	(0.91)	Divorced	41,018	(8.04)
Black	66,835	(13.10)	Legally Separated	7,637	(1.50)
Hispanic	62,051	(12.16)	Married	159,224	(31.21)
Other	9,111	(1.79)	Single	248,352	(48.68)
White	367,549	(72.04)	Widowed	53,979	(10.58)
Admission Type, n (%)			Behavioral Flag - Substance, n (%)	48,839	(9.57)
Emergency	294,541	(57.73)	Behavioral Flag - Non-substance, n (%)	143,041	(28.04)
Newborn	75,198	(14.74)	Ventilator Flag, n (%)	9,428	(1.85)
Routine	95,604	(18.74)	Length of stay, mean (SD)	4.19	(5.41)
Trauma	547	(0.11)	Days Since Last Discharge, mean (SD)		
Urgent	44,320	(8.69)	First Admission	323,422	(63.39)
Disease Severity Index, n (%)			0-15	31,528	(6.18)
Minor	190,199	(37.28)	16-30	14,820	(2.90)
Moderate	216,714	(42.48)	31-60	19,188	(3.76)
Major	86,482	(16.95)	61-182	38,723	(7.59)
Extreme	16,815	(3.30)	183-365	29,117	(5.71)
Discharge Disposition, n (%)			366+	53,412	(10.47)
Hospital	6,991	(1.37)	Hospital [Beds], n (%)		
Non-acute Facility	118,732	(23.27)	BayCare Alliant Hospital [48]	369	(0.07)
Routine Discharge	375,269	(73.55)	Mease Countryside Hospital [300]	64,527	(12.65)
Specialty Facility	3,732	(0.73)	Mease Dunedin Hospital [143]	25,797	(5.06)
Without Treatment	5,486	(1.08)	Morton Plant Hospital [687]	117,190	(22.97)
Charlson Comorbidity Index, mean (SD)	0.85	(1.35)	Morton Plant North Bay Hospital [154]	21,106	(4.14)
Language, n (%)			St. Anthony's Hospital [395]	46,005	(9.02)
English	405,643	(79.51)	South Florida Baptist Hospital [147]	26,600	(5.21)
Spanish	12,964	(2.54)	St. Joseph's Children's Hospital [186]	45,016	(8.82)
Other	9,580	(1.88)	St. Joseph's Hospital [527]	110,126	(21.58)
Missing	82,023	(16.08)	St. Joseph's Hospital-North [108]	3,959	(0.78)
Total Admissions within Prior Three	0.21	(0.57)	St. Joseph's Women's Hospital [157]	49,515	(9.70)

Months, mean (SD)		
Total Admissions within Prior Three to Six Months, mean (SD)	0.11	(0.43)

Table 1. Population characteristics across BayCare Health System over six years

groups from a predominately white (72.04%), English-speaking (79.51%) population made up of mostly singles (48.68%) and females (55.33%). The majority of admissions come through emergency (57.73%), while the largest payer class is Medicare (36.82%). Approximately one quarter (28.04%) of the admissions have at least one diagnosis associated with non-substance abuse related behavioral health problems, and nearly one tenth (9.57%) of the admissions have at least one diagnosis associated with substance abuse related behavioral health problems. The most common non-routine discharge dispositions are to non-acute care facilities (23.27%), which include home health care, rehabilitation facilities, skilled nursing facilities, and other similar extended/long-term care facilities.

Modeling and Methodology

A logistic regression model was used to predict the probability of a patient's readmission within 30 days for any given discharge. It was estimated by maximum likelihood estimation with penalization on the coefficients to avoid overfitting. By imposing a penalty factor on large fluctuations of the estimated parameters directly into the model development process, a more stable and accurate regression model could be achieved from the relatively high dimensional data set.

The patient characteristics serving as independent variables in the model were grouped into three categories: (1) characteristics representing the patient's demographics including age, gender, race, marital status, language, and payer class, (2) characteristics representing the patient's historical utilization including prior admissions, Charlson comorbidity index, and days since last discharge (calculated from the patient's previous hospitalization), and (3) characteristics representing the current utilization of the patient including admission type, disease severity index, flag indicating whether the patient spent time on a ventilator, length of stay, discharge disposition, flags indicating the presence of behavioral diagnoses associated with and without substance abuse, and the Agency for Healthcare Research and Quality's Clinical Classifications Software (CCS) single-level principal diagnosis and procedure codes (Elixhauser, Steiner, & Palmer, 2012).

To provide evidence of the ability of predictive readmission models to generalize across hospitals, the clean data set was split into derivation and validation subsets. The derivation subset consisted of the (cleaned) admissions occurring only at St. Joseph's Hospital (SJH), which is one of BayCare's major acute care hospitals. SJH was selected as the derivation hospital due to its size and comprehensive scope of care. This enabled the resultant cross-hospital derivation model to be as robust as possible. It was less likely that the smaller or more

focused care hospitals would have diagnoses or procedures not included in the SJH-derived model. The other ten hospitals were then used for validating the SJH-derived model.

In like manner, to provide evidence of the ability of predictive readmission models to generalize across time periods, the SJH clean data set was divided into six subsets comprised of the first six years of their data. Using the first year as model derivation data, the subsequent years were used to validate the model's ability to extrapolate into future time periods at SJH. Similarly, year two was then used to examine the model over years three through six, and so forth.

Results

Results from both validation analyses – cross-hospital and cross-time – are given below. While the SJH-derived model (over the entire time span) for the cross-hospital validation is described in detail, the analogous five SJH-derived models (each over one year time intervals) for the cross-time validation are omitted because of their similarity to the cross-hospital derivation model and for brevity.

Cross-hospital Validation

Model predictors used in the SJH-derived model for the cross-hospital analysis are seen in Table 2. The reference level for each categorical variable was chosen on the basis of either being of lowest risk or highest frequency.

The discrete variables recording the patient's principal diagnosis and procedures (CCS single-level) each had over 200 unique values. For both variables, the categories were ranked by the range of their odds ratio confidence intervals. Along with the reference value, the values with the five greatest lower bounds and the five smallest upper bounds on their odds ratio are displayed in the table.

The majority of the patient characteristics modeled as independent variables are significantly associated with the probability of 30-day readmission. All of the characteristics reflecting historical utilization are strongly associated with this risk. The characteristics that do not significantly add to the readmission model are the patient's gender and marital status. The model's C-statistic for the derivation cohort is 0.722.

Category	Independent Variable	Odds Ratio	95% CI	P value
Demographics	Gender			0.3117
	Female	Reference		
	Male	1.02	(0.98 – 1.07)	
	Age	0.998	(0.996 – 0.999)	0.008
	Race			0.0192
	Asian	0.88	(0.66 – 1.18)	
	Black	0.94	(0.89 – 1.00)	
	Hispanic	0.91	(0.85 – 0.96)	
	Other	1.01	(0.83 – 1.22)	
	White	Reference		
	Marital Status			0.1019
	Divorced	1.09	(1.01 – 1.17)	
	Legally Separated	1.14	(1.00 – 1.30)	

	Single	1.05	(0.99 – 1.11)	
	Widowed	1.04	(0.96 – 1.12)	
	Married	Reference		
	Language			0.0054
	English	Reference		
	Spanish	0.93	(0.83 – 1.04)	
	Other	0.90	(0.69 – 1.16)	
	Missing	1.10	(1.03 – 1.16)	
	Payer Class			< 0.0001
	Commercial	Reference		
	Medicaid	1.37	(1.27 – 1.46)	
	Medicare	1.30	(1.22 – 1.40)	
	Self-Pay	0.60	(0.46 – 0.79)	
	Pending Assistance	0.99	(0.88 – 1.11)	
Historical Utilization	Prior Admissions within last 3 months	1.39	(1.33 – 1.45)	< 0.0001
	Prior Admissions within last 3 to 6 months	1.34	(1.29 – 1.39)	< 0.0001
	Charlson Comorbidity Index	1.05	(1.04 – 1.07)	< 0.0001
	Days Since Last Discharge			< 0.0001
	First Admission	Reference		
	0-15	1.57	(1.42 – 1.73)	
	16-30	1.60	(1.43 – 1.79)	
	31-60	1.42	(1.27 – 1.57)	
	61-182	1.26	(1.16 – 1.37)	
	183-365	1.66	(1.53 – 1.81)	
	366+	1.38	(1.29 – 1.49)	
Current Utilization	Admission Type			
	Routine	Reference		< 0.0001
	Emergency	1.29	(1.16 – 1.42)	
	Trauma	1.28	(0.83 – 1.98)	
	Urgent	1.18	(1.05 – 1.33)	
	Disease Severity Index			< 0.0001
	1	Reference		
	2	1.22	(1.15 – 1.29)	
	3	1.39	(1.29 – 1.50)	
	4	1.35	(1.19 – 1.54)	

Table 2. SJH-derived predictors of 30-day hospital readmission

Category	**Independent Variable**	**Odds Ratio**	**95% CI**	**P value**
Current Utilization (cont.)	Time on Ventilator			0.0132
	No	Reference		
	Yes	0.79	(0.66 – 0.95)	
	Length of Stay	1.01	(1.004 – 1.01)	0.0001
	Discharge Disposition			< 0.0001
	Routine Discharge	Reference		
	Hospital	4.55	(3.65 – 5.68)	
	Non-acute Facility	1.26	(1.19 – 1.34)	
	Specialty Facility	1.40	(1.12 – 1.74)	
	Without Treatment	1.59	(1.36 – 1.84)	
	Behavioral Flag Substance	1.08	(1.01 – 1.15)	0.0317
	Behavioral Flag Non-substance	1.15	(1.10 – 1.22)	< 0.0001
	Principal Diagnosis (CCS single-level)			< 0.0001
	657 Mood disorders	Reference		
	61 Sickle cell anemia	2.06	(1.68 - 2.54)	
	659 Schizophrenia and other psychotic	1.21	(1.08 - 1.36)	

disorders			
144 Regional enteritis and ulcerative colitis	1.26	(0.99 - 1.60)	
143 Abdominal hernia	1.34	(0.92 - 1.96)	
6 Hepatitis	1.42	(0.92 - 2.21)	
234 Crushing injury or internal injury	0.33	(0.20 - 0.54)	
235 Open wounds of head; neck; and trunk	0.24	(0.11 - 0.56)	
93 Conditions associated with dizziness or vertigo	0.37	(0.22 - 0.62)	
245 Syncope	0.49	(0.37 - 0.65)	
112 Transient cerebral ischemia	0.51	(0.38 - 0.68)	
Principal Procedure (CCS single-level)			< 0.0001
No procedure	Reference		
102 Ureteral catheterization	3.56	(2.46 - 5.17)	
103 Nephrotomy and nephrostomy	3.27	(2.20 - 4.87)	
161 Other OR therapeutic procedures on bone	2.11	(1.53 - 2.91)	
43 Heart valve procedures	2.08	(1.42 - 3.04)	
101 Transurethral excision; drainage; or removal urinary obstruction	1.80	(1.29 - 2.51)	
85 Inguinal and femoral hernia repair	0.21	(0.07 - 0.63)	
201 Cardiac Stress tests	0.41	(0.19 - 0.88)	
146 Treatment; fracture or dislocation of hip and femur	0.66	(0.47 - 0.93)	
168 Incision and drainage; skin and subcutaneous tissue	0.63	(0.43 - 0.93)	
148 Other fracture and dislocation procedure	0.56	(0.32 – 0.98)	

Table 2 (cont.). SJH-derived predictors of 30-day hospital readmission

Applying the SJH model to the other 10 hospitals in the BayCare system achieves a C-statistic of 0.706. The prediction model generalizes quite well to BayCare's broad range of hospitals, as shown in Table 3. This indicates that the associations identified by the SJH model are rather robust across hospitals. The discriminative ability of the model compares favorably to existing general readmission models (Hasan et al., 2010).

Hospital	C-statistic
BayCare Alliant Hospital	0.722
Mease Countryside Hospital	0.705
Mease Dunedin Hospital	0.715
Morton Plant Hospital	0.704
Morton Plant North Bay Hospital	0.711
St. Anthony's Hospital	0.704
South Florida Baptist Hospital	0.718
St. Joseph's Children's Hospital	0.703
St. Joseph's Hospital-North	0.721
St. Joseph's Women's Hospital	0.707

Table 3. Cross-hospital validation C-statistics of SJH-derived model

Figure 2 shows a histogram of the estimated 30-day readmission risks for the ten BayCare hospitals. In order to illustrate the predicted frequency of these readmissions, they were grouped into bins of width 0.02. The number of admissions falling into each bin is indicated on the vertical axis.

Figure 3 is a calibration plot of the SJH-derived model applied to these same 10 hospitals. A perfectly calibrated model, represented by the 45-degree line, would have predicted risks exactly equal to the observed probability of readmission. The dashed lines show the thresholds of a 95% confidence interval. When the observed probabilities of readmission lie outside these dashed lines, there is evidence to reject the claim that the model is perfectly calibrated. As shown, the predictive model is very well calibrated for patients with probability of readmission within 30 days less than or equal to 0.40. The model remains well calibrated, although slightly less so, for patients with probability of readmission within 30 days between 0.40 and 0.50. For patients with predicted risk above 0.50, the model appears to be over-predicting their risks of readmission. The dispersion of the data in the right half of Figure 3 is due in part to the decreased sample size, as indicated by both the tail of the histogram in Figure 2 and the widening of the confidence interval in Figure 3. Of operational importance, this overestimation of risk only occurs with a relatively small percentage of the population (as indicated by the histogram) who are already observed to be at very high risk (above 0.50).

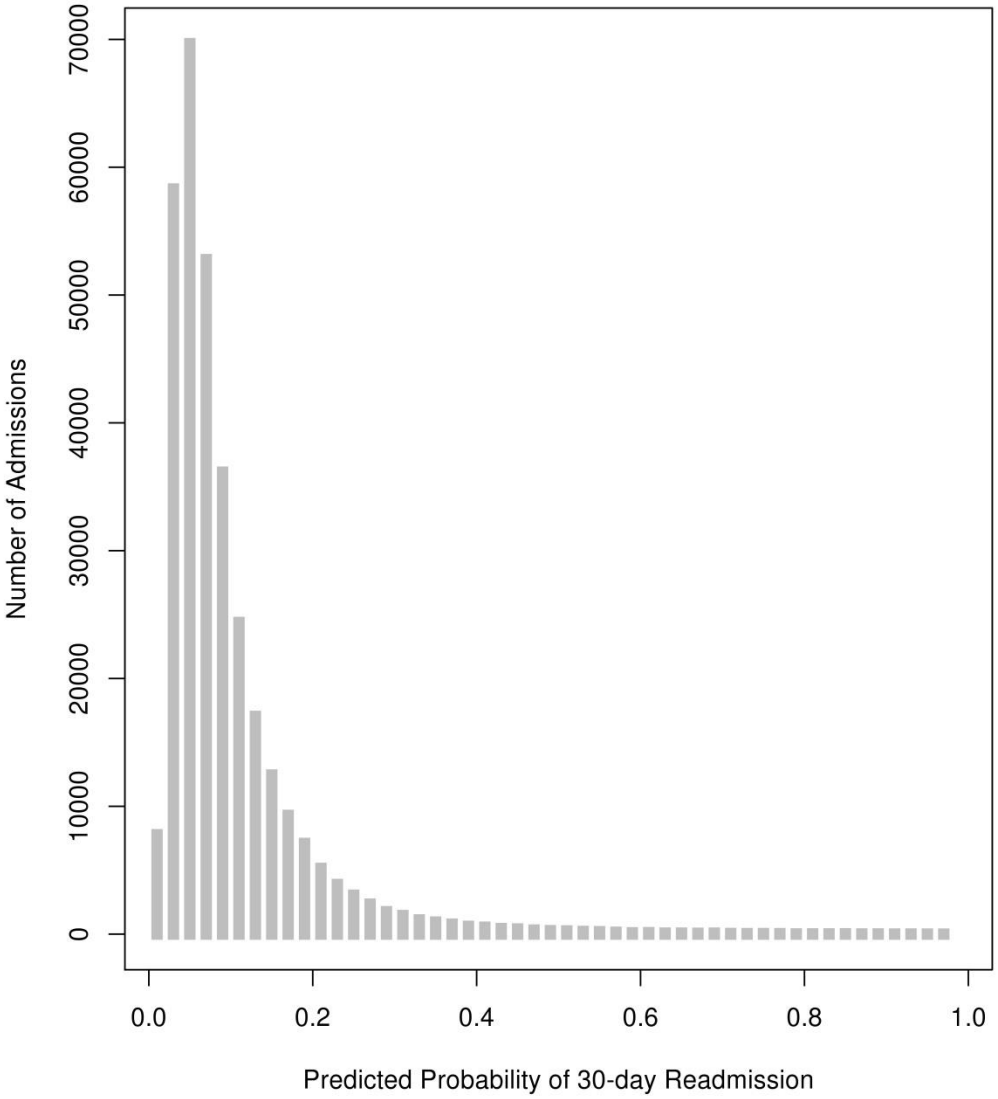

Figure 2. Histogram of predicted 30-day readmissions across ten BayCare hospitals

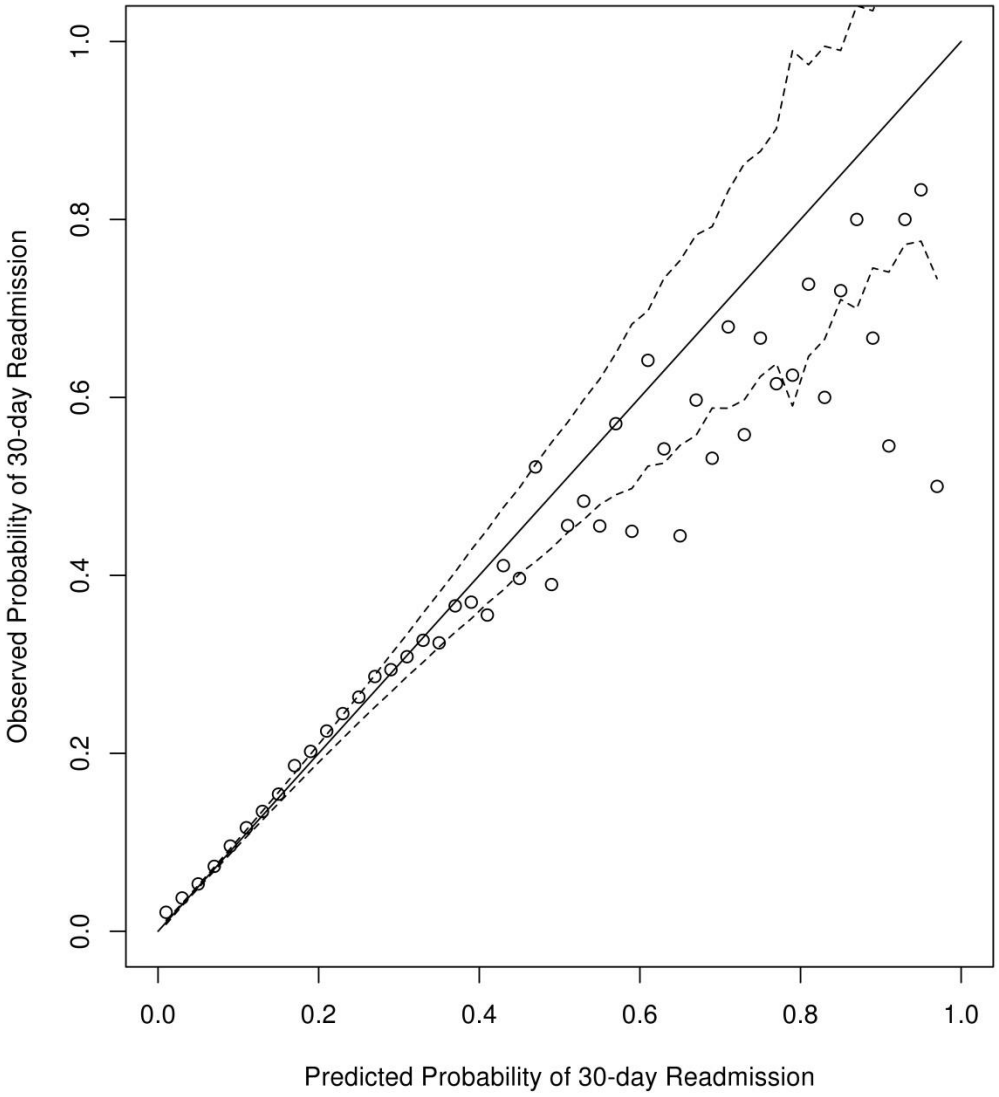

Figure 3. Calibration plot of predicted 30-day readmissions using SJH-derived model validated across ten other BayCare hospitals

Cross-time Validation

Turning now to the cross-time validation, five separate prediction models were derived from the SJH data, representing each of the first five years in the data set. The C-statistics resulting from this validation analysis are shown in Table 4. The results are quite similar to the cross-hospital results. The first time period SJH model (m_1) achieves discriminative C-statistics of 0.696, 0.689, 0.681, 0.681 and 0.688 when validated on years 2 through 6, respectively. Similarly, the

SJH models derived from years 2 through 5 (namely, m_2 through m_5) also achieve reasonable C-statistics when validated across future years.

Expectedly, the derivation years outperform the validation years. Yet, while this performance falls off, it remains relatively stable across these outer years.

Model / Year	1	2	3	4	5	6
m_1	0.755	0.696	0.689	0.681	0.681	0.688
m_2		0.750	0.682	0.683	0.688	0.690
m_3			0.742	0.689	0.683	0.697
m_4				0.738	0.682	0.701
m_5					0.736	0.697

Table 4. Cross-time validation C-statistics of SJH-derived model

Discussion

Preventable hospital readmissions remain a major concern in the United States. The Agency for Healthcare Research and Quality reported approximately 3.3 million adults in 2011 were readmitted within 30 days at an estimated cost of $41.3 billion (Hines, Barrett, Jiang, & Steiner, 2014). The ultimate purpose of a prediction model for patient risk of preventable readmissions is to improve patients' quality of care and reduce associated costs.

The intended use of a readmission risk model covers a continuum of time. Prior to a patient's actual admission, the model could be run to better prepare the discharge planner and the rest of the medical team to the likelihood of the incoming patient being readmitted. For any unknown factors (e.g., length of stay), reasonable predictions could be used. Then, throughout one's stay, the patient's risk could be revised as more factors become known. Finally, at discharge when the planner is coordinating with the medical team as to the patient's discharge instructions, the model could be run for a more accurate estimate of the patient's likelihood of returning. For factors not officially recorded until coding is complete, objective judgments could be made. Then, once coding is complete, a final run of the model could be made and the result communicated to the patient, if warranted, and recorded in the patient's record to support his or her next admission.

In the cross-hospital validation study, the readmission risk model was shown to be robust over a broad range of hospitals. These hospitals included both specialty and general with small to large bed sizes.

In the cross-time validation study, some decrease in accuracy was observed following each derivation year. However, the accuracy of these models remained stable in their respective outer years. This is not to suggest using the same prediction model for multiple years, but

should it be necessary, the use of a validated model over multiple years is not necessarily unwarranted.

Having identified factors associated with predicting a patient's risk of readmission within 30 days, the resultant model could now be leveraged to make pertinent operational decisions, leading to improvements in healthcare outcomes. Consider the case of deciding the most appropriate discharge intervention to assign to a patient. A discharge intervention can be generally thought of as an action taken during or after a patient's stay that serves to reduce his or her risk of readmission. It seeks to improve care coordination, provide medication education, increase post-discharge care adherence, or set expectations. These interventions, however, come with varying costs and efficacies. A rule-based decision support model could be constructed to optimally assign discharge interventions to various readmission risk classes. By combining a predictive risk model like the one discussed in this paper with an intervention assignment model, healthcare providers could assign transitional care services commensurate with each patient's level of risk. By better targeting interventions to patients, care quality would improve. Moreover, healthcare providers could possibly reduce their number of preventable readmissions to the point of precluding any financial penalties.

At a higher level, the combined model could also be used to assess the impact of these transitional care programs. By better targeting interventions, readmission rates for the associated patient classes would likely improve. Admittedly, the overall success of an intervention could, in turn, affect the prediction model, necessitating the need to adjust the model as the efficacy of the intervention is proven in the hospital's setting.

The combined model could also show where needlessly applying interventions to low-risk patients may not be advantageous. This would allow healthcare providers to avoid some unnecessary costs.

In summary, the varying costs and efficacies of interventions, the diverse risks presented by patients, and the continual need to provide patients with extended care make this combined decision support model a natural extension of the readmission prediction model. In the end, such a combined model could both improve care and save costs. One limitation of this study has to do with the absence of admissions and readmissions occurring at hospitals outside of the BayCare Health System. Patients who either had an index admission or were readmitted outside of BayCare were not identified as such in the data set. If an episode of care originated at a hospital other than a BayCare hospital, it was deemed to be out of scope. Readmissions to non-BayCare hospitals were also not considered for the same reason. If, however, the readmission occurred at a BayCare hospital, it was either combined with the patient's previous BayCare admission if admitted on the same day (assuming it to be either a billing convention or a continuance of care) or remained separated if the readmission occurred the next day or later.

Another limitation is the rationale used in the data cleaning process. While consistent with other conventions, the process is admittedly imperfect for it is based on medical codes. This means, for example, a significant trauma readmission, which was removed in this study, might have been preventable had the patient not been discharged in an unstable condition. In this case, it

could be argued that this readmission should have been included instead of being peremptorily removed.

Notably this data set lacks clinical observations that are often thought to be associated with risk for readmission and other adverse outcomes for specific diseases (e.g., blood pressure, HDL/LDL cholesterol, ejection fraction). Despite this absence, the readmission model performed quite well even though functioning over a broad range of diseases. Of course, the objective of predicting risk in a general population of patients would make the significance of any single clinical observation less valuable. The model indirectly accounted for clinical severity in two ways. First, it was likely that the measures of historical utilization were correlated with the clinical severity of the admitted patient, and hence tapped into some of the variability that would otherwise be explained by the patient's clinical record. Secondly, the disease severity index also likely captured some of this same variability.

A patient's historical utilization, in addition to capturing clinical variability, also pulled in social and environmental factors that were difficult to measure or were simply not recorded in electronic medical record systems (e.g., ability to adhere to care protocol, propensity to utilize hospital services).

Although the results of this study indicate that readmission models such as the ones considered here are general enough to be reasonably applied to hospitals and time periods outside of the derivation setting, the generalizability of such models is limited to the diagnoses and procedures presented in the derivation data set. Answers to questions such as the range of extrapolation and how readmission models can dynamically adjust are left for future research.

Acknowledgements
This research was partially supported by the Regenstrief Foundation and Information Technology at Purdue (ITaP).

References

Berry, J. G., Toomey, S. L., Zaslavsky, A. M., & et al. (2013). Pediatric readmission prevalence and variability across hospitals. *JAMA, 309*(4), 372-380. doi: 10.1001/jama.2012.188351

Bhat, K., Desai, M., Drye, E., Grosso, L., Krumholz, H. M., Lin, Z., . . . Wang, Y. (2012). 2012 Measures Maintenance Technical Report: Acute Myocardial Infarction, Heart Failure, and Pneumonia 30-Day Risk-Standardized Readmission Measure. In C. f. M. M. Services (Ed.).

Calvillo–King, L., Arnold, D., Eubank, K., Lo, M., Yunyongying, P., Stieglitz, H., & Halm, E. (2013). Impact of Social Factors on Risk of Readmission or Mortality in Pneumonia and Heart Failure: Systematic Review. *J Gen Intern Med, 28*(2), 269-282. doi: 10.1007/s11606-012-2235-x

Charlson, M. E., Pompei, P., Ales, K. L., & MacKenzie, C. R. (1987). A new method of classifying prognostic comorbidity in longitudinal studies: Development and validation. *J Chronic Dis, 40*(5), 373-383. doi: http://dx.doi.org/10.1016/0021-9681(87)90171-8

Cholleti, S., Post, A., Gao, J., Lin, X., Bornstein, W., Cantrell, D., & Saltz, J. (2012). *Leveraging derived data elements in data analytic models for understanding and predicting hospital readmissions.* Paper presented at the AMIA Annual Symposium Proceedings.

Cram, P., Lu, X., Kaboli, P. J., & et al. (2011). Clinical characteristics and outcomes of medicare patients undergoing total hip arthroplasty, 1991-2008. *JAMA, 305*(15), 1560-1567. doi: 10.1001/jama.2011.478

Dunlay, S. M., Weston, S. A., Killian, J. M., Bell, M. R., Jaffe, A. S., & Roger, V. L. (2012). Thirty-Day Rehospitalizations After Acute Myocardial InfarctionA Cohort Study. *Ann Intern Med, 157*(1), 11-18. doi: 10.7326/0003-4819-157-1-201207030-00004

Elixhauser, A., Steiner, C., & Palmer, L. (2012). Clinical Classifications Software (CCS), 2011. US Agency for Healthcare Research and Quality.

Hasan, O., Meltzer, D., Shaykevich, S., Bell, C., Kaboli, P., Auerbach, A., . . . Schnipper, J. (2010). Hospital Readmission in General Medicine Patients: A Prediction Model. *J Gen Intern Med, 25*(3), 211-219. doi: 10.1007/s11606-009-1196-1

Hines, A. L., Barrett, M. L., Jiang, H. J., & Steiner, C. A. (2014). Conditions With the Largest Number of Adult Hospital Readmissions by Payer, 2011: Statistical Brief #172. *Healthcare Cost and Utilization Project (HCUP) Statistical Briefs*. Retrieved from http://www.ncbi.nlm.nih.gov/pubmed/24901179

Horwitz, L., Partovian, C., Lin, Z., Herrin, J., Grady, J., & Conover, M. (2012). Hospital-wide all-cause unplanned readmission measure: final technical report. *Centers for Medicare and Medicaid Services*.

Joynt, K. E., & Jha, A. K. (2013). Characteristics of hospitals receiving penalties under the hospital readmissions reduction program. *JAMA, 309*(4), 342-343. doi: 10.1001/jama.2012.94856

Kaboli, P. J., Go, J. T., Hockenberry, J., Glasgow, J. M., Johnson, S. R., Rosenthal, G. E., . . . Vaughan-Sarrazin, M. (2012). Associations Between Reduced Hospital Length of Stay and 30-Day Readmission Rate and Mortality: 14-Year Experience in 129 Veterans Affairs Hospitals. *Ann Intern Med, 157*(12), 837-845. doi: 10.7326/0003-4819-157-12-201212180-00003

Kansagara, D., Englander, H., Salanitro, A., & et al. (2011). Risk prediction models for hospital readmission: A systematic review. *JAMA, 306*(15), 1688-1698. doi: 10.1001/jama.2011.1515

Keenan, P. S., Normand, S.-L. T., Lin, Z., Drye, E. E., Bhat, K. R., Ross, J. S., . . . Krumholz, H. M. (2008). An Administrative Claims Measure Suitable for Profiling Hospital Performance on the Basis of 30-Day All-Cause Readmission Rates Among Patients With Heart Failure. *Circulation: Cardiovascular Quality and Outcomes, 1*(1), 29-37. doi: 10.1161/circoutcomes.108.802686

Krumholz, H. M., Lin, Z., Keenan, P. S., & et al. (2013). Relationship between hospital readmission and mortality rates for patients hospitalized with acute myocardial infarction, heart failure, or pneumonia. *JAMA, 309*(6), 587-593. doi: 10.1001/jama.2013.333

Natale, J., Wang, S., & Taylor, J. (2013). *A decision tree model for predicting heart failure patient readmissions.* Paper presented at the 2013 Industrial and Systems Engineering Research Conference.

National Quality Forum (2012). Patient Outcomes: All-Cause Readmissions Expedited Review 2011. Technical Report 66 p.

Stefan, M., Pekow, P., Nsa, W., Priya, A., Miller, L., Bratzler, D., . . . Lindenauer, P. (2013). Hospital Performance Measures and 30-day Readmission Rates. *J Gen Intern Med, 28*(3), 377-385. doi: 10.1007/s11606-012-2229-8

Wan, H., Zhang, L., Witz, S., Musselman, K., Yi, F., Mullen, C., . . . Cure, L. (2012). *A Literature Review of Preventable Hospital Readmissions*. Regenstrief Center for Healthcare Engineering. Purdue University.

Appendix

Details of data cleaning and preprocessing

- Removed all admissions of patients for reasons of:
    - Hospice care discharge (discharge dispositions DSH HOSPICE GEN INPT CARE, DSH HOSPICE RESPITE CARE, HOSPICE HOME ROUTINE CARE, and HOSPICE HOME CONTINUOUS CR)
    - Cancer diagnosis (ICD-9 Diagnosis Codes 140-165, 170-176, 179-208, 209.0-209.3, 230-234)
    - Chemotherapy procedure code (ICD-9 Procedure Code 99.25)
    - Renal disease diagnosis (ICD-9 Diagnosis Codes 585.6, 585.9, 586)

- Removed specific admissions for reasons of:
    - Birthing mothers (MS-DRG Codes 765-768, 774, 775; if MS-DRG missing, DRG Codes 370-375)
    - Major or significant trauma (MS-DRG Codes 183-185, 955-959, 963-965; if MS-DRG missing, DRG Codes 083, 084, 484-487)
    - Rehabilitations (MS-DRG Codes 945, 946; DRG Code 462; MS-DRG or DRG Code with Case Mix Group (CMG) coding A-D)

- Binary flags indicating the presence of a diagnosis associated with behavioral health problems were created for both substance abuse related diagnoses and non-substance abuse related diagnoses. The ICD-9 codes associated with substance abuse related behavioral health problems are:

  291.1, 291.2, 291.3, 291.81, 291.89, 292, 292.11, 292.12, 292.81, 292.84, 292.85, 292.89, 292.9, 303, 303.01, 303.02, 303.9, 303.91, 303.92, 303.93, 304, 304.01, 304.1, 304.11, 304.2, 304.21, 304.22, 304.31, 304.7, 304.71, 304.8, 304.9, 304.91, 305, 305.01, 305.02, 305.03, 305.2, 305.21, 305.4, 305.41, 305.5, 305.51, 305.6, 305.61, 305.62, 305.63, 305.7, 305.9, 305.91, and 305.93.

  The ICD-9 codes associated with non-substance abuse related behavioral health problems are:

  290, 290.1, 290.12, 290.2, 290.21, 290.3, 290.4, 290.41, 290.42, 290.43, 291, 291.5, 291.9, 293, 293.81, 293.83, 293.89, 294.2, 294.21, 294.8, 294.9, 295.1, 295.12, 295.14, 295.2, 295.22, 295.24, 295.3, 295.31, 295.32, 295.33, 295.34, 295.4, 295.6, 295.62, 295.64, 295.7, 295.72, 295.73, 295.74, 295.8, 295.82, 295.84, 295.9, 295.92, 295,94, 296, 296.04, 296.2, 296.21, 296.22, 296.23, 296.24, 296.25, 296. 26, 296.3, 296.31, 296.32, 296.33, 296.34, 296.35, 296.4, 296.41, 296.42, 296.43, 296.44, 296.45, 296.46, 296.5, 296.51, 296.52, 296.53, 296.54, 296.6, 296.61, 296.62, 296.63, 296.64, 296.65, 296.7, 296.8, 296.89, 296.9, 296.99, 297.1, 297.3, 297.8, 297.9, 298, 298.2, 298.3, 298.8, 298.9, 299, 299.8, 299.9, 300, 300.01, 300.02, 300.09, 300.1, 300.11, 300.12, 300.14,

300.15, 300.16, 300.19, 300.21, 300.29, 300.3, 300.4, 300.7, 300.81, 300.82, 300.89, 300.9, 301.13, 301.3, 301.4, 301.7, 301.83, 302.85, 302.9, 304.5, 305.3, 306.8, 306.9, 307, 307.1, 307.3, 307.46, 307.47, 307.5, 307.51, 307.54, 307.89, 307.9, 308, 308.2, 308.3, 308.4, 308.9, 309, 309.1, 309.21, 309.24, 309.28, 309.3, 309.4, 309.81, 309.89, 309.9, 310, 310.8, 310.9, 311, 312.3, 312.31, 312.34, 312.39, 312.81, 312.82, 312.89, 312.9, 313.23, 313.81, 313.89, 314, 314.01, 314.9, 315.39, 315.8, 316, 318.1, 758, 758.39, 780.02, 780.1, 780.5, 780.54, 780.58, 799.22, V62.84, and V71.09.

This list of ICD-9 codes for behavioral health problems was provided by BayCare Health System.