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A Decision Support Algorithm for Referrals to Post-Acute Care

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Abstract

Objectives: Although hospital clinicians strive to effectively refer patients who require post-acute care (PAC), their discharge planning (DP) processes often vary greatly, and typically are not evidence-based.

Design: Quasi-experimental study employing pre-post design. Aimed at improving patient-centered discharge processes, we examined the effects of the DIRECT algorithm that provides clinical decision support (CDS) regarding which patients to refer to PAC and to what level of care (home care or facility).

Setting and Participants: Conducted in two hospitals, DIRECT data elements were collected in the pre-period (control) but discharging clinicians were blinded to the advice and provided usual discharge care. During the post-period (intervention), referral advice was provided within 24 hours of admission to clinicians, and updated twice daily. Propensity modeling was utilized to account for differences between the pre-/post- patient cohorts.

Measures: Outcomes compared between the control and the intervention periods included PAC referral rates, patient characteristics, and same-, 7-, 14-, and 30-day readmissions or emergency department (ED) visits.

Results: Although 24–25% more patients were recommended for PAC referral by DIRECT algorithm advice, the proportion of patients receiving referrals for PAC did not significantly differ between the control (3,302) and intervention (5,006) periods. However, the characteristics of patients referred for PAC services differed significantly and inpatient readmission rates decreased significantly across all time intervals when clinicians had DIRECT CDS compared to without.

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There were no differences observed in return ED visits. Largest effects were observed when clinicians agreed with the algorithm to refer (yes/yes).

Conclusions/Implications: Our findings suggest the value of timely, automated, discharge CDS for clinicians to optimize PAC referral for those most likely to benefit. Although overall referral rates did not change with CDS, the algorithm may have identified those patients most in need resulting in significantly lower inpatient readmission rates.

Keywords

patient discharge; decision support systems; nursing informatics; post-acute care; readmission; home health care; skilled nursing facility; long term care

Introduction

The goals of patient-centered care are to produce outcomes valued by patients and their caregivers. To that end, referrals from acute to post-acute care (PAC) are an important component. However, health care providers are increasingly pressured by policies and initiatives to decrease health care utilization and contain costs. The homebound requirement for skilled home health care (HHC),[1] a three day hospital stay to qualify for skilled nursing facility care (SNF),[2] or bundled payments seeking the least costly site of care may limit options.[3–5] These policies may result in patients not getting the optimal level of PAC needed to prevent poor discharge outcomes.

To optimize PAC referral decision making our team developed, validated and tested a two-step CDS algorithm called Discharge Referral Expert System for Care Transitions (DIRECT).[6] Based on patients' needs, the algorithm provides support for two decisions: whether or not to refer a patient for PAC, and if so, to which level of care, HHC or facility care such as SNF, inpatient rehabilitation (IPR), and nursing home (NH). The study purpose was to evaluate the effects of DIRECT on PAC referrals and patients' acute care utilization.

Methods

We used a quasi-experimental pre-post design with propensity modeling to account for differences between the two study cohorts (control=standard care versus intervention=DIRECT CDS).

The DIRECT CDS and Hospital Implementation.

The DIRECT CDS is a two-step algorithm calculated from the values of structured patient data drawn from the electronic health record. The data paints a profile of characteristics of the patient known from the literature and our prior work to be associated with the need for post-acute care or readmission risk. The first step of the algorithm advises whether or not a patient needs post-acute care. The second step recommends the level of care as home care or facility level care if the first step is yes refer. The DIRECT CDS was developed using expert consensus of multi-disciplinary clinicians (doctors, nurses, social workers and physical therapists) on the discharge disposition of 1,498 case studies of hospitalized adults (age 55 and older), with at least a 48 hour stay, and discharged alive from six hospitals. Discharge disposition choices included home to self-care (no PAC referral) or yes refer to home health care or facility level care (SNF, Nursing home, inpatient rehabilitation). Details of the algorithm development and validation using a randomly selected hold-out sample are described elsewhere.[6,7] The first step of the algorithm (*yes/no refer to PAC)* contains 17 unique patient characteristics (e.g. fall risk,[8] equipment use at home, activities of daily living (ADL) function). The second step suggests the *level of care* from 13 unique characteristics (e.g. Braden pressure ulcer risk,[9] caregiver information). In validation, the area under the curve (AUC) for the refer *yes/no* step was 91.5%. The AUC for the *level of care* step was 89.7%. An AUC greater than 70% indicates an acceptable model.[10]

The study took place at two hospitals within one health system; a 660 bed regional, teaching hospital and a suburban, 140 bed community hospital. All data needed for the CDS were routinely collected by nurses from patients or their caregivers and documented in the EHR upon admission and daily throughout the hospital stay. The health system's data analyst wrote a query to the EHR database to obtain the patient assessment data needed to calculate the two-step algorithm. The study was approved and a consent waiver was granted by the Institutional Review Boards of the university and the study hospitals.

The Control Phase

The study included patients age 55 years and older, admitted to and discharged alive (after at least a 48 hour stay) from the following units: Cardiac Surgical Intensive Care, Cardiovascular Step Down, Heart Failure, Medical/Surgical, Medical Intensive Care, Neuro Critical Care, Neurology, Oncology, Orthopedic, Progressive Care, Surgical, Surgical Trauma, Telemetry, and Telemetry Overflow. In the control phase, between May 8, 2015 and September 11, 2015, the DIRECT advice was calculated but <u>not shared</u> with the staff conducting the DP. This represented a period of usual care without decision support.

The Intervention Phase.

The principal investigator (PI) educated 30 case managers on how the DIRECT CDS was built and validated, its contents, and the workflow for using it in practice. Then, a report containing the CDS advice on whether or not to refer the patient, and the level of care, along with the characteristics of the patient associated with those decisions was emailed to the DP staff twice daily. CDS <u>was provided</u> for patients admitted to the above units between October 29, 2015 to April 30, 2016. The last subject was discharged on May 4, 2016 and outcomes data were collected 30-days post discharge.

Outcome Measures

Outcomes data on referral rate; same, seven, 14, and 30-day readmission; and ED use were obtained from the hospital administrative and admission, discharge and transfer (ADT) databases. Referral rate was determined by the proportion of patients with a discharge disposition coded as nursing home, IPR, HHC, hospice, or SNF; home to self-care equated to no referral.

Data Analysis

We described and compared the samples using descriptive statistics and chi square or Kruskal-Wallis tests. We calculated propensity scores using a probit model and used the scores to adjust for differences in cohort demographic and clinical characteristics between the two phases.[11] Variables used in creating the propensity scores included age, gender, race, education, employment status, living arrangement, length of stay (LOS), self-rated health, fall risk, Braden score, number of comorbidities, number of hospitalizations in the past six months, primary diagnosis category, discharged on narcotics, ADL function prior to admission, change in ADL function from prior to current, and DIRECT score. Variables were included in the PS scores if they influenced either the treatment selection and/or the outcome of readmission, as shown to be preferable by Austin, Grootendorst, & Anderson.[12] Comparisons between the control and intervention samples' readmission rates were computed using logistic regression with inverse probability weights (IPW) and robust standard errors. Secondary analyses in subsets of the samples used similar, though unweighted, methods to compare the intervention and control samples, plus Holm-Sidak adjustment for multiple comparisons.

Results

The control phase, without decision support, had 3,302 patients, average age 75.9, 52.5% female and 85.5% white. The intervention phase, with decision support, had 5,006 patients, average age 75.9, 54.6% female, and 85.4% White (Table 1). Due to admission timing, some patients (n =455; 5.8%) had more than one qualifying index stay and were included in both phases since independent discharge disposition decisions were made for each discharge. Table 2 shows a comparison of the clinical characteristics of the patients in each of the study phases.

The mean IPW was 1.7 +/− 0.4 in the intervention cohort and 2.5 +/− 0.8 in the control cohort. A number of methods were used to test the balance diagnostics. The largest absolute standardized difference between the intervention and control cohorts was 0.23 in the unweighted groups and 0.03 in the weighted sample. Boxplots of continuous variables showed similar distributions between continuous variables in the two weighted cohorts.

Outcomes

Referral rates.—The proportion of patients referred for PAC by DPs between the two phases did not change significantly. In the control phase 59.5% were discharged to PAC, and 59.3% were in the intervention phase (P=0.55). The DIRECT algorithm recommended PAC for 83.3% in control and 84.9% in the intervention phase (P=0.64). Therefore, the CDS identified 24% and 25.6% more patients for PAC than actual discharge dispositions in both the control and intervention phases respectively.

Referral location.—Among patients with a PAC disposition, the proportions referred to HHC or facility level care did not change significantly between control and intervention phases. The hospital clinicians referred 22.8% versus 23.6% to HHC and 36.6% versus 35.5% for facility care in the control phase and intervention phases respectively (P=0.55).

The DIRECT algorithm recommended HHC for 15.4% versus 16.6% and 67.9% versus 68.3% for facility care in the control phase and intervention phases respectively (P=0.64).

Health care utilization.—There was a statistically significant decline in readmission rates across all time periods (same, seven, 14 and 30 days) after applying the DIRECT algorithm in the intervention phase compared to the control phase without CDS (Table 3). The adjusted odds of same day readmission were 12.6 times higher in the control phase (OR, 12.62; 95% CI, 6.69–23.82; P<.001). Same day readmission rates declined by 2.4% between study periods (2.6% control to 0.2% intervention). This was a 92% relative reduction in same day readmissions.

The readmission rates within a 7-day period decreased 2.6% between study periods (7.3% control to 4.7% intervention) for a 36% relative reduction. Patients were 58% more likely to experience seven-day readmission in control than in the intervention phase (OR, 1.58; 95% CI, 1.14–1.77; P=.001).

The readmission rates within a 14-day period decreased 2.8% between study periods (10.3% control to 7.5% intervention) for a 27% relative reduction. Patients were 40% more likely to experience 14-day readmission in control than in the intervention phase (OR, 1.40; 95% CI, 1.20–1.65; P<.001).

The 30-day readmission rates decreased 2.7% between study periods (15.1% control to 12.4% intervention) for an 18% relative reduction. Patients were 24% more likely to experience 30-day readmission in control without CDS compared to the intervention phase with CDS (OR, 1.24; 95% CI, 1.08–1.41; P=.002).

There were no significant differences in ED use across the two study phases for all time periods.

Secondary analysis: Other measures of effectiveness.

Hospital length of stay.—We compared the average LOS based on the premise that receiving CDS shortly after admission might promote earlier DP and therefore impact LOS. There was a statistically significantly decrease in LOS from 4.9 days ± 4.8 in the control phase to 4.8 days ± 4.7 in the intervention phase, a 2% relative reduction (P=.003).

Readmission rates over time in a concurrent group.—The hospital administration provided the monthly readmission rates for the entire study period across all hospitalized patients to compare to our study patient outcomes. We found no trends in either direction for readmission over time among the concurrent sample indicating stable rates over time.

Characteristics of patients referred.—The characteristics of the patients referred and their sites of referral changed significantly between the study phases, indicating the CDS may have influenced the type of patient to refer and where.

Patients who self-rated their health as poor (N=220 intervention and 168 control) and patients who had four or more prior hospitalizations in the past six months (N= 72 intervention and 59 control), were less likely to be discharged to self-care in the intervention phase than in the control phase, (15.9% versus 25.6% control, $P<.001$); and (19.4% intervention versus 33.9% control) respectively, and were more likely to be referred for facility level care instead (64.1% versus 57.1%, $P<.001$), (52.8% versus 37.3%, $P<.001$) respectively.

In the intervention phase, patients who showed improvement in bathing (N=316) and transferring (N=343) were less likely to be discharged to facility level care (46.8% intervention versus 51.0% control) and (44.6% intervention versus 45.6% control) respectively, and more likely to receive a HHC referral instead (27.8% intervention versus 22.9% control, $P<.001$) and (25.1% intervention versus 23.2% control, $P<.001$) respectively.

Interactions.—We also examined interactions between agreements of the discharge disposition with the DIRECT recommendations.

Agreement between discharge disposition and DIRECT advice.—We saw 3% and statistically significant reductions in readmissions across seven, 14, and 30 day intervals when the discharge disposition and DIRECT advice agreed either to refer or not (Table 4). This effect was strongest when comparing those patients when CDS said refer and disposition agreed in referral (Table 5, CDS Yes=Actual Yes). Their readmission rates in the intervention phase were 4% lower, a 22% relative reduction in the rate of readmission (18.3% to 14.3%), representing 26% lower odds of readmission in the intervention phase (OR, .74, 95% CI=0.60–0.92; $P=.002$). Other combinations of algorithm advice compared to actual discharge disposition showed nonsignificant for reductions in readmission rates (ie, yes/no, no/no, no/yes) and represented smaller numbers of patients. (Table 5)

Limitations

Testing of this algorithm was limited to two hospitals with one DP model. Referral was measured by discharge disposition code and may not reflect referrals suggested by DP staff but not executed due to ineligibility, or patient or physician refusal. Therefore, the agreement rate between CDS advice and actual clinician decisions may be higher. For example, patients sent home to self-care may have been offered services and refused, or those recommended for facility level care may have only agreed to accept home health care. This information was not systematically collected by the DP team and was therefore not accessible.

The readmission and ED outcomes are limited to those that occurred at the study hospitals. Patients may have been readmitted to other hospitals, however, this limitation was the same across both phases and the regional and suburban hospitals involved have defined catchment areas. Further, although we minimized potential patient differences using propensity scores, unmeasured variation could have affected the results. However, analysis of a concurrent sample from the same hospitals indicated stable readmission rates across the study periods.

Discussion

Application of the DIRECT CDS was associated with reductions in readmissions across all intervention time periods. The greatest benefits were seen when the CDS and hospital disposition agreed. The characteristics of patients referred to the various settings differed between the control and intervention phases and the average LOS decreased by 0.1 day (2.4 hours/day) in the intervention phase. The proportion of patients referred overall and to each site of care did not differ significantly between phases.

Our algorithm provided advice on who to refer, and the level of care, and showed the case managers the important patient characteristics that led to that advice such as fall risk, unmet caregiver needs, or who declined in ADL function, and in which activity.[13] The shift in the characteristics of patients referred in the intervention period was congruent with their needs. Those with greater declines in function, and therefore needing rehabilitation, were referred for facility care more often once the CDS was applied. The declines in readmissions seen after providing DIRECT CDS is consistent with our previous work where an algorithm called the Discharge Decision Support System (D2S2) provided CDS to identify those in need of PAC (similar to step one of the current study algorithm) and readmissions decreased significantly in two separate studies.[14,15] The DIRECT CDS takes the advice a step further with a recommendation of the level of care.

The value of CDS for DP is highlighted by a survey of 37 social workers conducting DP in 36 hospitals. The social workers reported that assessment of home support and help with ADLs was the most demanding, important, and time consuming task. They reported spending less time on counseling and more time on concrete tasks such as determining services.[16] Automating the assessment and supporting decision making may be of great value in decreasing their work and cognitive load. Our CDS utilized existing data normally collected during patient care, negating the need to collect new information or collect it again for DP. The CDS also summarized ADL function and reported it as the same, improved or declined thereby removing the cumbersome scanning of different sections in the EHR. Furthermore, large caseloads prevent clinicians from having enough time to deal with psychosocial problems and relationship issues.[17] CDS could lift some of this burden by alerting about high need patients and recommending levels of care as a “heads up,”[18–20] thereby allowing more time for the important counseling interventions that engage patients and caregivers in shared decision-making.

Identifying patients who need PAC.

Across both study phases, the DIRECT CDS identified 24 and 26% more patients for PAC than hospital disposition indicated. There are several plausible explanations for the discrepancy. First, is the large amount of variability in referral decision making and the potential to miss patients in need, which is precisely why evidence-based CDS is needed, and is consistent with our prior work.[18,19] Chen and colleagues found considerable variation in SNF referrals for heart failure (HF) and acute myocardial infarction (AMI) patients.[21] A 2015 report by Avalere[22] showed PAC referral rates for Medicare beneficiaries varying by state from 16%−52%. Huge network sizes also make it difficult to refer patients to the right setting. The mean PAC network size for U.S. hospitals included 37.5 SNFs and 23.4 HHC agencies. The burden during decision making is high calling for CDS to assist this important process.

Differences between the DIRECT recommendations and discharge disposition may also be due to patient refusal, patient preference to accept home care instead of facility level care, or barriers created by service qualification. Previous studies report that up to 28% of patients refuse PAC.[23] Discharge planners may have agreed with the DIRECT recommendation and offered PAC, but there was no documentation about refusal rates or reasons available to the research team. Further, the DIRECT CDS was developed based on patient need, without regard for insurance or policies such as a three-day acute care stay requirement for SNF admission or homebound status for HHC. Therefore, policy, financial, or insurance barriers may have prevented PAC referral regardless of CDS advice. Future study should examine this issue and its impact on patient outcomes.

Length of stay.—It is recommended that DP starts on admission. The CDS was delivered within 24 hours of admission and was updated twice per day. The LOS decrease we saw with CDS may be due to earlier discharge decision making. Although not statistically significant, the 2% decrease in LOS may be financially significant when multiplied by 10 million hospital stays per year for Medicare patients.[24]

Site of care.—Our study achieved the best results when the discharge disposition and CDS agreed. The CDS may have helped the case managers to better match who needed a referral and information on functional decline or improvement may have influenced the PAC location. PAC site does matter. In a study that compared functional gains for stroke patients, those referred to IPR compared to HHC or SNF had six month functional scores at least eight points higher after controlling for other factors.[25]

Conclusions/Relevance

The DIRECT CDS assisted clinicians in identifying those patients most in need of PAC, and suggested a particular level of care. CDS advice was provided early in the hospital stay providing clinicians with more time to arrange for services, perhaps accounting for the slightly shorter LOS with the DIRECT CDS. Although actual referral rates were lower than CDS advice, the change in patient characteristics of those referred and the resultant lower readmission rates suggest that those patients most at-risk may have been appropriately referred to the right PAC site. The DIRECT CDS indicates potential as a useful tool to optimize PAC decision making and improve patient outcomes. It may also identify patients who need PAC but are unable to receive it due to policy or insurance barriers. Future studies examining the outcomes of these patients may have policy implications.

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Table 1.

Sociodemographic characteristics of the control and intervention samples.

Characteristic	Control n=3,302		Intervention n=5,006		p-value
Age (years)	75.9 ± 11.3		75.9 ± 11.3		0.966
Gender					0.174
Female	1740	52.7%	2735	54.6%	
Male	1559	47.2%	2264	45.2%	
Unknown	3	0.1%	7	0.1%	
Race					0.674
White	2824	85.5%	4274	85.4%	
Black	392	11.9%	580	11.6%	
Other	74	2.2%	133	2.7%	
Unknown	12	0.4%	19	0.4%	
Ethnicity - Hispanic or Latino					0.690
No	3245	98.3%	4914	98.2%	
Yes	31	0.9%	56	1.1%	
Unknown	26	0.8%	36	0.7%	
Marital Status					0.117
Married/Partnered	1648	49.9%	2491	49.8%	
Divorced/Separated	231	7.0%	365	7.3%	
Widowed/Single	1247	37.8%	1941	38.7%	
Unknown	176	5.3%	209	4.2%	
Education					<.001
<High School	128	3.9%	189	3.8%	
High School / GED	1633	49.5%	2442	48.8%	
Some post High School	225	6.8%	326	6.5%	
Bachelors / graduate degree	1200	36.3%	1742	34.8%	
Unknown	116	3.5%	307	6.1%	
Employment Status					<.001
Currently Employed	504	15.3%	758	15.1%	
Unemployed	225	6.8%	236	4.7%	
Retired	2302	69.7%	3385	67.6%	
Other/Unknown	271	8.2%	627	12.5%	
Living Arrangement					0.343
House/Apartment	2534	76.8%	3784	75.6%	
Assisted living	192	5.8%	296	5.9%	
Extended care/Residential Facility	286	8.6%	486	9.7%	
Group home, Other, Unknown	290	8.7%	410	8.8%	

Table 2.

Clinical characteristics of the control and intervention samples.

Characteristic	Control n=3,302		Intervention n=5,006		p-value
Hospital LOS (days)	4.9 ± 4.8		4.8 ± 4.7		0.003
Fall Risk Score	48.5 ± 22.9		48.3 ± 22.0		0.764
Braden Score	18.8 ± 2.9		18.6 ± 2.9		0.001
Number of Co-existing Conditions	3.2 ± 1.9		2.7 ± 1.9		<.001
Self-Rated Health					0.625
Excellent/Good	1436	43.5%	2206	44.1%	
Average	1074	32.5%	1627	32.5%	
Fair/Poor	760	23%	1127	22.5%	
Unknown	32	1.0%	46	0.9%	
Depression - Hopelessness					0.278
No	3080	93.3%	4643	92.7%	
Yes	126	3.8%	226	4.5%	
Unknown	96	2.9%	137	2.7%	
Depression - Lost Interest					0.590
No	3142	95.2%	4755	95.0%	
Yes	63	1.9%	111	2.2%	
Unknown	97	2.9%	140	2.8%	
Past 6 Months Hospitalizations					0.003
0	2053	62.2%	3315	66.2%	
1	802	24.3%	1096	21.9%	
2–3	311	9.4%	404	8.1%	
4+	59	1.8%	72	1.4%	
Unknown	77	2.3%	119	2.4%	
Primary Diagnosis ICD-9 Code					<.001
001–139 Infectious/Parasitic Diseases	251	7.6%	380	7.6%	
140–239 Neoplasms	145	4.4%	233	4.7%	
240–279 Endocrine/Metabolic/Immunity	152	4.6%	198	4.0%	
280–289 Blood and Blood-Forming Organs	49	1.5%	63	1.3%	
290–319 Mental/Neurodevelopmental	27	0.8%	44	0.9%	
320–389 Diseases of the Nervous System	61	1.8%	81	1.6%	
390–389 Diseases of the Circulatory System	853	25.8%	1234	24.7%	
460–519 Diseases of the Respiratory System	331	10.0%	692	13.8%	
520–579 Diseases of the Digestive System	392	11.9%	636	12.7%	
580–629 Diseases of Genitourinary System	256	7.8%	344	6.9%	
680–709 Diseases of the Skin	103	3.1%	128	2.6%	

Characteristic	Control n=3,302		Intervention n=5,006		p-value
710–739 Musculoskeletal Diseases	192	5.8%	245	4.9%	
740–759 Congenital Anomalies	2	0.1%	8	0.2%	
780–799 Symptoms, Signs, & Ill-Defined	108	3.3%	148	3.0%	
800–999 Injury and Poisoning	365	11.1%	562	11.2%	
V01–V89 Supplementary Classification	15	0.5%	10	0.2%	
Expected to be discharged on opioids					0.536
No	2459	74.5%	3758	75.1%	
Yes	801	24.3%	1174	23.5%	
Unknown	42	1.3%	74	1.5%	

LOS = Length of Stay, ICD9 = International Classification of Diseases, Ninth Revision

Table 3:

Health care utilization in the control to intervention phases, unadjusted and adjusted relative risks and odds ratios of outcomes relative to the intervention phase.

	Control n=3,302	Intervention n=5,006	Unadjusted		Adjusted	
			RR (95% CI)	OR (95% CI)	OR (95% CI)	p-value
Inpatient Readmissions						
Within 30 Days	15.1%	12.4%	1.03 (1.01–1.05)	1.26 (1.11–1.43)	1.24 (1.08–1.41)	0.002
Within 14 Days	10.3%	7.5%	1.03 (1.02–1.05)	1.42 (1.22–1.65)	1.40 (1.20–1.65)	<.001
Within 7 Days	7.3%	4.7%	1.03 (1.02–1.04)	1.61 (1.33–1.93)	1.58 (1.30–1.92)	<.001
Same Day	2.6%	0.2%	11.99 (6.41–22.42)	12.29 (6.62–22.82)	12.62 (6.69–23.82)	<.001
ER/Observation Visit						
Within 30 Days	6.2%	6.1%	1.00 (0.99–1.01)	1.01 (0.84–1.22)	1.05 (0.87–1.27)	0.62
Within 14 Days	3.9%	3.7%	1.00 (0.99–1.01)	1.04 (0.83–1.31)	1.09 (0.86–1.38)	0.49
Within 7 Days	2.6%	2.2%	1.00 (0.99–1.01)	1.15 (0.87–1.53)	1.24 (0.92–1.67)	0.15

Comparisons between control & intervention phase show the risk/odds ratio with respect to the intervention phase. Adjusted comparisons were computed using Inverse Probability Weights (IPW), calculated from propensity scores, with robust standard errors.

Table 4.

Readmission rates in the subset where hospital disposition and DIRECT CDS advice agree on referral or not.

	Control n=2,288	Intervention n=3,417	Unadjusted		Adjusted	
			RR (95% CI)	OR (95% CI)	OR (95% CI)	Holm-Sidak pvalue[a]
Inpatient Readmissions						
Within 30 Days	16.5%	13.2%	1.04 (1.02–1.06)	1.30 (1.12–1.51)	1.28 (1.10–1.50)	0.020
Within14 Days	11.4%	8.4%	1.03 (1.02–1.05)	1.40 (1.18–1.68)	1.40 (1.16–1.68)	<.001
Within 7 Days	8.4%	5.4%	1.03 (1.02–1.05)	1.62 (1.31–2.00)	1.61 (1.29–2.01)	<.001
ER/Observation Visit						
Within 30 Days	5.8%	6.4%	0.99 (0.98–1.01)	0.91 (0.73–1.14)	0.94 (0.75–1.18)	0.84
Within 14 Days	3.3%	3.9%	0.99 (0.98–1.00)	0.86 (0.64–1.14)	0.91 (0.67–1.22)	0.87
Within 7 Days	2.3%	2.3%	1.00 (0.99–1.01)	0.97 (0.68–1.38)	1.07 (0.74–1.55)	0.71

DIRECT CDS = Discharge Referral Expert System for Care Transitions Clinical Decision Support

[a]Odds ratios and p-values are from comparisons between control and intervention within each row, with Holm-Sidak adjustment for multiple comparisons.

Table 5.

Readmission rates by agreement between the algorithm advice to refer yes or no (Y/N).

Algorithm Referral Recommendation yes/no	Discharge Disposition Refer yes/no	Control % (CI) N= 3,302	Intervention % (CI) N=5,006	OR	p-value[a]
No	No	6.8% (4.5–9.3)	8.5% (6.3–10.8)	0.79	0.80
No	Yes	10.4% (4.7–16.1)	14.3% (8.6–20.0)	0.69	0.83
Yes	No	12.0% (9.9–14.2)	10.5% (8.9–12.2)	1.16	0.73
Yes	Yes	18.3% (16.5–20.2)	14.3% (13.0–15.7)	1.34	0.002

Readmission rates calculated from the logistic model with inverse probability weights.

[a]Odds ratios and p-values are from comparisons between control and intervention within each row, with Holm-Sidak adjustment for multiple comparisons.