# Comprehensive electronic medical record implementation levels not associated with 30-day all-cause readmissions within Medicare beneficiaries with heart failure.

M. E. Patterson[1]; P. Marken[1]; Y. Zhong[2]; S. D. Simon[3]; W. Ketcherside[4]

[1]Division of Pharmacy Practice and Administration, University of Missouri-Kansas City School of Pharmacy, Kansas City, Missouri; [2]Department of Biostatistics, University of Kansas Medical Center, Kansas City, Kansas; [3]Department of Informatics Medicine and Personalized Health, University of Missouri-Kansas City, Kansas City, Missouri; [4]Ketcherside Group, L.L.C., Kansas City, Missouri



**Keywords**

Electronic health records, quantitative evaluation, inpatient care

**Summary**

**Background:** Regulatory standards for 30-day readmissions incentivize hospitals to improve quality of care. Implementing comprehensive electronic health record systems potentially decreases readmission rates by improving medication reconciliation at discharge, demonstrating the additional benefits of inpatient EHRs beyond improved safety and decreased errors.

Objective: To compare 30-day all-cause readmission incidence rates within Medicare fee-for-service with heart failure discharged from hospitals with full implementation levels of comprehensive EHR systems versus those without.

**Methods:** This retrospective cohort study uses data from the American Hospital Association Health IT survey and Medicare Part A claims to measure associations between hospital EHR implementation levels and beneficiary readmissions. Multivariable Cox regressions estimate the hazard ratio of 30-day all-cause readmissions within beneficiaries discharged from hospitals implementing comprehensive EHRs versus those without, controlling for beneficiary health status and hospital organizational factors. Propensity scores are used to account for selection bias.

**Results:** The proportion of heart failure patients with 30-day all-cause readmissions was 30%, 29%, and 32% for those discharged from hospitals with full, some, and no comprehensive EHR systems. Heart failure patients discharged from hospitals with fully implemented comprehensive EHRs compared to those with no comprehensive EHR systems had equivalent 30-day readmission incidence rates (HR = 0.97, 95% CI 0.73 – 1.3)

**Conclusions:** Implementation of comprehensive electronic health record systems does not necessarily improve a hospital's ability to decrease 30-day readmission rates. Improving the efficiency of post-acute care will require more coordination of information systems between inpatient and ambulatory providers.

**Correspondence to:**
Mark E. Patterson, Ph.D., M.P.H.
Division of Pharmacy Practice and Administration
University of Missouri-Kansas City School of Pharmacy
4245 Health Sciences Building
2464 Charlotte Street
Kansas City, Missouri 64108–2718
p: (816)-235–6320
f: (816)-235–6008

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## Background

Unplanned readmissions for any disease costs Medicare over $17.4 billion annually, with heart failure being the most frequent cause of readmission [1]. A recently published study [2] found a 30-day all-cause risk-standardized readmission rate of 24.6% for heart failure patients, which costs the American public over $15 billion per year [3]. These significant costs underscore hospitals' need to continually improve processes and quality of care as a means of improving efficiency, especially with the recent implementation of the Hospital Readmission Reduction Program under the Affordable Care Act that began in fiscal year 2013 imposing financial penalties on hospitals with excess Medicare readmissions [4].

Concurrent with these regulations are those associated with meaningful use policies for electronic health records (EHRs), which require hospitals to implement specific functional components within their electronic health record system in order to achieve a certain level of certification. The most recent policies require hospitals to fully implement across all units in their hospital 24 different EHR components. These components potentially improve discharge planning, medication management, and readmissions if implemented and used effectively [5]. Since considerable overlap exists between standards of meaningful use of EHRs and of patient-centered medical home establishment [6], providers achieving meaningful use would also be motivated to establish patient-centered medical homes within their organizations.

Although studies have demonstrated the impact of EHRs on reduced inpatient mortality [7, 8], less is known about the impact of EHRs on hospital re-admissions. If improved prescribing of medications for Medicare beneficiaries with heart failure is associated with decreased risk of re-admissions [9] and EHR is associated with improved prescribing patterns [10–14] and decreased medication errors [10–11], hospitals' use of comprehensive EHR systems should theoretically decrease readmissions via improved prescribing or decreased medication errors at the point-of-care. The few studies that have examined associations between EHR and hospital efficiency have found higher implementation levels of computerized provider order entry and clinical decision support to be significantly associated with higher Hospital Quality Alliance metric process outcomes for chronic heart failure, although these did not translate into improved length of stay or decreased readmissions [15]. In contrast, another study found EHR utilization to be associated with reduced length of stay [16] while a more recent study found that the use of risk stratification software embedded into electronic health records significantly reduces readmissions [17]. These latter studies illustrate the potential of comprehensive EHR systems to reduce hospital readmissions and in turn improve hospital efficiency.

Examining the impact of EHR on individual-level admissions instead of a hospital-aggregate would provide greater insights as to how hospital level systems impact an individual heart failure patient's risk of readmission. To the best of our knowledge, no studies have examined the impact of hospital EHR on individual-level readmission rates, especially within Medicare beneficiaries diagnosed with heart failure.

## Objective

The objective of this analysis is to compare 30-day all-cause readmission incidence rates within Medicare fee-for-service with heart failure discharged from hospitals with full implementation levels of comprehensive EHR systems versus those without. We hypothesize that Medicare beneficiaries with heart failure discharged from hospitals with fully implemented comprehensive electronic medical record systems across all units will have a significantly lower incidence of 30-day all-cause readmissions than those discharged from hospitals that have not implemented any component of comprehensive EHRs.

## Methods

Our beneficiary, hospital, and county-level data originated from multiple sources, all of which were merged either by hospital Medicare identification codes or county-level zip codes. Beneficiary hospitalizations, demographics, and health status variables originated from 2008 and 2009 Medicare Provider and Analysis Review (MedPAR) administrative claims and the 2008 Medicare demographics and eligibility files. Hospital EHR implementation levels and other EHR-related covariates originated from the fiscal year 2007 health IT supplement [18] associated with the 2008 AHA annual survey [19]. More specifically, the supplement data were collected from hospitals between March 2008 and December 2008, which aligned closely with the MedPAR 2008 discharge dates. Hospital organizational factors originated from the 2008 AHA annual survey [19] and county-level aggregate covariates originated from the 2012–2013 Area Resource File (ARF) that contained data from 2008 [20].

We included Medicare beneficiaries discharged in 2008 with a diagnosis of heart failure from acute care hospitals responding to the American Hospital Association (AHA) electronic health record survey [18]. Using unique Medicare hospital identifier codes, we merged beneficiary-level data from a 5% sample of 2008 and 2009 Medicare Provider and Analysis Review (MedPAR) administrative claims with hospital-level data from the health IT supplement of the 2007 AHA annual survey. This health IT supplement survey associated with the 2008 AHA annual survey was collected from hospitals between March 2008 and December 2008. The intent of the health IT survey was to measure EHR functionality levels of member AHA hospitals, and was administered to an employee identified by the hospital's CEO who was deemed knowledgeable about the health IT system implementation levels. The survey response rate among AHA members was approximately 63% (N=3,049) of the 4,832 hospitals receiving the survey [21].

We used a retrospective cohort design to determine if 30-day all-cause readmissions within Medicare FFS heart failure beneficiaries differed in those beneficiaries discharged from hospitals that fully, partially, or did not implement all of the 24 functionalities of a comprehensive EHR system, as defined in a previous study [15]. We used the health IT supplement to the 2007 AHA annual survey, which was collected between March 2008 and December 2008, to align EHR implementation levels as closely as possible to heart failure readmissions occurring between January 1 and December 31, 2008. Including the 2009 MedPAR administrative claims allowed us to follow for 30 days individuals who were discharged during periods as late as December 1 through December 31, 2008.

We selected 52,084 Medicare beneficiaries who were discharged for heart failure anytime during the calendar year 2008 (01/01/08 through 12/31/08) as indicated by the following ICD-9 codes present as either a primary or secondary diagnosis within MedPAR claims: 398.91, 402.01, 402.11, 402.91, 404.01, 404.11, 404.91, 404.03, 404.13, 404.93, and 428.x. Including ICD-9 codes for rheumatic heart failure (398.91); hypertensive disease concomitant with heart failure (402.01, 402.11, 402.91); hypertensive and renal disease concomitant with heart failure (404.01, 404.11, 404.91); and hypertensive and renal disease concomitant with renal and heart failure (404.03, 404.13, 404.93) in addition to chronic heart failure (428.x) allowed us sufficient sensitivity to capture all cases.

Using pre-determined classification coding flags in the MedPAR claims database, we further restricted our cohort to 42,081 beneficiaries who had full coverage of Medicare Part A and B, during calendar year 2008, and no HMO coverage during 2008, were not disabled, did not have end-stage renal disease, or died prior to discharge. We included only those covered with both Part A and Part B since those with only Part A likely have incomplete FFS Medicare claims data due to coverage by other sources such as Medicare Advantage Plans, Indian Health Service, or the VA. We excluded those with HMO because CMS does not necessarily receive complete claims from Medicare Advantage plans, HMOs, or PPOs [22]. We excluded beneficiaries with end-stage renal disease since these individuals differ significantly from typical Medicare beneficiaries with respect to costs, comorbidities, and outcomes. We further limited the cohort to 30,325 beneficiaries discharged from acute care hospitals located within the 50 states or D.C. who responded to the health IT survey, and finally to 27,568 after excluding those who died within 30 days of being discharged. Each beneficiary was then assigned an index date corresponding to their 2008 heart failure discharge date.

We defined our hospital-level EHR implementation level predictor using a 3-level categorical variable (▶Table 1) classifying hospitals on the extent to which they implemented 24 EHR components that comprise comprehensive electronic health record systems as originally developed by a federally sponsored expert advisory panel [15]. We defined hospitals as 'full implementation' if they reported implementing *all* 24 of these components across *all* units within the hospital, a definition used in prior studies [15] (▶Table 2). Full implementation according to the AHA survey was defined as hospitals having fully integrated these electronic systems and no longer relied on paper records [18]. In contrast, we defined hospitals as 'no implementation' if they reported either "having resources to implement in next year", "not having resources but considering implementing', or 'not having in place and not considering implementing" for *all* of the 24 functionalities. Although this definition to the best of our knowledge has not been used in previous studies, this group of hospitals serves as an appropriate control group since they do not have *any* of the 24 components that comprise a comprehensive EHR system. Classifying hospitals into these two extreme categories left a middle category of 'some implementation' for hospitals reporting either "fully implementing in at least one unit" or "beginning to implement in at least one unit" for *any* of the 24 functionalities that comprise a comprehensive EHR system (▶Table 1).

The main outcome measure was readmission within 30 days after the index admission date occurring within the calendar year 2008. We defined readmission as the first subsequent inpatient admission for any reason. We chose to limit our follow-up period to 30-days given that if any beneficial effect were to occur post-discharge, we would be most likely to detect this within 30 days. Furthermore, focusing on 30-day readmissions increase the relevance of our analysis to current CMS value-based purchasing policies surrounding 30-day all-cause readmissions.

We included beneficiary-level, hospital-level, and county-level covariates in order to account for potential confounders in and minimize potential bias. For beneficiaries, we controlled for age, gender, and race. To control for baseline health status corresponding to 6-months prior to index readmission we included the number of heart failure hospitalization as a proxy for heart failure severity [23] and an adapted Charlson index to classify comorbidities [24]. We also controlled for baseline heart failure medication utilization since baseline adherence is a strong predictor of future adherence [25] which in turn impacts readmissions [26]. We defined heart failure medication utilization as a binary variable specifying whether or not beneficiaries had evidence at least one prescription claim for either a beta blocker or an ACE inhibitor during the 6 month period preceding the index admission date.

We included hospital-level geographic region, ownership status, and size as covariates in order to account for regional differences and resource utilization differences which are known to impact both quality of care and adoption of electronic health records. Hospitals were classified as small, medium, or large based upon the number of beds; ownership status as for-profit, non-profit, or government owned; and geographic location by census region. Given the significant impact that medication reconciliation activities have on post-discharge adherence for heart failure patients, we used data from survey items assessing medication reconciliation activities, including "Does your electronic system allow you to compare a patient's inpatient and preadmission medication lists", and "Does your electronic system allow you to provide an updated medication list at time of discharge". Furthermore, we included a measure for the percentage of inpatients for which medication orders are written electronically.

Since beneficiary socioeconomic status is most likely related to readmissions via access to quality of care and ability to understand discharge instructions, we used county-level 2008 data from the 2012–2013 release of the Area Resource File [20] in order to approximate the income and education levels of beneficiaries residing within the same county of the hospital responding to the AHA health IT survey. These variables were matched to hospitals by the county in which the hospital was located by merged together data from the Area Resource File and the county and state names of the hospitals provided within the AHA health IT survey. Income was defined by county-level per-capita income, and education was defined as the percentage of individuals within counties achieving a particular educational level. Since rural compared to urban hospitals differ with respect to availability of electronic health records as well as quality of care, we also controlled for rural/urban status of the county in which hospitals were located. This rural predictor also serves to capture some of the variation due to individuals distance to the hospital, which impacts access to care. Missing data for any of the covariates, which in all cases were missing in less than 10% of the cases, were imputed with either the mean or the most frequent, for continuous and categorical variables, respectively.

We used multivariable Cox regressions to estimate the beneficiary's 30-day all-cause readmission rate conditional upon hospitals' implementation level of the 24 components comprising a comprehensive EHR system. Individuals who died during the 30-day post-discharge period were excluded from the analysis, and those who did not experience a readmission within 30 days were censored. To account for selection bias due to healthier patients selecting hospitals with higher implementation levels of electronic health records, we calculated propensity scores that were included as covariates in one of the final models. The propensity score model required a multivariable ordinal regression to estimate predicted probabilities of beneficiaries being discharged from hospitals with our three-level electronic health record classification predictor, conditional upon all of the beneficiary-, hospital-, and county-level covariates included in Cox regression. We then used the inverse probability of treatment weighting (IPTW) technique to adjust for propensity scores by weighting the beneficiaries within the Cox regression with their propensity score. We also adjusted our standard errors to account for the clustering of beneficiaries within hospitals. All analyzes were conducted using SAS v9.2 (Cary, NC). Since this study does not directly involve human subjects, the Institutional Review Board (IRB) at the University of Missouri-Kansas City classified this study as exempt.

## Results

The sample of heart failure Medicare fee-for-service beneficiaries is 71% female and 85% white with a mean age of 81. During the 6-month baseline period, fifty-nine percent of the sample had 1 or 2 comorbidities, and 20% experienced at least 1 heart-failure related hospitalization. Sixty-one percent had at least 1 Medicare Part D claim for an ACE inhibitor or beta blocker at baseline. Patients discharged from hospitals reporting fully, partially, or not implementing comprehensive EHR systems did not significantly differ with respect to demographics or health status indicators (▶Table 3). Twenty-nine percent of the beneficiaries within the sample were readmitted for any-cause within 30 days of discharge. These 30-day all-cause readmission rates did not significantly differ in those discharged from hospitals of various implementation levels of comprehensive EHRs. Patients discharged from hospitals with full, partial, and no comprehensive EHR systems had readmission rates of 30%, 29%, and 32%, respectively and these differences were not statistically significant ($p=0.35$) according to the unadjusted chi-square analyses. (▶Table 3).

Over half of the hospitals within the sample were located within the central region of the United States, and 63% were located within counties classified as metropolitan areas. Twelve percent of the hospitals were classified as large, having over 400 beds, while 46% and 41% were classified as medium and small, respectively. Sixty-one percent of hospitals reported not writing electronic medication orders for any inpatients, and 71% reported having capabilities of providing updated medication lists at discharge. Most hospitals were classified as non-profit, and were located within counties having a mean per-capita income of $37,170 (▶Table 4).

Hospitals with varying levels of comprehensive EHR implementation levels significantly differed with regards to rural location, size, additional EHR capabilities related to medication reconciliation activities, proportion of patients for whom medication orders are written electronically (▶Table 4). Hospitals reporting full implementation were more likely to be small or medium hospitals located within metropolitan areas within counties with relatively higher mean per-capita income and education compared to hospitals reporting either partial or no implementation. Furthermore, the full implementers compared to others had a greater proportion of hospital reporting capabilities of medication reconciliation both at admission and discharge (▶Table 4).

In the final multivariate survival analysis incorporating propensity score weightings, beneficiaries discharged from hospitals reporting full implementation of comprehensive EHRs versus no implementation were equally likely to be readmitted within 30 days for any cause (HR=0.97, 95% CI 0.73 – 1.3)(▶Table 5). This same null effect was present for beneficiaries discharged from hospitals with at least some implementation compared to none (HR=0.96, 95% CI 0.76–1.2).

## Discussion

Medicare fee-for-service beneficiaries diagnosed with heart failure discharged from hospitals reporting fully implemented comprehensive electronic health records were equally likely to be readmitted within 30 days for any cause compared to beneficiaries discharged from hospitals with basic or other sub-optimal implementation level of EHR. Although we expected 30-day readmissions to be significantly lower in patients discharged from hospitals with comprehensive EHR systems via improved processes of care, prescribing, and decreased errors, our null findings do not support this hypothesis. Our results are consistent with a prior study finding similar rates of hospital-level aggregate 30-day readmission rates in hospitals with comprehensive versus basic or no electronic health records [15]. The null findings imply readmission rates are not necessarily associated with hospital EHR system-level implementation. Null associations may be attributed to a the fact that only a small number of providers had fully implemented systems at that time, or the learning curve in 2008 was not sufficient enough to impact readmissions. In addition, the survey instrument is likely not sufficiently sensitive to detect differences in actual use since self-reported implementation levels likely do not capture variation in the quality or appropriateness of EHR use.

Our ability to link individual beneficiaries to hospital from which they were discharged allowed to us to measure associations between a specific hospital's EHR implementation level and an individual's risk of being readmitted within 30 days. Although a previous study did measure associations between EHR implementation levels and readmissions, the aggregated hospital-level readmission rates may dilute variations in individual-level readmission rates. In contrast, having the readmission dates for each beneficiary allowed us to conduct a survival analysis to directly test our hypothesis of the impact of hospital-level EHR on beneficiary-level readmission rates. Furthermore, we accounted for many potential confounders by controlling for health status, demographics, hospital organizational factors, as well as county-level income and hospital admissions data that would have led to biased results if omitted from the analysis. Accounting for hospital medication reconciliation activities as well as patient baseline medication adherence are particularly useful, given that medication utilization and management are important mediators. Finally, using propensity scores helped account for selection bias.

Our study has several limitations worth noting. First we are limited to conclude these are associations and not necessarily causal because we could not necessarily account for many other sources of heterogeneity, which could partially account for the null findings. The self-reported implementation levels of EHR systems does not account for variation in the quality or appropriateness of use which are the actual factors that impact readmissions and unmeasured provider characteristics cannot account for this variation in quality or appropriateness. The omission of hospital-level volume and staffing levels, for example, could have led to biased estimates. In the absence of these types of data, we did our best to at least account for additional beneficiary or hospital-level factors associated with readmissions. For example, including hospital size in our models should account for some of the variation due to volume or staffing; and including county-level educational level and income should account for variation associated with differences in quality of care. Understandably, county-level proxies of hospital factors are insufficient to account for important hospital or beneficiary-level confounders, so future studies need to include hospital-level volume, staffing, years of implementation, as well as actual utilization patterns of EHR systems. Second, the middle grouping of our 3-level predictor may not be homogeneous enough to detect differences in readmissions, if these differences in fact exist. Despite this, directly comparing the full and no implementation hospitals helped increase the signal-to-noise ratio to enable us to find any differences. Third, our 2008 data does not reflect current implementation levels of comprehensive EHR systems, which have improved from 1.6% in 2008 to 16% in 2012. If these systems truly do have a protective effect, our small sample size in conjunction with a potentially lower learning curve may have not allowed us to detect a protective effect. Future studies should incorporate more recent data while also controlling for how many years the system has been in use. Fourth, our 30-day readmission outcome did not exclude unplanned readmissions, those leaving against medical advice, this most likely led to an upwardly skewed readmission rate compared to the CMS standardized 30-day rate. Our outcome also did not account for whether these readmissions occurred at the same hospital from which patients were discharge, which, if an effect was present, would make it more difficult to attribute the reduced readmission to the EHR of the discharge hospital.

Despite these study limitations, these findings introduce important research methodological issues that need to be considered in future studies, especially if we are wanting to improve the ability to measure unbiased estimates. Given all the various provider-level variation in the use of EHRs, researchers would benefit from a provider-level survey that would better capture variation in use compared to current hospital-level surveys. Once more data has accrued, alongside the improved learning curves among providers, more sophisticated longitudinal hierarchal models incorporating patient, provider, and hospital-level covariates would result in more accurate estimates that eliminate many of the sources of unobserved heterogeneity that are difficult to avoid in the absence of provider-level behavior data.

In addition to research perspectives, these findings also introduce an alternate perspective of the benefits of EHR, offering a cautionary note as to the limits of the benefits of EHR on individual patients. Despite all of the evidence promoting the effectiveness of inpatient EHRs, our null findings imply EHRs may not necessarily be the panacea for improved efficiency. If EHRs are still not sufficient in significantly improving readmissions, hospitals need to continue providing adequate training to staff members in order to optimize the potential benefit these systems have to improve care. Furthermore, expanding EHRs to include health information exchanges will help prevent gaps in post-acute care that most likely contribute to readmissions even more so than potentially deficient electronic health record systems. As meaningful use policies begin to phase in requirements for health information exchange, the benefits of expanded health IT infrastructure beyond the hospital will most likely begin to take more effect.

## Conclusions

In conclusion, future studies need to further explore this direct benefit of health IT on Medicare heart failure patients, as well as other vulnerable at-risk populations who would most likely benefit from these systems. The potential of EHRs to impact patients beyond discharge speaks volumes to the significance to public health, especially with the advent of accountable care organizations and patient-centered medical homes which will become reliant upon EHR and health information exchange infrastructures in order to improve medication management, patient education, and continuity of care. Achieving meaningful use will enable institutions to better manage medications, exchange information with both patients and providers, streamline medication reconciliation, and improve the discharge process.

### Clinical Relevance

The EHR infrastructure therefore creates a stronger foundation for ACOs and PCMHs to do a better job gathering patient information into one clearinghouse, creating a more efficient system that hopefully reduces medical errors and improves patient outcomes. The movement of our health care system toward a structure including more accountable care organizations and patient-centered medical homes underscores the urgent need of health care delivery systems to implement health IT systems to help optimize the delivery and quality of care.

### Conflict of Interest

Authors have not conflicts of interest to report. This research was conducted with the support of a grant from the University of Missouri Research Board (UMRB).

### Protection of Human and Animal Subjects

The Institutional Review Board (IRB) at the University of Missouri-Kansas City classified this study as exempt given it uses de-identified data from administrative claims and hence does not directly involve human subjects.

**Table 1** Definitions of Electronic Health Record Implementation Levels with corresponding survey question

| Predictor Definition | Self-reported implementation levels on survey |
|---|---|
| Full implementation of all the 24 functionalities comprising comprehensive EHRs[1] | Fully implemented across all units |
| Some implementation of some of the 24 functionalities comprising comprehensive EHRs | Fully implemented in at least one unit (or)<br>Beginning to implement in at least one unit |
| No implementation of any of the 24 functionalities comprising comprehensive EHRs | Have resources to implement in the next year (or)<br>Do not have resources but considering implementing (or)<br>Not in place and not considering implementing |

[1]As defined by DesRoches et al., 2010

**Table 2** Definition of comprehensive electronic health records (As defined by DesRoches et al., 2010)

| Function Category | Hospital has completely replaced the paper record for this function with an electronic version across all units within the hospital |
|---|---|
| **Electronic Clinical Documentation** | |
| Patient demographics | X |
| Physician notes | X |
| Nursing assessments | X |
| Problem lists | X |
| Medication lists | X |
| Discharge summaries | X |
| Advanced Directives | X |
| **Results Viewing** | |
| Lab reports | X |
| Radiology reports | X |
| Radiology images | X |
| Diagnostic test results | X |
| Diagnostic test images | X |
| Consultant reports | X |
| **Computerized Provider Order Entry** | |
| Laboratory tests | X |
| Radiology tests | X |
| Medications | X |
| Consultation requests | X |
| Nursing orders | X |
| **Decision Support** | |
| Clinical guidelines | X |
| Clinical reminders | X |
| Drug allergy alerts | X |
| Drug-drug interactions alerts | X |
| Drug-lab interactions alerts | X |
| Drug dosing support | X |

**Table 3** Baseline characteristics of Medicare fee-for-service beneficiaries diagnosed with heart failure (N = 27,568)

| Implementation level of the 24 functionalities that comprise a comprehensive EHR | | | | | |
|---|---|---|---|---|---|
| **Baseline Characteristic** | **Overall N=27,568 N (%)** | **Implementation** | | | **p-value** |
| | | **Full[1] N=510 N (column %)** | **Some[2] N=26,801 N (column %)** | **No[3] N=257 N (column %)** | |
| **Gender** | | | | | 0.11 |
| Male | 8,096 (29.4) | 169 (33.1) | 7,858 (29.3) | 69 (26.8) | |
| Female | 19,472 (70.6) | 341 (66.9) | 18,943 (70.7) | 188(73.1) | |
| **Race** | | | | | <0.0001 |
| White | 23,573 (85.5) | 438 (85.8) | 22,931 (85.5) | 204 (79.4) | |
| Black | 2,713 (9.8) | 56 (11.0) | 2,607 (9.7) | 50 (19.5) | |
| Other | 1,282 (4.6) | 16 (3.1) | 1,263 (4.8) | 3 (1.1) | |
| **Total Number of comorbidities[4] 6m prior to index date** | | | | | 0.96 |
| 0 | 6,906 (25.0) | 119 (23.3) | 6,726 (25.1) | 61 (23.7) | |
| 1 | 9,365 (34.0) | 177 (34.7) | 9,094 (33.9) | 94 (36.6) | |
| 2 | 7,033 (25.5) | 143 (28.0) | 6,826 (25.4) | 64 (25.0) | |
| ≥3 | 4,768 (15.9) | 71 (13.9) | 4,155 (15.5) | 38(14.7) | |
| **At least 1 HF hospitalization during baseline** | 5,661 (20.5) | 95 (18.6) | 5,513 (20.6) | 53 (20.6) | 0.56 |
| **Mean age (sd)** | 81.4 (8.2) | 81.6 (8.1) | 81.4 (8.2) | 82.1 (8.4) | 0.91 |
| **Proportion of those on at least 1 HF medication during baseline** | 16,909 (61.3) | 294 (57.6) | 16,470 (61.4) | 145 (56.4) | 0.06 |
| **Readmission within 30-days** | 7,936 (28.8) | 154 (30.2) | 7,699(28.7) | 83 (32.3) | 0.35 |

[1]*Full* implementation of *all* the 24 functionalities that comprise a comprehensive EHR.
[2]*Some* implementation of *some* of the 24 functionalities that comprise a comprehensive EHR
[3]*No* implementation of *any* of the 24 functionalities that comprise a comprehensive EHR
[4]One of 15 various chronic conditions from ICD-9 codes within inpatient claims, as used to construct the Charlson comorbidity index: Acute myocardial infarction; Congestive heart failure; Peripheral vascular disease; Cerebral vascular accident; Dementia; Pulmonary disease; Peptic ulcer; Liver disease; Diabetes; Diabetes complications; Paraplegia Renal disease; Cancer; Metastatic cancer; Severe liver disease; HIV

**Table 4** Characteristics of hospitals from which Medicare fee-for-service beneficiaries were discharged (N = 2,539)

| Implementation level of the 24 functionalities that comprise a comprehensive EHR | | | | | |
|---|---|---|---|---|---|
| | Overall (N=2,539) N (%) | Implementation | | | p-value |
| | | Full[1] (N=45) N (column %) | Some[2] (N=2,434) N (column %) | No[3] (N=60) N (column %) | |
| **Census Region** | | | | | 0.12 |
| New England | 125 (4.9) | 0 (0) | 124 (5.1) | 1 (1.7) | |
| Atlantic | 665 (26.2) | 11 (24.4) | 643 (26.4) | 11 (18.3) | |
| Central | 1355 (53.3) | 26 (57.8) | 1,284 (52.7) | 45 (75.0) | |
| Mountain | 158 (6.2) | 2 (4.4) | 155 (6.3) | 1 (1.7) | |
| Pacific | 236 (9.3) | 6 (13.3) | 228 (9.3) | 2 (3.3) | |
| **Rural status of county in which hospital is located** | | | | | 0.0003 |
| Large Metropolitan | 1602 (63.1) | 34 (75.5) | 1544 (63.4) | 24 (40.0) | |
| Small Town | 829 (32.6) | 9 (20.0) | 794 (32.6) | 26 (43.3) | |
| Isolated Rural | 108 (4.2) | 2 (4.4) | 96 (3.9) | 10 (16.7) | |
| **Hospital Size (number of beds)** | | | | | <0.0001 |
| Small (0 to 99) | 1058 (41.7) | 18 (40.0) | 989 (40.6) | 51 (85.0) | |
| Medium (100 to 399) | 1174 (46.2) | 19 (42.2) | 1147 (47.1) | 8 (13.3) | |
| Large (400 plus) | 307 (12.1) | 8 (17.8) | 298 (12.2) | 1 (1.7) | |
| **Electronic system features related to medication reconciliation** | | | | | |
| Compares inpatient and preadmission medication lists. | 1367 (53.8) | 40 (88.9) | 1317 (54.1) | 10 (16.6) | <0.0001 |
| Provides an updated medication list at discharge | 1805 (71.1) | 41 (91.1) | 1748 (71.8) | 16 (26.7) | <0.0001 |
| **% of inpatients at hospital for whom medication orders are written electronically** | | | | | <0.0001 |
| 0% | 1557 (61.3) | 5 (11.1) | 1493 (61.3) | 59 (98.3) | |
| 1 to 25% | 321 (12.6) | 4 (8.9) | 317 (13.0) | 0 (0) | |
| 26 to 50% | 110 (4.3) | 2 (4.4) | 108 (4.4) | 0 (0) | |
| 51 to 90% | 160 (6.3) | 13 (28.9) | 146 (6.0) | 1 (1.7) | |
| 91 to 100% | 391 (51.4) | 21 (46.7) | 370 (15.2) | 0 (0) | |
| **Ownership Status** | | | | | 0.41 |
| Government | 526 (20.7) | 12 (26.7) | 496 (20.4) | 18 (30.0) | |
| Proprietary | 287 (11.3) | 5 (11.1) | 272 (11.2) | 10 (16.7) | |
| Non-profit | 1726 (67.8) | 28 (62.2) | 1666 (68.4) | 32 (53.0) | |
| **County-level statistics of county where hospital located** | | | | | |
| Income per capita ($), mean (s.d) | 37,170 (9,216) | 39,070 (15,029) | 37,054 (10,191) | 33,807 (5,549) | 0.02 |

 

**Table 4** Continued

| Implementation level of the 24 functionalities that comprise a comprehensive EHR | | | | | |
|---|---|---|---|---|---|
| | Overall (N=2,539) N (%) | Implementation | | | p-value |
| | | Full[1] (N=45) N (column %) | Some[2] (N=2,434) N (column %) | No[3] (N=60) N (column %) | |
| **County-level percentage of educational level** | | | | | |
| % persons 25+ with 4 plus years of college, (s.d.) | 23.9 (9.5) | 26.7 (10.3) | 24.0 (9.5) | 18.9 (6.5) | 0.0002 |
| % persons 25+ with high school diploma or more, (s.d.) | 84.6 (5.9) | 85.8 (5.4) | 84.6 (6.0) | 82.8 (5.6) | 0.02 |
| % persons 25+ with less than a high school diploma (s.d.) | 15.4 (5.9) | 14.2 (5.4) | 15.4 (6.0) | 17.2 (5.6) | 0.02 |

[1] *Full* implementation of *all* the 24 functionalities that comprise a comprehensive EHR.
[2] *Some* implementation of *some* of the 24 functionalities that comprise a comprehensive EHR
[3] *No* implementation of *any* of the 24 functionalities that comprise a comprehensive EHR

**Table 5** Likelihood of re-hospitalization among Medicare fee-for-service beneficiaries with heart failure discharged from hospitals with differing implementation levels of comprehensive electronic health records systems (N = 27,568)

| EHR Implementation Level | Unadjusted | | Adjusted[1] | | Propensity Score Adjusted | |
|---|---|---|---|---|---|---|
| | HR (95% CI) | p-value | HR (95% CI) | p-value | HR (95% CI) | p-value |
| Full (N=510) | 0.83 (0.61 – 1.1) | 0.24 | 0.96 (0.72 – 1.3) | 0.77 | 0.97 (0.73 –1.3) | 0.84 |
| Some (N=26,801) | 0.80 (0.62 – 1.0) | 0.09 | 0.95 (0.75 – 1.2) | 0.65 | 0.96 (0.76 – 1.2) | 0.75 |
| None (N=257) | Reference | | Reference | | Reference | |

[1] Adjusted for beneficiary age, race, gender, baseline comorbidities, heart failure hospitalizations at baseline, heart failure medication utilization at baseline. Adjusted for hospital ownership status, size, census region, rural status of the county in which the hospital is located, electronic systems related to medication reconciliation, percentage patients for which medications are written electronically, county-level income per-capital, county-level educational level

## References


1. Jencks SF, Williams MV, Coleman EA. Rehospitalizations among patients in the Medicare fee-for-service program. N Engl J Med 2009; 360(14): 1418-1428.
2. Krumholz HM, Lin Z, Keenan PS, Chen J, Ross JS, Drye EE, Bernheim SM, Wang Y, Bradley EH, Han LF, Normand SL. Relationship between hospital readmission and mortality rates for patients hospitalized with acute myocardial infarction, heart failure, or pneumonia. JAMA 2013; 309(6):587–593.
3. Medicare Payment Advisory Commission (MedCAP). Report to the Congress: creating greater efficiency in Medicare. http://www.medpac.gov/documents/Jun07_EntireReport.pdf
4. Health Policy Brief: Medicare Hospital Readmissions Reduction Program, *Health Affairs*, November 12, 2013.
5. Kleeberg, P. Leveraging meaningful use to assist in reducing hospital readmissions. Key Health Alliance: Regional Extension Assistance Center for HIT. RARE Campaign Webinar. August 24, 2012. http://www.rarereadmissions.org/documents/Slides_Meaningful_Use_20120824.pdf. Accessed March 22, 2014
6. HealthIT.gov. Frequently asked questions for providers & professionals: Do electronic health records align with patient-centered medical home initiatives? http://www.healthit.gov/providers-professionals/faqs/do-electronic-health-records-align-patient-centered-medical-home-initia. Accessed March 22, 2014
7. Jones SS, Heaton P, Friedberg MW, Schneider EC. Today's 'meaningful use' standard for medication orders by hospitals may save few lives; later stages may do more. Health Aff (Millwood) 2011; 30(10): 2005-2012.
8. Longhurst CA, Parast L, Sandborg CI, Widen E, Sullivan J, Hahn JS, Dawes CG, Sharek PJ. Decrease in hospital-wide mortality rate after implementation of a commercially sold computerized physician order entry system. Pediatrics 2010; 126(1): 14–21.
9. Patterson ME, Hernandez AF, Hammill BG, Fonarow GC, Peterson ED, Schulman KA, Curtis LH. Process of care performance measures and long-term outcomes in patients hospitalized with heart failure. Med Care 2010; 48(3): 210-216.
10. Bates DW, Cullen DJ, Laird N, Petersen LA, Small SD, Servi D, Laffel G, Sweitzer BJ, Shea BF, Hallisey R, et al. Incidence of adverse drug events and potential adverse drug events. Implications for prevention. ADE Prevention Study Group. JAMA 1995; 274(1): 29–34.
11. Bates DW, Leape LL, Cullen DJ, Laird N, Petersen LA, Teich JM, Burdick E, Hickey M, Kleefield S, Shea B, Vander Vliet M, Seger DL. Effect of computerized physician order entry and a team intervention on prevention of serious medication errors. JAMA 1998; 280(15): 1311–1316.
12. Reckmann MH, Westbrook JI, Koh Y Lo C, Day RO. Does computerized provider order entry reduce prescribing errors for hospital inpatients? A systematic review. J Am Med Inform Assoc 2009; 16(5): 613–623.
13. Shamliyan TA, Duval S, Du J, Kane RL. Just what the doctor ordered. Review of the evidence of the impact of computerized physician order entry system on medication errors. Health Serv Res 2008; 43(1 Pt 1): 32–53.
14. Wolfstadt JI, Gurwitz JH, Field TS, Lee M, Kalkar S, Wu W, Rochon PA. The effect of computerized physician order entry with clinical decision support on the rates of adverse drug events: a systematic review. J Gen Intern Med 2008; 23(4): 451-458.
15. DesRoches CM, Campbell EG, Vogeli C, Zheng J, Rao SR, Shields AE, Donelan K, Rosenbaum S, Bristol SJ, Jha AK. Electronic health records' limited successes suggest more targeted uses. Health Aff (Millwood). 2010; 29(4): 639-646.
16. Hillestad R, Bigelow J, Bower A, Girosi F, Meili R, Scoville R, Taylor R. Can electronic medical record systems transform health care? Potential health benefits, savings, and costs. Health Aff (Millwood) 2005; 24(5): 1103–1117.
17. R. Amarasingham, P. C. Patel, K. Toto, Nelson LL, Swanson TS, Moore BJ, Xie B, Zhang S, Alvarez KS, Ma Y, Drazner MH, Kollipar U, Halm EA. „Allocating scarce resources in real time to reduce heart failure readmissions: A prospective, controlled study," BMJ Quality & Safety, published online July 31, 2013
18. American Hospital Association. 2007 Hospital EHR Adoption Database [supplement to FY2008 AHA Annual Survey Database]. Chicago: Health Forum, 2009.
19. American Hospital Association. FY2008 AHA Annual Survey Database. Chicago: Health Forum, 2009
20. Area Health Resources Files (AHRF). 2012–2013. US Department of Health and Human Services, Health Resources and Services Administration, Bureau of Health Professions, Rockville, MD.
21. Jha AK, DesRoches CM, Campbell EG Donelan K, Rao SR, Ferris TG, Shields A, Rosenbaum S, Blumenthal D. Use of electronic health records in U.S. hospitals. N Engl J Med 2009; 360 (16): 1628–1638.
22. National Center for Health Statistics, Office of Analysis and Epidemiology. Analytic issues in using the medicare enrollment and claims data linked to NCHS surveys. December 2012. Hyattsville, Maryland.
23. Stroupe KT, Teal EY, Weiner M, Gradus-Pizlo I, Brater DC, Murray MD. Healthcare and medication costs and use among older adults with heart failure. Am J Med 2004; 116(7): 443-450.


 

24. Sundararajan V, Henderson T, Perry C, Muggivan A, Quan H, Ghali WA. New ICD-10 version of the Charlson comorbidity index predicted in-hospital mortality. J Clin Epidemiol 2004; 57(12): 1288-1294.
25. Jonikas MA, Mandl KD. Surveillance of medication use: early identification of poor adherence. J Am Med Inform Assoc 2012; 19(4): 649-654.
26. Fonarow GC, Abraham WT, Albert NM, Stough WG, Gheorghiade M, Greenberg BH,O'Connor CM, Sun JL, Yancy CW, Young JB; OPTIMIZE-HF Investigators and Coordinators. Influence of beta-blocker continuation or withdrawal on outcomes in patients hospitalized with heart failure: findings from the OPTIMIZE-HF program. J Am Coll Cardiol 2008; 52(3): 190-199.