Impact of Prior Clinical Information in an EHR on Care Outcomes of Emergency Patients

Nawanan Theera-Ampornpunt[1], MD, Stuart M. Speedie[1], PhD, Jing Du[2], MPH, Young-Taek Park[1], MPH, Boonchai Kijsanayotin[1], MD, PhD, Donald P. Connelly[1], MD, PhD
[1]Institute for Health Informatics, [2]Division of Health Policy and Management, University of Minnesota, Minneapolis, Minnesota

Abstract

A patient's prior clinical information available electronically can be helpful during the care process, particularly in the emergency department (ED). The effect of such information on quality and efficiency of ED patient care has not been adequately studied. This study uses secondary data to investigate its impact on surrogate measures of care quality and efficiency among 6,143 congestive heart failure, diabetic, and asthmatic patients in 3 EDs. Results show that in some subgroups of chronic patients in some EDs, availability of prior clinical information in the electronic health records was associated with significantly lower hospitalization rates, shorter inpatient length of stay, and reduction in the numbers of laboratory tests and diagnostic procedures ordered during the ED visit. However, there were also contradictory effects and lack of significance in other subgroups. The effects vary by ED and disease, highlighting the possibility of contextual differences influencing the effects of such clinical information.

Introduction

Continuity of care is critical for the quality and efficiency of patient care. A key component to ensure continuity of care is the existence of prior clinical history which can enhance providers' decision-making. For instance, knowledge of recent laboratory tests or diagnostic procedures might prevent redundant testing which not only incurs additional costs but might also put the patient at increased risk. In addition, knowing the patient's past history, allergies, and list of medications may prevent many errors and adverse events from happening.

The ED is one of the settings in the hospital where errors and adverse events are likely to occur, due to the urgency of the presenting problems, the usually limited clinical information available, and the time and resource constraints, to name a few.[1] It is a point of transition from the ambulatory to the emergency settings, and potentially to the inpatient setting. At this critical transition point, clinicians need to know about a patient's prior history to ensure continuity of care, but the very nature of many emergency patients makes self-report a limited or unreliable source of such information, putting their own care in jeopardy. Stiell et al. reported that 32% of emergency visits had at least 1 information gap.[2] The most common gap was medical history and laboratory test results that were believed to be essential to patient care in 48% of those cases. Lack of critical information is compounded by the fact that the most vulnerable population - older, more severely ill patients and those with serious chronic illnesses - experienced the gaps.[2] Implementation of health information technology (HIT) and health information exchange (HIE) is expected to close such gaps and improve care quality and efficiency.[3-4]

Prior research on information gaps and HIE has been limited in scope and sample size and has produced mixed results. Canadian researchers showed that such gaps were associated with a significantly longer ED length of stay (LOS) but had no effect on hospitalization.[2] However, a recent HIE study revealed that information access via HIE at the point of care might lead to more ED visits and hospitalizations among medically indigent adults.[5] Another study focusing on the effect of automated records on inpatient outcomes in a large number of hospitals found that notes and records automation was associated with a decrease in inpatient mortality and costs but an increase in complications in patients with heart failure, and no significant effect on hospital LOS.[6] With the literature's mixed and inconsistent effects of clinical information made available by health IT, additional investigation is warranted.

The purpose of the present study is to evaluate the impact of prior clinical information that is readily available in an electronic health record system (EHR) on quality and efficiency of care, focusing on emergency patients who presented with problems associated with congestive heart failure (CHF), diabetes, or asthma. Because of the high prevalence and chronic nature of these illnesses, we believe that these patients are more likely to benefit from the existence of prior clinical information.

Methods

Study Site, Setting, and Study Population

Three large Minnesota-based health systems have collaborated with the University of Minnesota to

assess the impact of HIE on patient care in EDs. One ED from each health system was selected based on its volume of emergency patients, high presence of out-of-system patients, broad geographic coverage of care, and availability of clinical data in its EHR.

ED providers from these systems were only able to access clinical information available in the EHR for their "internal" patients, that is, patients who had received care within the health system that operated the ED and thus had clinical records in the health system. No such information was available for "external" patients who never received care within the system. Each health system used the same commercial ambulatory EHR to document information about a patient's ambulatory visits, and records from these visits were accessible within the same health system. Two of the health systems also used the same commercial EHR for inpatients whereas the other ED used a different commercial EHR to document inpatient and emergency care. Clinicians within a health system had access to both inpatient and ambulatory records. However, whether or not such records were accessed and the extent of that access would depend on many factors such as the recognition of information need, ease of information access, time pressures, and practice style.

The study sample was drawn from the three designated EDs in an 18-month period from May 31, 2006 to December 31, 2007 (except in one system which used a 12-month period from July 1, 2006 to June 30, 2007). The study sample consists of patients 18 years or older who presented to one of the 3 EDs within the timeframe and had a diagnosis of CHF, diabetes, or asthma associated with their ED visits.

Data Collection

We used the International Classification of Diseases, Ninth Revision - Clinical Modification Codes (ICD-9-CM) to identify patients with a diagnosis of CHF, diabetes, or asthma in each health system's billing data. We did not differentiate type I from type II diabetes. Patients with multiple chronic diseases were listed in more than one disease category.

The first ED visit of each identified patient during the timeframe serves as that patient's index ED visit. We extracted from each system's data warehouse both patient-level data (including patient age at the index ED visit, sex, and information about the patient's previous visits) and encounter-level data (index ED visit's arrival and departure times, ED disposition status, laboratory tests and diagnostic procedures ordered during the visit, and if hospitalized, hospital admission and discharge times and discharge status).

To assess the value of EHR-accessible clinical information, an indicator was created to determine whether a patient had prior clinical information available in the system. A Charlson comorbidity index[7] was calculated based on ED visit diagnoses to adjust for case severity using existing algorithms[8-9] with minor modifications. Date/time data were based on system timestamps, and those with unreliable timestamps were excluded. We also excluded 32 patients with ED LOS longer than 24 hours from the relevant analysis because, upon confirmation from each health system, such cases most likely represented data entry problems.

This study protocol was reviewed and approved by the University of Minnesota's IRB as well as by the IRB of each of the participating health systems. All data provided to the research team were de-identified.

Study Outcomes

We hypothesized that the existence of prior clinical information accessible in the EHR would be associated with better quality and efficiency of care, compared to patients for whom such information was not available at the time of the index ED visit. We used the existence of a substantive clinical record in the EHR prior to the index visit as a binary proxy for the existence of prior clinical information. As surrogates for quality of care, we used the hospitalization rate, ED LOS, inpatient LOS, and inpatient mortality rate. The numbers of laboratory orders and diagnostic procedures ordered during the index ED visit were used as surrogates of resource utilization and costs.

It is assumed that with the availability of useful clinical information such as lists of medications, allergies, and diagnoses, patients would be less likely to experience medical errors and adverse events.[10] This could translate into shorter LOS and lower rates of hospitalization and mortality. Knowledge of recent laboratory tests and diagnostic procedures could also curtail redundant testing and diagnostic procedures.

Statistical Analysis

We first characterized the data with simple descriptive analyses. Then, depending on the nature of the dependent variables, different regression methods were applied. First, we assessed the impact on hospitalization and inpatient mortality (for hospitalized patients) using logistic regression, adjusting for age, sex, and the Charlson comorbidity index as potential confounders. Next, we studied its relationships to index ED LOS and inpatient LOS (if hospitalized) using a generalized linear model (GLM). The modified Park test was performed to identify the proper variance structure of the GLM analysis.[11]

Finally, we analyzed the association between the numbers of laboratory tests and procedures ordered

during the index ED visit and the existence of clinical information using a variety of count data models including the Poisson, negative binomial, and Hurdle (two-part) models. Each model has its own strengths and limitations in dealing with overdispersion and excess zeroes common in count data.[12] We selected the best fit model using the Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC), and the likelihood ratio tests as appropriate.

The same set of potential confounders was included in all analyses. All p-values were considered significant if lower than or equal to 0.05. Statistical analyses were performed with SAS version 9.1.3.

Results

The descriptive statistics are portrayed in Table 1. The numbers of patients from each site were comparable, but the rest of the characteristics evidenced differences. The proportions of patients with clinical information and hospitalization rates varied widely. Study outcomes by site and disease category are shown in Table 2. The outcomes, especially hospitalization rates, again, varied largely by site and disease.

Logistic regression showed that in almost all patient subgroups and study sites, ED patients with prior clinical information who were hospitalized had lower odds of mortality during the hospitalization compared to patients without, although none of the associations was significant after adjusting for potential confounders (Table 3). The lack of significance could be attributed, at least in part, to the relatively small number of expired cases. Even without statistical significance, the consistent pattern (with one exception) suggests that the effect might exist and doing further studies with sufficient number of cases is warranted.

The effect of the existence of electronic clinical information on hospitalization appears mixed. In Sites A and B, it did not have a significant impact on hospitalization. In Site C, existence of clinical information was associated with a significantly lower hospitalization rate in the CHF subgroup. But the opposite effect was demonstrated in the asthma subgroup, where clinical information was significantly associated with a 68% increase in hospitalization. The mixed pattern only confirms the mixed findings in the literature, where the effect of additional clinical information on hospitalization was not significant in one study[2] but it increased hospitalizations in another.[5] It is possible that an increase in hospitalization associated with patients with information was due to the increased tendency of a provider to admit a patient if he had knowledge of a patient's history of frequent admissions and this tendency may vary, accounting for the mixed pattern.

For ED and inpatient LOS, the value in each cell of Table 3 shows the change by that factor in LOS associated with the existence of clinical information. ED LOS was not significantly affected in any subgroups except for asthmatic patients at Site C. The effect of clinical information on inpatient LOS again varied by the study site. Inpatient LOS was 30% shorter for diabetes subgroup at Site A, not significantly affected by additional clinical information at Site B, and 21% longer in the asthma subgroup at the last study site.

Table 1. Descriptive statistics of study patients

Characteristic	Site A	Site B	Site C
Number of patients	1,957	2,050	2,136
Mean age in years ± SD	57.8 ± 22.6	50.9 ± 20.0	58.3 ± 22.8
Percentage of females	59.2%	52.3%	62.2%
Mean Charlson index ± SD	1.6 ± 1.3	1.1 ± 0.5	1.3 ± 0.7
Percentage of patients with existing clinical information	70.8%	85.0%	47.4%
Hospitalization rate	27.9%	47.2%	61.6%

To analyze the numbers of laboratory tests and diagnostic procedures ordered during the index ED visit, we first chose the appropriate count data model based on measures of model fit. Interpreting results from the Poisson and negative binomial models is straightforward because both models have one part and include all of the cases in the regression. A significant value indicates that the predictor is associated with a change by that factor in the count outcome. If the Hurdle model is the best fit model, interpretation is more complex. The Hurdle model consists of two separate parts because they are designed to handle count data with excess zeroes problems by modeling the data into a two-step decision.[12] The first part is the logistic regression that evaluates the association the predictors have on zero versus non-zero counts. To interpret this logistic part, a significant odds ratio over 1.0 for a predictor means that the predictor is significantly associated with the zero count of the outcome of interest, whereas an odds ratio below 1.0 would indicate the predictor's association with one or more counts of the outcome. On the other hand, the second part is the Poisson regression evaluating the effect the predictors have on the outcome *only* among cases with non-zero outcomes. For this Poisson part, a significant value over 1.0 indicates that, among cases with *at least one* count, the predictor is significantly associated with an increase in the count outcome with the predicted count changing by that factor, whereas a value below 1.0 suggests a relationship, again among cases with *at least one* count, between the predictor and a decrease in the count outcome with the predicted count changing by that factor.

Table 2. Descriptive statistics of study outcomes by study site and disease category

Site	Patient Subgroup	Number of Patients	Outcome					
			Inpatient Mortality Rate	Hospitalization Rate	ED LOS (Hours)*	Inpatient LOS (Days)*	Count of Lab Orders*	Count of Procedure Orders*
A	CHF	392	4.0%	56.9%	4.2 ± 2.3	5.1 ± 4.4	7.2 ± 4.5	2.2 ± 1.6
	Diabetes	970	4.3%	26.5%	3.8 ± 2.3	4.6 ± 5.1	4.7 ± 4.6	1.4 ± 1.5
	Asthma	751	3.0%	13.3%	3.2 ± 2.1	3.4 ± 3.0	2.7 ± 4.0	1.0 ± 1.2
B	CHF	472	6.1%	92.3%	3.0 ± 2.0	4.8 ± 4.8	7.6 ± 3.7	1.4 ± 0.9
	Diabetes	1081	1.3%	59.1%	3.4 ± 2.5	4.9 ± 6.8	6.8 ± 4.7	0.9 ± 1.1
	Asthma	781	0.5%	21.0%	2.5 ± 1.9	3.1 ± 3.8	1.7 ± 3.4	0.6 ± 0.7
C	CHF	844	6.7%	94.8%	2.5 ± 1.1	6.2 ± 6.5	6.8 ± 2.9	2.0 ± 0.8
	Diabetes	498	3.1%	65.3%	2.8 ± 1.2	4.6 ± 5.4	4.6 ± 3.1	1.1 ± 1.1
	Asthma	820	0.5%	26.3%	2.3 ± 1.2	4.6 ± 5.2	1.9 ± 2.7	0.8 ± 1.0

* Numbers are means ± SD.

Table 3. Impact of the existence of clinical information on measures of quality and efficiency of care

Site	Patient Subgroup	Outcome									
		Inpatient Mortality Odds Ratio	Hospitalization Odds Ratio	ED LOS Change	Inpatient LOS Change	Change in Count of Lab Orders			Change in Count of Procedure Orders		
						Model	Part 1	Part 2	Model	Part 1	Part 2
A	CHF	0.21	0.82	1.10	0.91	H	0.70	0.85*	N	0.89	
	Diabetes	0.63	1.16	1.03	0.70*	H	0.71*	1.00	N	1.01	
	Asthma	N/A†	1.42	1.05	1.09	H	0.74	1.06	N	1.07	
B	CHF	1.56	0.76	1.00	1.09	N	0.92		H	1.21	0.94
	Diabetes	0.66	0.72	1.10	1.07	H	1.05	0.94	H	1.31	0.71*
	Asthma	0.33	0.70	1.08	1.09	H	1.09	0.98	H	1.24	0.47*
C	CHF	0.59	0.35*	1.02	1.00	H	0.94	0.98	H	0.46	0.90
	Diabetes	0.57	1.37	0.99	1.17	H	0.92	0.97	H	0.94	0.87
	Asthma	N/A†	1.68*	1.11*	1.21*	H	0.54*	0.99	H	0.71	1.11

H - Hurdle model N - Negative binomial model N/A - Not Available

* Significant difference at p <= 0.05 † Number of cases too low for the analysis Underlined Significance is in hypothesized direction

All analyses were adjusted for age, sex, and Charlson comorbidity index. A value of 1.0 indicates a null effect. See text for interpretation.

Table 3 shows that at Site A, the diabetes group demonstrated that prior clinical information was significantly associated with one or more (versus zero) laboratory orders (logistic part). A similar significant effect was found in the asthma subgroup at Site C. However, when only patients with at least one laboratory order were considered, the CHF group at Site A demonstrated the hypothesized effect that additional clinical information was associated with a 15% reduction in the number of laboratory orders. However, when looking across the study sites, no consistently demonstrable beneficial impact of clinical information on laboratory testing was found.

The number of diagnostic procedures ordered also showed an inconsistent pattern. A total lack of significance at Sites A and C contradicted the significant relationships in the Poisson part at Site B, which indicated that the existence of clinical information was significantly associated with 29% and 53% fewer numbers of procedures ordered in the diabetes and asthma subgroups respectively, but only when considering cases with *at least one* procedure.

When considering the results in Table 3 within each study site, some patterns emerge. At Site A, there were significant benefits of prior clinical information on reducing inpatient LOS and the number of laboratory tests ordered in the ED. Site B demonstrated some benefits on the number of procedures ordered, but not the same benefits Site A enjoyed. Site C showed the smallest benefits, and even negative effects of clinical information on the hospitalization rate, ED and inpatient LOS, and the number of laboratory orders opposite to our hypothesized directions.

Discussion and Conclusions

This study did find some evidence that prior clinical information accessible in an EHR may be associated with better patient outcomes and more efficient care. But these findings were not consistent across either organizations or patient subgroups. At one site it was associated with significantly poorer outcomes and less efficient care. The varying patterns suggest that its value may depend on the setting and the nature of the patient's presenting problem.

Different settings have different contextual characteristics such as organizational structures, information systems, policies, workflows, and practice styles, all of which could well influence our effects of interest but which were not captured in this study. Through these differences, clinical information translates into care outcomes in different ways across the sites. For example, an organization's internal

policies and quality initiatives could influence the decision of clinicians with regard to hospitalization, discharge, and orders for services. The large difference in overall hospitalization rates among the study sites was a possible evidence of such organizational influences beyond different patient demographics. It is also possible that the different composition of clinicians with their different practice styles contributed to the pattern inconsistencies. Findings from this study should not dissuade informaticians from encouraging adoption of HIT and HIE solutions in the ED, as evidence of the benefits of the information do exist. The variations in this study should highlight the statement that HIT by itself is not a panacea for better care but rather the right combination of HIT and the setting in which it operates, particularly the people and organizational factors, may be the key to better outcomes. This study should instead encourage more research to identify the organizational settings and characteristics that influence the value of HIT and electronic clinical information so that a conducive environment that maximizes its effect on care could be created.

Limitations of this study include its cross-sectional design, which makes it unable to establish causation. The use of secondary data also presents challenges that limited the extent of our analysis. Specifically, many data elements that could confound the relationships and thus should be adjusted for were either not available, unreliable, or likely inaccurate. These data elements include additional characteristics of the patients such as their insurance status and race as well as the extent to which the prior clinical information was used during the care process. Ideally, clinicians' actual use of clinical information, not its mere existence, should be used to evaluate the effects, because the literature suggests that clinicians' access to available electronic clinical information in an ED might be infrequent.[13] Unfortunately, such data were not available to us, which could explain some of the lack of significant effects. Lastly, the heterogeneity of the participating EDs also makes the patterns harder to distill and limits its generalizability. More research is needed to incorporate IT use and account for the limitations faced in this study.

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