Results: After exclusions, 18872 and 17886 patient visits were analyzed before and after the intervention respectively. Overall, there was a statistically significant increase in WT of 5 minutes ($P = .036$) and LOS of 10 minutes ($P = .001$) after CPOE implementation, while LWBS increased from 7.2% to 8.1% ($P = .002$). The subgroup analysis revealed admitted patients' ED LOS increased by 63 minutes ($P < .001$), CTAS 3 and 5 patients increased their WT by 6 minutes ($P = .001$) and 39 minutes ($P = .005$), and LWBS proportion increased significantly for CTAS 3-5 patients, worsening from 24.3% to 42.0% ($P < 0.001$) for CTAS 5 patients specifically.

Conclusions: CPOE implementation at this health care organization detrimentally impacted patient flow in the ED. All throughput variables are involved, some with greater significance than others. The most striking clinically relevant result is the increase in LOS of 63 minutes for admitted patients. One has to ask if the potential patient safety risks outweigh the benefits when considering CPOE implementation.

275 The Operational Effects of Implementing Electronic Provider Documentation in the Emergency Department

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Study Objectives: The implementation of electronic health records (EHRs) has the potential to improve care in the emergency department (ED) setting, but may also impact ED operations. Previous studies have shown mixed effects on ED efficiency following EHR implementation and have not isolated the effects of individual EHR features. Typically, an EHR is implemented with multiple features simultaneously, such as patient tracking, computerized provider order entry (CPOE), and provider documentation. However, at our institution, we implemented a custom, provider documentation system (eDoc) to replace paper documentation in the setting of existing patient tracking and CPOE. This provided an opportunity to characterize the isolated impact of implementing electronic documentation, perhaps the most time-consuming EHR function, on ED operational performance.

Methods: We performed a retrospective analysis of operational data for 1-year periods before and after eDoc implementation (March 18, 2013) in a single, high-volume, urban ED. We computed operational statistics for each day of the study period (reflecting 60,870 pre-implementation and 59,337 post-implementation patient encounters). The pre-specified primary outcome variable was mean length of stay (LOS); secondary outcomes were mean LOS for admitted (LOSa) and discharged patients (LOSd) and mean arrival time to disposition for admitted patients (TTD). We used regression modeling to identify differences in outcomes while controlling for several pre-specified confounding variables: month, day, daily visits, visits from the preceding day, mean patient age, daily boarding hours, and proportion of (1) female patients, (2) admissions, observation admissions and discharges, (3) patients with ESI $\leq$ 2, and 4) arrivals by ambulance. As a sensitivity analysis, we performed coarsened exact matching (CEM) analysis for similar days across the pre- and post-implementation periods based on pre-specified variables of month, day, visits, visits from the previous day, admission rate, proportion of patients with ESI $\leq$ 2, and boarding hours.

Results: Primary and secondary outcomes are shown in the Table. In unadjusted analysis, there was a net increase in all outcome variables. Using regression analysis to control for variations in operational variables, there were significant increases in LOS (+0.10 hours) and LOSd (+0.08 hours). CEM analysis was concordant with regression, demonstrating a significant net positive change in LOS (+0.19 hours) and LOSd (+0.17 hours).

Conclusion: In our single center study, the isolated implementation of electronic provider documentation was associated with significant, sustained increases in overall length of stay and length of stay for discharged patients. Though these increases were small in magnitude, our findings suggest that electronic provider documentation may negatively affect patient throughput in the ED. Interventions to mitigate this effect, such as improving EHR usability or adding clinical staff, scribes, or voice recognition software, would be valuable areas of inquiry for future research.

Table. ED Operational Performance Before and After Implementation of Electronic Provider Documentation

	Pre, hrs (SD)	Post, hrs (SD)	Unadjusted Δ, hrs (CI)	Adjusted Δ, hrs (CI)	CEM, hrs (CI)
Length of Stay	4.29 (0.72)	4.43 (0.82)	+ 0.14 (0.03-0.16)	+ 0.10* (0.05-0.15)	+ 0.19* (0.04-0.36)
Length of Stay (Admitted Pts)	6.47 (1.75)	6.66 (2.20)	+ 0.19 (-0.10-0.48)	+ 0.02 (-0.05-0.10)	+ 0.12 (-0.24-0.48)
Length of Stay (Discharged Pts)	3.49 (0.47)	3.52 (0.41)	+ 0.03 (-0.03-0.09)	+ 0.08* (0.03-0.14)	+ 0.17* (0.05-0.28)
Time to Disposition (Admitted Pts)	3.00 (0.41)	3.03 (0.38)	+ 0.03 (-0.03-0.09)	+ 0.05 (-0.01-0.10)	+ 0.09 (-0.01-0.20)

SD, Standard deviation; *CI*, 95% confidence interval; *CEM*, coarsened exact matching.
*$P < .05$.

276 Predicting Emergency Department Patient Throughput Times Utilizing Machine Learning

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Study Objectives: Patient throughput time in the emergency department is a critical metric affecting patient satisfaction and service efficiency. We performed a retrospective analysis of electronic medical record (EMR) derived data to evaluate the effectiveness of multiple modeling techniques in predicting throughput times for patient encounters in an academic emergency department (ED). Analysis was conducted using various modeling techniques and on differing amounts of information about each patient encounter. We hypothesized that more comprehensive and inclusive models would provide greater predictive power.

Methods: Retrospective medical record review was performed on consecutive patients at a single, academic, university-based ED. Data were extracted from an EMR derived dataset. All patients who presented from January 1, 2011 to December 31, 2013 and met inclusion criteria were included in the analysis. The data were then partitioned into two sets: one for developing models (training) and a second for analyzing the predictive power of these models (testing). The Table lists model types used. The primary outcome measured was the ability of the trained models to accurately predict the throughput times of test data, measured in terms of mean absolute error (MAE). Secondary outcomes were R2 and mean squared error (MSE). Model factors included a mix of patient specific factors such as triage vital signs, age, chief complaint; factors representing the state of the ED such as census and running average throughput time; and timing factors such as time of day, day of week, and month. The most comprehensive models included a total of 29 distinct factors.

Results: Of the 134,194 patients that were seen in the 3-year period of the study 128,252 met the inclusion criteria; the mean throughput time was 183.327 min (SD = 98.447 min). Compared to using a single average throughput time as a naïve model (MAE = 80.801 min), univariate models provided improved predictive abilities. More sophisticated models, using machine learning methods and including all available factors provided greater predictive power with the lowest MAE achieved at 73.184 min.

Conclusion: We have demonstrated that including information about incoming patients and the state of the ED at the time of an arrival can aid in the prediction of individual patients' throughput times. The Multiple Linear Regression model, including all available factors, had the highest predictive accuracy, reducing mean absolute error by over 9% compared to the naïve model. While this represents an improvement in the current state of the art, we believe there is room for further work to generate high quality individual patient predictions. More sophisticated models based on ED workflows may lead to greater predictive power to prospectively estimate patient throughput times at arrival.

Table. Model types used and mean absolute error (MAE) in min.

Model	MAE (min)
Naïve	80.801
Univariate - Primary Chief Complaint	76.407
Univariate - Census	80.551
Univariate - Hour of Arrival	80.244
Multiple Linear Regression	73.184
Lasso Regression	75.538
Decision Tree	101.157
Random Forest	75.442

277 Single-Item Health Literacy Screening Validation in Predicting Limited Health Literacy in an Academic Emergency Department

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Background: Prior literature has supported that single-item health literacy screening (SILS) may identify individuals with limited health literacy in an outpatient setting. To our knowledge, there are no studies in the emergency department (ED) population. In addition, it is uncertain if single-question screens are comparable to the Newest Vital Sign (NVS), a 6-question validated scale to determine patients at risk for limited health literacy. SILS may be advantageous over NVS in a busy clinical environment given its ease of administration.

Study Objective: The goal of the study was to determine whether either of 2 SILS questions was valuable for detecting patients at risk for limited health literacy in an ED setting.

Methods: Using a prospective convenience sample, English-speaking patients between the ages of 18-99 who presented to triage between November 2014 and March 2015 were recruited and interviewed in an academic urban trauma center. Participants were excluded if they presented with a complaint of altered mental status, if they required immediate clinical stabilization or if they declined to participate. Participants were interviewed using the 6-point NVS screen, as well as 2 single-question literacy screens with 5 possible responses. Those at risk for limited health literacy were defined as having NVS scores of 0-3; those with adequate health literacy were defined as scoring a 4-6. SILS1 was "How confident are you filling out medical forms by yourself?" SILS2 was "How often do you have someone help you read hospital materials?" We compared the two SILS questions to the dichotomized NVS using area under the receiver operating characteristic curves (AUC). After dichotomizing the SILS questions based on receiver operating characteristic (ROC) curve cut points, we determined the sensitivity, specificity, positive and negative predictive values, and kappa compared to the dichotomized NVS.

Results: Two hundred fifty participants completed the NVS and the two SILS questions. The prevalence of patients at risk for limited health literacy were 125/250 (50%) based on the NVS. Inadequate health literacy was found in 73/250 (29%) according to SILS1 and in 61/250 (61%) according to SILS2. AUCs are listed in the table. Based on the ROC curves, each question was dichotomized at the best cut point and compared to the NVS as shown in the table.

Conclusions: Agreement between each of the two SILS and the NVS for detecting limited health literacy was fair. Given the high specificity, scores indicating inadequate health literacy on either of the two SILS questions may be helpful in identifying patients at risk for limited health literacy in an academic ED.

	AUC	Sensitivity	Specificity	PPV	NPV	Kappa
SILS1	0.66(0.59,0.73)	44%	86%	75%	60%	0.30
SILS2	0.70(0.63,0.76)	38%	90%	79%	59%	0.28

278 Effect of Electronic Medical Record Transition on Emergency Department Length of Stay

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Study Objectives: Regulatory changes within the health care market have driven adoption of electronic medical records (EMRs) in the emergency department (ED) with anticipated benefits of improved documentation, compliance, hand-offs, and efficiency. Although EMRs in the ED are now nearly ubiquitous, there is still relatively little published experience regarding the operational effects of their implementation. We report the impact of a transition from one EMR (IDX Systems, General Electric) to another (Cerner Millennium, Cerner Corporation) on ED length of stay (LOS).

Methods: *Design:* Retrospective analysis of routinely acquired operational data. *Setting:* Tertiary 23-bed ED without an emergency medicine training program. *Type of Participants:* Visits in the one year (September 5, 2009 through September 4, 2010) prior to EMR transition and the year (September 5, 2010 through September 4, 2011) after EMR transition. We categorized post-transition visits as early (first 180 days; September 5 through March 4) versus sustained (days 181-365; March 5 through September 4) and compared them to a similar time cohort from the previous year. In the primary analysis, we performed a simple pre-post comparison of LOS. In the secondary analysis, we evaluated the effects of both the transition and confounders (patient age, ED daily volume, nursing staffing, physician staffing, and effective hospital occupancy) using univariable and multivariable linear regression models. Statistical analyses were performed using version 9.3 of the SAS software package (SAS Institute, Cary, NC). All tests were two-sided and $P < .05$ were considered statistically significant.

Results: There were 24,640 visits post-transition (12,325 early and 12,315 sustained) and 23,348 visits pre- transition (12,058 corresponding to early and 11,290 corresponding to sustained). In the primary analysis, mean (standard deviation, SD) LOS in the early phase post-transition was 264 (133) minutes, and in the corresponding dates pre-transition was 241 (131) minutes; the difference was 23 minutes ($P < .001$). Mean (SD) LOS in the sustained phase post-transition was 248 (129) minutes, and in the corresponding dates pre-transition was 233 (130) minutes; the difference was 15 minutes ($P < .001$). In the secondary analysis, after adjusting for covariates, the mean LOS increased post-transition by 28 minutes in the early phase ($P < .001$) and by 20 minutes in the sustained phase ($P < .001$).

Conclusions: In a single-facility study, transition from one EMR to another was associated with an increase in LOS, even when adjusting for covariates. This increase in LOS was seen in both the early phase after adoption and in the sustained phase as well. While this work is consistent with several previous descriptions of the effects of EMR transition, it is inconsistent with others. It is not clear if our observed association was related to the impact of EMR transition in general, the use of this EMR in particular, local site factors, or other factors yet to be considered. This work adds to the growing knowledge of the effect of EMRs on ED operations.

279 Post-Intubation Care in the Emergency Department Remains Sub-Optimal Despite the Introduction of an Electronic Order Set

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Study Objectives: To determine if the introduction of an electronic intubation order set (OS) improves compliance with standard post-intubation practice in the emergency department (ED) of an urban, tertiary care hospital.

Methods: We conducted a retrospective review of all patients intubated in the ED of an urban, tertiary care hospital, with an annual volume of greater than 100 thousand visits. An electronic airway order set (OS) was introduced on September 4, 2012 to prompt providers entering orders. Data during the 11-month period before (October 1, 2011 to September 3, 2012) and the equivalent 11-month period after (October 1, 2012 to September 3, 2013) the implementation of the OS were compared. Exclusion criteria were any patients whose ED disposition was "deceased." Primary outcomes included the percentage of patients with time to blood gas (BG)