HOPSCORE: AN ELECTRONIC OUTCOMES-BASED EMERGENCY TRIAGE SYSTEM

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ABSTRACT

Purpose

The study objective was to prospectively evaluate a machine-learning-based electronic triage (e-triage) support tool aimed at improving outcomes-based differentiation at triage.

Scope

Emergency department (ED) triage standards demonstrate deficiencies in risk-stratification and reliability.

Methods:

E-triage supports triage decision-making by applying a machine learning algorithm to predict patients' risk of acute outcomes and hospitalization in parallel. Risk is predicted from patient's complaint, vital signs, demographics, and medical history and translated to an e-triage level recommendation. Clinical outcomes and measures of timeliness were compared for patients triaged with the Emergency Severity Index (ESI) pre-implementation to those using e-triage post-implementation.

Results

The distribution of acuity changed post e-triage implementation; low acuity (Level 4 and 5) patients increased by 55% (16.6% pre- to 25.8% post-), mid-acuity (Level 3) decreased 15% (64.6% to 54.6%), while high-acuity (Level 1 and 2) patients remained constant (18.8% to 19.6%). This resulted in improved risk stratification, notably in identifying low-risk patients originally part of the heterogeneous ESI Level 3 group. Filtering low-risk patients diverted attention to higher-severity patients resulting in a 58 min decrease in arrival-to-admission decision (474.9 to 417.1) overall and a 56 min decrease (299.5 to 243.3) for the high-acuity sub-group. Concordance with e-triage was 80% with outcome measures supporting the value of combining e-triage with nurse clinical judgment. Harmonizing nurses' clinical judgment with e-triage decision support was able to improve risk-stratification of patients at triage and operational performance. Using advanced data-science at the point-of-care provides opportunity to enhance decision-making and reduce untoward variability in practice.

Key Words

Emergency Medicine, Triage, Clinical Decision Support, Machine Learning, Predictive Analytics, Health Informatics

PURPOSE

The objective of this study was to deploy e-triage in a single ED and assess its uptake and impact on discerning clinical outcomes, timeliness of care, and triage nurse concordance. The principal purpose of implementing e-triage was to reduce and appropriately redistribute the large and clinically uncertain group of ESI Level 3 patients (~ 65% of ED visits) based on risk. In addition, e-triage was installed to mitigate nurse between-rater variability common across ESI users and directly measured within our study site's hospital system. The study was conducted as a pre- ESI and post- e-triage implementation comparative analysis.

SCOPE

Triage has become a foundational process for safe and efficient management of emergency department (ED) patients at presentation. Despite the many flavors of front-end operations, the Emergency Severity Index (ESI) is used in most EDs across the United States (US) and is expanding globally. The ESI represented a major advancement in triage over 20 years ago by establishing a national practice standard; a 5-Level system that considers projected resource use. While the ESI's ease-of-use and -adoption are advantageous, there are important deficiencies that have been well recognized in the literature. First, validation against patient outcomes indicating critical care needs is lacking. Next, ESI relies heavily on provider judgment making it prone to high between-rater variation. Last, ESI has demonstrated a limited ability to differentiate and risk-stratify mid-acuity patients in modern EDs; about half of adult ED visits nationally (65% at our ED study site) were triaged to a large heterogeneous ESI Level 3 group. This inability to differentiate poses safety risks to those under-triaged and limits the precision of ED resource distribution to low-risk patients over-triaged.

To address these shortcomings, we derived an electronic clinical decision support tool, e-triage, which leverages large-scale electronic health record (EHR) data at the point of care. E-triage applies machine-learning methods to routinely available triage data (vital signs, chief complaint, and active medical history) to predict patients' need for critical care (in-hospital mortality or intensive care unit admission), an emergency procedure, and inpatient hospitalization in parallel. E-triage translates risk to triage level recommendations viewable directly in the EHR. A retrospective derivation of the e-triage algorithm and its ability to improve differentiation of patients with respect to clinical outcomes has been previously published in *Annals of Emergency.* The machine learning concepts behind e-triage and its anticipated use to support clinical judgment at triage via an e-triage level recommendation is described.

METHODS

Setting and Selection of Participants

E-triage was evaluated for 52,720 adult (age $\geq$ 18) visits from an urban academic ED between Nov-1-2016 and Nov-1-2017. Patients were excluded who did not receive a final disposition or presented with psychiatric conditions. Psychiatric patient exclusions were identified according to a set of electronic health record complaint entries such as "anxiety," "depression," and "panic attack," among others defined by an emergency physician panel. Patients presenting with substance abuse (e.g., overdose, withdrawal) were not considered psychiatric and were included in our cohort. The post-intervention (e-triage) cohort was compared to a pre- ESI cohort of 53,115 between Oct-1-2015 and Oct-1-2016 using identical exclusion criteria allowing for a one-month (Oct-2016) transitional period to steady-state use. Institutional review board approval was obtained for this prospective study.

Implementation

E-triage was integrated into the EHR to provide an acuity recommendation viewable immediately above the input for nurse-entered acuity as seen in Figure 1 (below). The e-triage acuity recommendation is populated seconds after the chief complaint and final vital signs have been entered. A brief definition of each level (H1 to H5 with 'H' denoting the Hopkins Triage Level) is always displayed as well as supplemental information to: (1) caution users of missing information, (2) identify data entry errors, and (3) acknowledge abnormal vital signs that may lead to high-acuity recommendations. Supplemental information has evolved to support interpretation of e-triage level recommendations over time. Next the triage nurse may agree with (yes) or override (no) the e-triage level recommendation and provide rationale for overrides in the form of free-text and structured categories: elicited from the patient/family, prior medical or surgical history, home medications. Regardless, the nurse still assigns an acuity level (Figure 1) identical to the original ESI workflow. The override and discordance feedback gathered from users during early-stage implementation was used to hone and improve the algorithm and train nurse users. For example, the frequency of the prior medical/surgical history button input prompted integration of these available EHR data into the e-triage algorithm.

Methods of Measurement

Patient acuity level distributions, clinical outcomes, and measures of timeliness of ED care stratified by triage level were compared pre- ESI and post- e-triage implementation. Clinical outcomes included: (1) a critical care outcome compositely defined as either in-hospital mortality or direct admission to an intensive care unit (ICU), (2) emergency procedure was defined as any surgical procedure, including cardiac catheterization, that occurred in an operating room within 12 hours of ED disposition, (3) hospitalization comprised of any admission to an inpatient care site including ward or direct transfer to an external acute care hospital; patients transitioned to observation status or care areas were not considered admitted unless their observation ultimately resulted in inpatient hospitalization. In addition to the predicted outcomes, markers of secondary clinical outcomes for time-sensitive conditions were evaluated. This included elevated troponin level (>0.06 ng/mL) indicating acute coronary syndrome, and elevated lactate level (>2.4 mmol/L) indicating hypoperfusion, including potential for septic shock. The rate of 72-hour returns, defined 72-hours from the index ED discharge, exclusively for discharged patients was also measured.

Triage levels used to stratify outcomes were grouped into high-acuity (Level 1 and 2), mid-acuity (Level 3), and low-acuity (Level 4 and 5) groups because they discern the three distinct pathways of ED care triggered at triage. High-acuity patients are deemed unsafe to wait and are brought immediately back to a private room with a bed. Mid-acuity patients are safe to wait and may be treated in a private room or in a non-private ED care area with chairs based on additional clinical information gathered after triage. Low-acuity patients are 'fast-tracked' to an urgent care area for a less intensive work-up and anticipated swift discharge. Last, it's important to note that the e-triage predictive model and algorithm translating risk to triage level recommendation was not static over the study period; the algorithm was adapted and improved based on user feedback and outcomes data monitoring.

RESULTS

ED volumes and patient visit characteristics pre- ESI and post- e-triage implementation are displayed in Table 1. There were no appreciable differences in volume, patient demographics, complaints or medical history over the full study period. Post e-triage implementation, the distribution of patient acuity changed substantially overtime as seen in Figure 2. By design, low acuity (Level 4 and 5) patients increased by 55% (16.6% pre- to 25.8% post-implementation), mid-acuity Level 3 patients decreased by 15% (64.6% to 54.6%), while the proportion of high-acuity Level 1 and 2 patients remained stable (18.8% to 19.6%).

The daily volume, predicted and secondary outcome rates, vital signs, and complaints stratified by acuity level is displayed in Table 2. The proportion of vital sign abnormalities generally increased for both the high-acuity and mid-acuity patient population post- e-triage implementation. Detection of patients with elevated troponin and lactate as high acuity increased 32% (6.8% positive to 9.0%) and 22% (11.8 to 14.4%), respectively. The rates of all predicted outcomes remained similar pre- and post-implementation with the exception of a 3% increase (25.4% to 28.5%) in hospitalizations for e-triage mid-acuity patient group. Despite the large increase (56%) in low-acuity patients, vital sign abnormalities for this group was reduced and the proportion of patients hospitalized increased marginally from 2.4% to 4.4%; 2 more hospital admissions per 100 patient visits. Notably, the composition of low-acuity complaints post-implementation included low-risk chest pain and abdominal pain that were almost never present during the ESI pre-implementation time period as seen in Table 2.

Broad measures of the timeliness of core ED care events including arrival to - triage, first provider, disposition decision (admit and discharge), and admission decision to transfer (i.e., boarding time) were compared pre- and post- implementation. These time interval distributions for the total cohort and high-acuity (Level 1 and 2) patients may be seen in Figure 3. By filtering low-risk patients that were originally ESI Level 3's (Figure 2) attention was diverted to higher-severity patients destined to be hospitalized resulting in a 58 min decrease in mean arrival-to-admission decision (474.9 pre- ESI to 417.1 post- e-triage) overall and a 56 min decrease (299.5 to 243.3) for the high-acuity sub-group. The overall time from arrival to provider was also reduced by 10 min (55.2 to 45.1) with other measures of timeliness including arrival-to-discharge-ready holding stable (480.4 to 482.9). Similar time measurements for mid-acuity (Level 3) and low-acuity (Level 4-5) patients may be seen in Supplemental Figure S1.

The concordance with e-triage was 80.1% overall and 83.4% for the mid-acuity patient population that increased over the course of the post-implementation study period. Table 3 demonstrates clinical outcome rates for patients where there was mid-acuity agreement between nurse and e-triage compared to where discordance was present. Patients that were up-triaged by the nurse to high-acuity (e-triage recommended mid-acuity) represented higher risk population; all outcome probabilities were increased compared to patients where there was mid-acuity agreement. For example, this up-triaged group's rate of hospitalization was 41.0% compared to 28.1% for the agreement group. The inverse trends existed for those down-triaged as seen Table 3. Alternatively, similar patterns existed for patients that were assigned Level 3 by the triage nurse, but e-triage recommended high-acuity or low-acuity (i.e., discordance). Discordant patients where e-triage recommended high-acuity had increased risk of all outcomes, including 41.3% rate of hospitalization, compared to the agreement group. Likewise, e-triage recommended low-acuity patients demonstrated a lower outcome rate with the exception of emergency procedure. Triage nurses were particularly adept in identifying e-triage recommended low-acuity patients that did have a slightly heightened risk of emergency procedure (1.6% agreement to 3.4% discordant).

DISCUSSION

Limitations

There were several limitations to this study important to consider when interpreting results. First, our pre- and post-intervention study was quasi-experimental and susceptible to temporal confounding. Although a randomized or interrupted time-series study design may better mitigate confounding, this approach was not feasible given requirements to adhere to a uniform triage system to maintain operational consistency and straightforward implementation. We also sought to evaluate population-based clinical and timeliness measures of the ED as a system which would have been difficult using other study designs. Overall, the large comparator sample sizes and stability in total population outcome measures across pre- and post-intervention periods may mitigate much of this confounding. However, elevated troponin and lactate were an exception and did increase post-intervention limiting interpretation for these outcomes. Beyond this, no other major initiatives impacting patient flow or triage were conducted during the study period.

Additional limitations existed in consistency of data collection and e-triage algorithm over the study period. The shift from a legacy clinical information system to the system-wide EHR for surgery during the pre-intervention period (prior to Jul-1-2016; Figure 2) created inconsistency in data solely for the emergency procedure outcome. As a result, all pre-intervention emergency procedure outcomes data were reported for the most recent 3-month (Jul-1-2016 to Oct-1-2016) sample (Table 1 and 2) instead of the full 12-months. Further, the e-triage algorithm was not static over the post-intervention time period. An Agile user-centered approach was in place to rapidly gather user feedback (Figure 1) and adapt the algorithm in response, particularly during the early stages of implementation. While this improved the algorithm and led to increased uptake (Figure 2), it did create some variation post-intervention. A final limitation to consider is that e-triage was executed at a single ED study site. Future work to evaluate e-triage at multiple study sites will be able to assess its ability to generalize.

Significance

In this study we deployed and prospectively evaluated a machine-learning-based triage (e-triage) support tool. The tool was designed to address general deficiencies in the ESI triage process including lack of ESI Level 3 differentiation and low inter-rater reliability. E-triage drove a substantial change in the acuity distribution by increasing low-acuity (Level 4 and 5) designations 55%, decreasing mid-acuity (Level 3) designations by 15% while the proportion of high-acuity (Level 1 and 2) patients remained constant. Beyond proportional differences, the patients in each of these acuity groups were different post-implementation as well (Table 2). This shift served to filter out low-risk patients that would have originally been part of the ESI mid-acuity group (i.e., pre-implementation). From a systems engineering perspective, the ability to separate signal (higher-risk encounters) from a larger amount of noise (lower-risk encounters) at triage likely channeled attention toward the higher severity hospitalized patients. This resulted in a one hour decrease in arrival to admit decision, while other aggregate measures of timeliness went unchanged (Figure 3; Total).

Although this study was formulated as an ESI pre-implementation and e-triage post-implementation comparison, each approaches the objective of triage differently. ESI is based on subjective assessment of acute need for Level 1 and 2 designations while considering projected resource use for Level 3 through 5. E-triage recommendations are objectively determined by risk for critical care, emergency procedure, and hospitalization outcomes.[8] There is a large degree of overlap between each triage systems objectives (e.g., patients likely to be hospitalized are also likely to be resource intensive), but there is some divergence as well (e.g., low-risk female with abdominal pain requiring blood tests and privacy for a pelvic exam). The implementation of e-triage did represent a major change from heavy reliance on subjective assessment (ESI) that is prone to high inter-rater variation, to an objective and outcomes-based anchor (e-triage). However, e-triage is not purely objective in that it incorporates subjective information (e.g., chief complaint, prior medical history) from the EHR and more importantly, it must be partnered with critical judgment in practice (Table 3).

Implications

E-triage, as an example within the broader context of machine learning in medicine, raises some meaningful concepts at a research intersection that will progress; use of integrated EHR systems and housing of large-scale clinical data is now commonplace. Emergency medicine, in particular, is apt to lead innovation and benefit from these data-driven technologies for multiple reasons: (1) decision-making demands with high variability under time pressure provide ripe opportunity for decision support; particularly support tools that are aimed at saving time and avoid alarm fatigue, (2) the rapid accumulation of clinical data in the ED provides fodder to drive data-science technologies that may be applied both within and external to the ED (e.g., in-home, pre-hospital), (3) the unique role of ED providers simultaneously managing patients across a wide spectrum of medical conditions and illness severity calls for on-going prioritization of patients' risks that machine learning methods are well-equipped for, and (4) data-driven decision support has the potential to improve emergency medicine providers' connection to patients' pre-encounter context and post-encounter outcomes (closed-loop learning); this can mitigate challenges with episodic emergency care delivery where providers often have no relationship to patients before or after their care. Successful machine-learning-based decision support applications in the ED will be able to distill large volumes of patient data to actionable information at the point of care. The objectives will most commonly focus on risk estimation and/or aggregation of historical patient data that ED providers may not otherwise have time to consume or be unaware of. In either case, separating useful information (signal) from the abundance of data not relevant to the ED visit (noise), advancing interpretation and trust of these 'black-box' methods, and understanding the risks of supporting self-fulfilling processes, will be the on-going science and art of machine learning in emergency medicine.

Conclusions

Importantly, the e-triage application did maintain a core principle in harmonizing data-driven decision support with nurses' clinical judgment. This theme was messaged throughout implementation and exhibited in results (Table 3). While machine-learning-based algorithms continue to improve and evolve, the aim to support decision-making, and not replace, will likely remain a key to gaining desired improvements. Overall, e-triage does serve as an example of where advanced data-science at the point-of-care provides opportunity to enhance decision-making and reduce untoward variability in practice.

LIST OF PUBLICATIONS AND PRODUCTS

Refereed Journal Articles

1. Dugas A, Kirsch T, Toerper M, Korley F, Yenokyan G, France D, Hager D, Levin S. An Electronic Emergency Triage System Improves Patient Distribution. *J Emerg Med*. 50(6):910-918, 2016. PMID 27133736.

2. Levin S, Toerper M, Hamrock E, Hinson J, Barnes S, Gardner H, Dugas A, Linton B, Kirsch T, Kelen G. Machine Learning-Based Triage More Accurately Differentiates Patients with Respect to Clinical Outcomes Compared to the Emergency Severity Index. *Ann Emerg Med*. 71(5):565-574, 2017. PMID 28888332

3. Balhara K, Mistry B, Hinson J, Levin S, De Ramirez S. Nursing perceptions of the Emergency Severity Index as a Triage Tool in the United Arab Emirates. *J Emerg Nurs*. 44(4):360-367, 2017. PMID 29167033

4. Mistry B, Stewart De Ramirez S, Kelen G, Schmitz P, Balhara K, Levin S, Martinez D, Psoter K, Anton X, Hinson J. Accuracy and Reliability of Emergency Department Triage using the Emergency Severity Index: An International Multicenter Assessment. *Ann Emerg Med*. 71(5):581-587, 2017. PMID 29174836

5. Hinson J, Martinez D, Schmitz P, Toerper M, Radu D, Scheulen J, Stewart De Ramirez S, Levin S. Accuracy of the Emergency Severity Index and Independent Predictors of Under-Triage and Over-Triage in Brazil: A Retrospective Cohort Analysis. *Int J Emerg Med.* 11(1), 2018. PMID 29335793

6. Barnes S, Saria S, Levin S. An Evolutionary Computation Approach for Optimizing Multi-Level Data to Predict Patient Outcomes. *Journal of Healthcare Engineering*. ID 7174803, 2018. PMID 29744026

7. Lentz B, Jenson A, Hinson J, Levin S, Cabral S, George K, Hsu E, Kelen G. Validity of Emergency Department Triage Tools: Addressing Heterogeneous Definitions of Over-Triage and Under-Triage. *Am J Emerg Med*. (In Press), 2017.

8. Hinson J, Martinez D, Cabral S, George K, Whalen M, Hansoti B, Levin S. Triage Performance in Emergency Medicine: A Systematic Review. *Ann Emerg Med*. (In Press) 2018.

Refereed Journal in Preparation

9. Levin S, Toerper M, Hinson J, Henry S, Gardener H, Mackenzie C, Barnes S, Hamrock E, Martinez D, Whalen M, Kelen G. Machine-Learning-Based Electronic Triage: A Prospective Evaluation of Clinical and Operational Outcomes (In Prep), 2018.

10. Whalen M, Toerper M, Hinson J, Henry S, Gardener H, Mackenzie C, Barnes S, Hamrock E, Martinez D, Whalen M, Levin S. Nursing Implementation of a Machine-Learning-Based Triage Decision Support Tool (In Prep), 2018.

Patents

1. E-Triage: An Electronic Emergency Triage System, Unites States Patent No. US62296753 application filed, Primary Inventor, Scott Levin. Electronic triage tool for advanced prognostication of emergency department patient

Software Products

1. This award contributed to the early development of computing infrastructure to develop e-triage algorithms and deploy by integrating into the Epic electronic health record (EHR) system.

Conference Presentations and Invited Talks

4/2016	Risk Adaptive E-Triage in Emergency Medicine, Johns Hopkins Malone Center for Engineering in Healthcare Inaugural Research Symposium, Baltimore, MD
11/2016	Machine Learning Based Clinical Decision Support. INFORMS Annual Meeting, Nashville, TN
11/2016	Nurse-Engineering Innovation in Emergency Medicine, Johns Hopkins Development Office Event, Seattle, WA
4/2017	EHR Data Science in Emergency Medicine. Miami University of Ohio Department of Chemistry and Biochemistry Research Seminar Series. Oxford, OH
5/2017	EHR Data Science in Emergency Medicine for Clinical Practice and Research. NIH National Institutes on Drug Abuse (NIDA). Exploring Substance Use Relevant Measures in EMR & Clinical Quality Measurement in Emergency Department Settings, Rockville, MD.
9/2017	E-Triage: A new machine learning-based emergency department triage system. Mediterranean Emergency Medicine Congress, Lisbon, Portugal.
6/2018	Emergency Medicine Risk Forum, University of Maryland Medical System
6/2018	Implementation of an innovative machine learning-based triage support tool: translating technology and research to practice. Sigma Theta Tau International European Nursing Conference. Cambridge, United Kingdom.
9/2018	Machine Learning Based Electronic Triage. MCIC Vermont Leadership Committee, New Haven, CT.
9/2018	Implementing an Innovative Machine Learning-Based Triage Support Tool. Emergency Nursing Association Conference, Pittsburgh, PA.

FIGURES

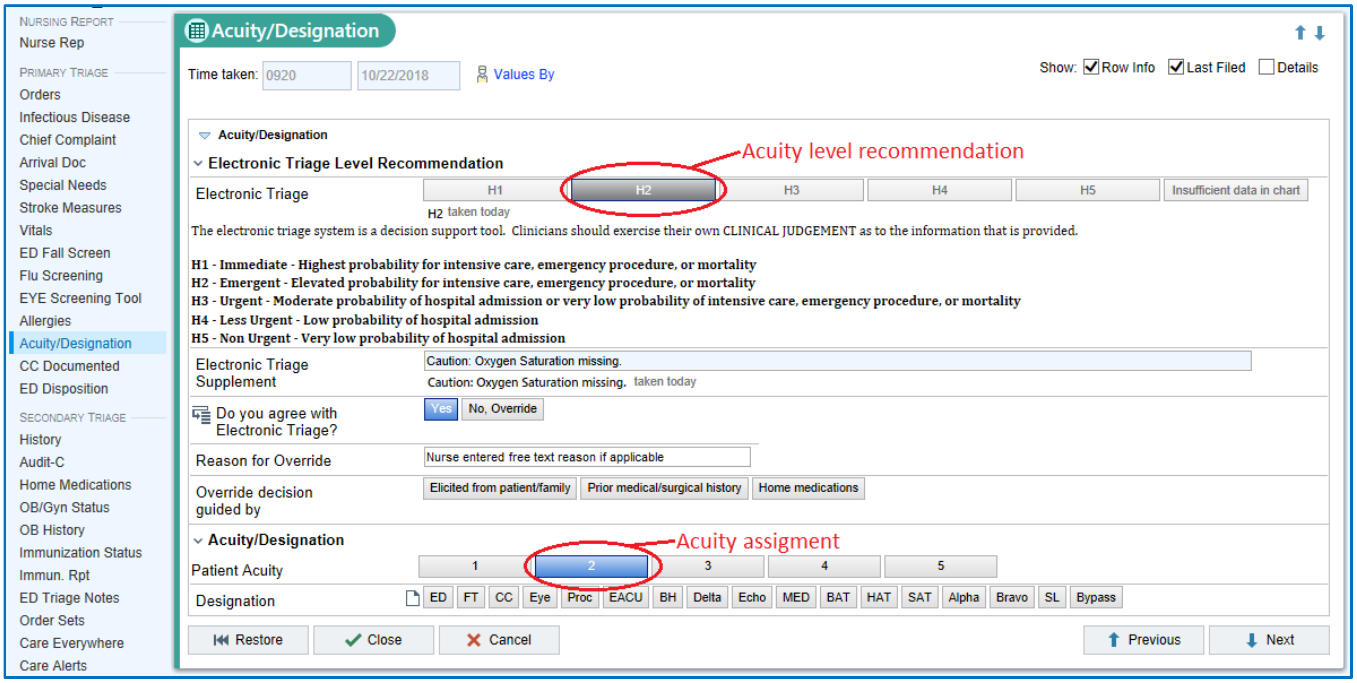

Figure 1. E-Triage electronic health record (EHR) interface

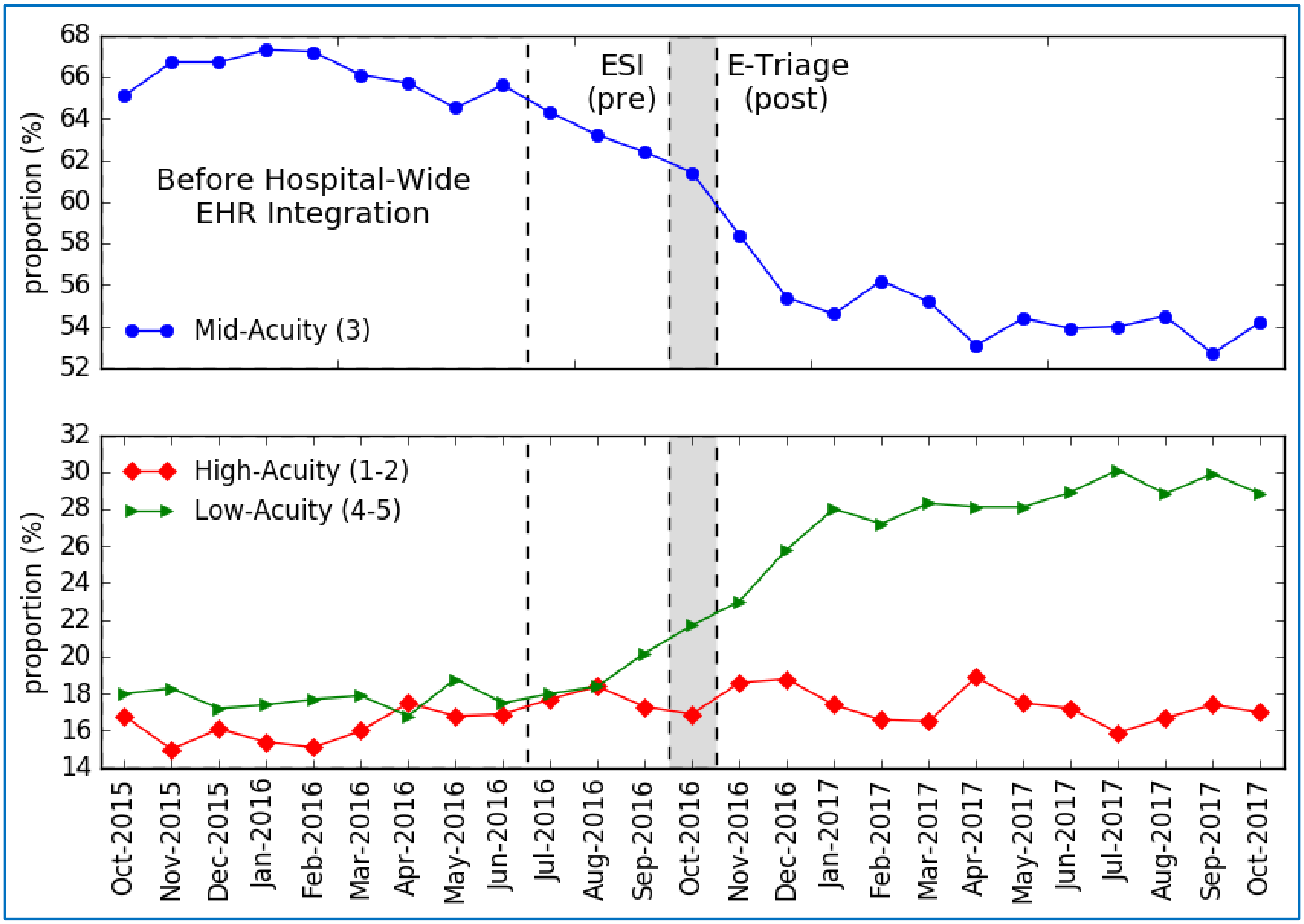

Figure 2. Distribution of triage acuity over the study period

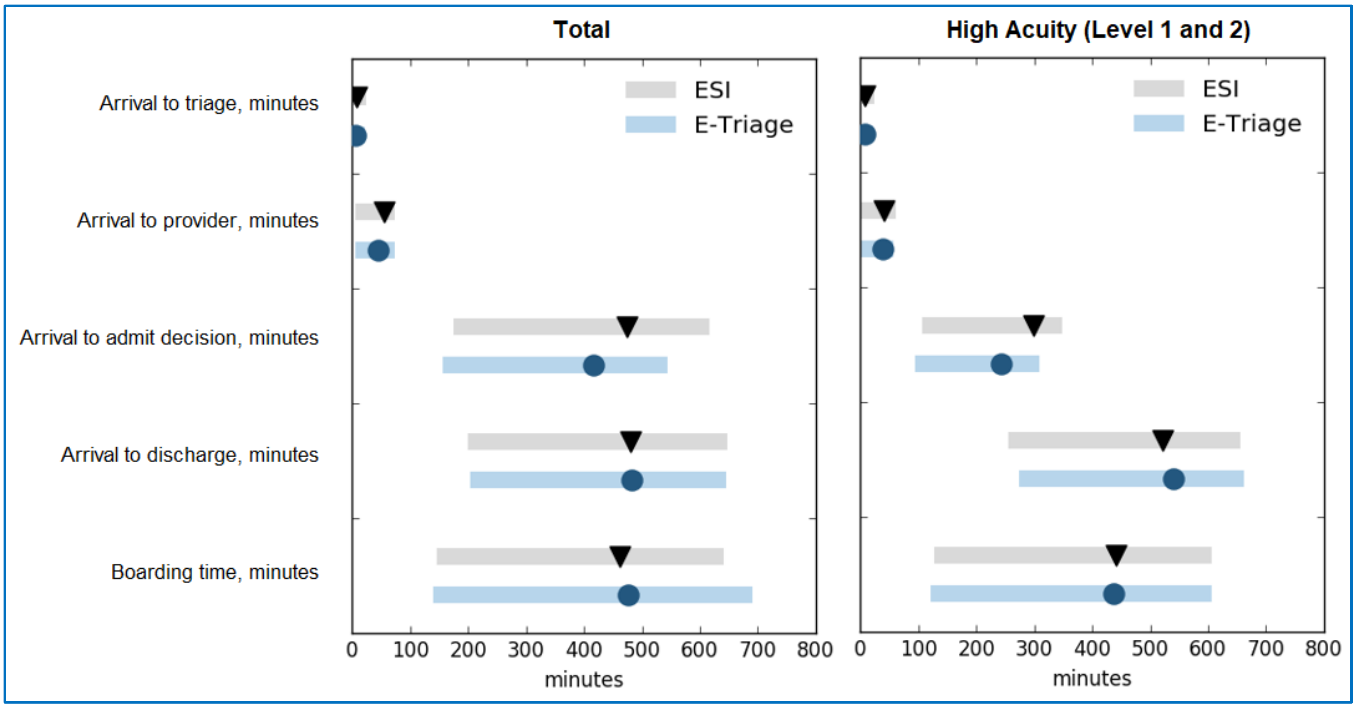

Figure 3. Outcome measures of timeliness pre- ESI and post- e-triage implementation. Box ends represent the interquartile range with the filled triangle (ESI) and circle (e-triage) denoting the mean.

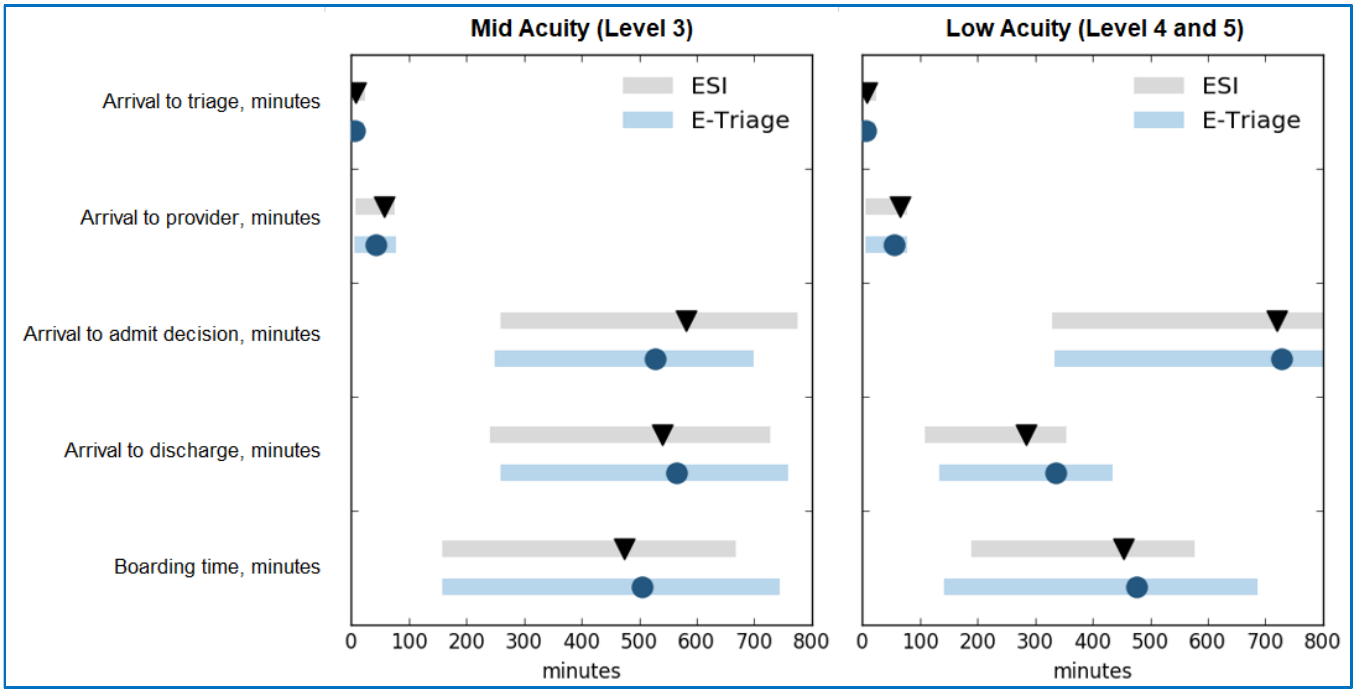

Figure S1. Outcome measures of timeliness pre- ESI and post- e-triage implementation. Box ends represent the interquartile range with the filled triangle (ESI) and circle (e-triage) denoting the mean.

TABLES

Table 1. ED volume and patient visit characteristics pre- and post-implementation

Characteristic	**ESI (pre)**	**E-Triage (post)**
Cohort size, N	53,115	52,720
Daily volume, median (interquartile range)	145 (134 - 156)	144 (134 - 154)
Predicted outcomes, % (95% confidence interval)		
Critical care outcome	2.8 (2.7-3.0)	2.9 (2.8-3.1)
In-hospital mortality	0.8 (0.7-0.9)	0.9 (0.8-1.0)
Intensive care unit admission	2.3 (2.2-2.4)	2.3 (2.2-2.4)
Emergency procedure	2.2 (1.9-2.4)*	2.3 (2.2-2.4)
Hospitalization	27.3 (26.9-27.7)	27.8 (27.4-28.2)
Secondary outcomes, % (95% confidence interval)		
Elevated troponin	2.6 (2.5-2.7)	3.3 (3.1-3.4)
Elevated lactate	4.8 (4.7-5.0)	5.6 (5.4-5.8)
72-hour return visits	2.4 (2.3-2.6)	2.6 (2.5-2.7)
Demographics and arrival mode		
Age, median (interquartile range)	45.0 (30.0-58.0)	46.0 (31.0-59.0)
Sex, female, %	51.6 (51.2-52.1)	51.5 (51.1-51.9)
Arrival by ambulance, %	21.4 (21.1-21.7)	21.6 (21.2-21.9)
Vital signs, low | normal | high		
Temperature, °F[a]	0.4 | 97.3 | 2.3	0.3 | 97.2 | 2.5
Pulse rate, beats/minute[b]	0.3 | 89.0 | 10.7	0.4 | 88.2 | 11.4
Respiratory rate, breaths/minute[c]	0.3 | 97.2 | 2.5	0.4 | 97.4 | 2.3
Systolic blood pressure, mmHg[d]	2.7 | 94.9 | 2.4	2.7 | 94.7 | 2.6
Oxygen saturation, %[e]	3.6 | 96.4 | -	3.8 | 96.2 | -
Primary complaints		
Abdominal pain, %	8.9 (8.6-9.1)	8.5 (8.3-8.7)
Chest pain, %	7.1 (6.9-7.4)	7.1 (6.9-7.4)
Shortness of breath, %	4.6 (4.4-4.7)	4.8 (4.6-5.0)
Back pain, %	2.7 (2.6-2.9)	2.8 (2.7-3.0)
Headache, %	2.8 (2.6-2.9)	2.8 (2.7-3.0)

[a] Temperature: low < 95° | normal = 95 to 99 | high > 99
[b] Pulse rate: low < 50 beats/min | normal = 50 to 109 | high > 109
[c] Respiratory rate: low < 14 breaths/min | normal = 14 to 27 | high > 27
[d] Systolic blood pressure: low < 100 mmHg | normal = 100 to 199 | high > 199
[e] Oxygen saturation: low < 95% | normal = 95 to 100 | -
* The emergency procedure rate reported for the most recent 3-months (July-1-2016 to Oct-1-2016) during the pre-implementation period because of inconsistency in outcomes data extraction prior to house-wide implementation of an integrated electronic health record (HER) system

Table 2. Outcomes and patient visit characteristics stratified by triage group pre- ESI and post e-triage implementation

Characteristic	High Acuity (Level 1 and 2) ESI (pre)	High Acuity (Level 1 and 2) E-Triage (post)	Mid Acuity (Level 3) ESI (pre)	Mid Acuity (Level 3) E-Triage (post)	Low Acuity (Level 4 and 5) ESI (pre)	Low Acuity (Level 4 and 5) E-Triage (post)
Cohort size, N	10,006 (18.8%)	10,340 (19.6%)	34,306 (64.6%)	28,769 (54.6%)	8,803 (16.6%)	13,611 (25.8%)
Daily volume, median (interquartile range)	27 (23 - 31)	29 (25 - 32)	92 (86 - 102)	78 (71 - 87)	24 (19 - 28)	37 (32 - 42)
Predicted outcomes, % (95% conf. interval)						
Critical care outcome	11.5 (10.8-12.1)	11.5 (10.9-12.1)	1.0 (0.9-1.1)	1.2 (1.1-1.3)	0.0 (0.0-0.1)	0.1 (0.0-0.1)
In-hospital mortality	3.5 (3.1-3.8)	3.8 (3.4-4.1)	0.2 (0.2-0.3)	0.2 (0.2-0.3)	0.0 (0.0-0.0)	0.0 (0.0-0.0)
Intensive care unit admission	9.2 (8.6-9.7)	8.8 (8.3-9.4)	0.9 (0.8-1.0)	1.0 (0.9-1.1)	0.0 (0.0-0.1)	0.1 (0.0-0.1)
Emergency procedure*	4.5 (3.7-5.3)*	5.4 (5.0-5.9)	1.9 (1.6-2.2)*	1.9 (1.8-2.1)	0.2 (0.0-0.4)*	0.7 (0.6-0.9)
Hospitalization	55.5 (54.6-56.5)	57.1 (56.1-58.0)	25.4 (24.9-25.9)	28.4 (27.8-28.9)	2.4 (2.1-2.8)	4.4 (4.0-4.7)
Secondary outcomes, % (95% conf. interval)						
Elevated troponin	6.8 (6.4-7.3)	9.0 (8.4-9.5)	2.0 (1.8-2.1)	2.7 (2.5-2.9)	0.2 (0.1-0.3)	0.1 (0.0-0.1)
Elevated lactate	11.8 (11.2-12.5)	14.4 (13.7-15.0)	4.0 (3.8-4.2)	4.8 (4.6-5.1)	0.3 (0.2-0.4)	0.7 (0.5-0.8)
72-hour return visits	0.3 (0.2-0.4)	0.3 (0.2-0.4)	1.6 (1.5-1.8)	1.5 (1.4-1.6)	2.7 (2.4-3.1)	3.8 (3.4-4.2)
Demographics and arrival mode						
Age, median (interquartile range)	52.0 (34.0-64.0)	54.0 (37.0-66.0)	45.0 (30.0-58.0)	49.0 (34.0-60.0)	36.0 (27.0-52.0)	33.0 (26.0-47.0)
Sex, female, %	43.3 (42.3-44.3)	44.1 (43.1-45.0)	55.5 (54.9-56.0)	53.5 (52.9-54.1)	46.2 (45.1-47.2)	52.9 (52.1-53.8)
Arrival by ambulance, %	56.5 (55.5-57.5)	54.7 (53.7-55.6)	15.1 (14.7-15.4)	18.0 (17.5-18.4)	6.2 (5.7-6.7)	4.0 (3.7-4.3)
Vital signs, low | normal | high						
Temperature, °F	1.3 | 93.8 | 4.9	1.0 | 93.3 | 5.7	0.2 | 97.7 | 2.1	0.2 | 97.3 | 2.5	0.1 | 99.6 | 0.3	0.1 | 99.9 | 0.1
Pulse rate, beats/minute	1.1 | 73.7 | 25.2	1.4 | 72.4 | 26.1	0.2 | 91.4 | 8.4	0.2 | 89.4 | 10.4	0.1 | 96.4 | 3.5	0.0 | 97.6 | 2.4
Respiratory rate, breaths per minute	1.3 | 89.3 | 9.4	1.6 | 89.0 | 9.4	0.1 | 98.8 | 1.2	0.1 | 99.1 | 0.8	0.0 | 99.8 | 0.2	0.0 | 99.9 | 0.1
Systolic blood pressure, mmHg	9.3 | 85.6 | 5.1	9.8 | 84.2 | 6.1	1.4 | 96.6 | 2.1	1.3 | 96.2 | 2.5	0.6 | 98.6 | 0.8	0.3 | 99.5 | 0.3
Oxygen saturation, %	11.8 | 88.2 | -	11.8 | 88.2 | -	2.1 | 97.9 | -	2.6 | 97.4 | -	0.7 | 99.3 | -	0.3 | 99.7 | -
Primary complaints						
Abdominal pain, %	3.4 (3.0-3.7)	2.9 (2.6-3.2)	12.7 (12.3-13.0)	11.3 (10.9-11.6)	0.3 (0.2-0.4)	6.9 (6.5-7.4)
Chest pain, %	5.9 (5.4-6.3)	5.0 (4.6-5.5)	9.3 (9.0-9.6)	9.5 (9.2-9.8)	0.2 (0.1-0.3)	3.7 (3.4-4.1)
Shortness of breath, %	8.7 (8.2-9.3)	9.7 (9.1-10.3)	4.4 (4.2-4.7)	5.2 (4.9-5.4)	0.3 (0.2-0.4)	0.2 (0.1-0.3)
Back pain, %	1.4 (1.1-1.6)	1.3 (1.1-1.5)	3.7 (3.5-3.9)	4.4 (4.2-4.7)	0.6 (0.5-0.8)	0.6 (0.5-0.7)
Headache, %	0.5 (0.3-0.6)	0.5 (0.3-0.6)	1.9 (1.8-2.1)	2.2 (2.0-2.4)	8.5 (7.9-9.1)	6.1 (5.7-6.5)

Table 3. Nurse and e-triage concordance for mid-acuity patients

Concordance		N	Critical care outcome	In-hospital mortality	ICU admission	Emergency procedure	Hospitalization	Elevated troponin	Elevated lactate
E-Triage recommended Level 3	Nurse and e-triage agreement	23,197 (83.4)	1.1 (1.0-1.2)	0.3 (0.2-0.3)	0.9 (0.8-1.0)	1.6 (1.4-1.8)	28.1 (27.6-28.7)	2.7 (2.5-2.9)	4.8 (4.5-5.0)
	Nurse up-triaged to high-acuity	2,691 (9.7)	4.1 (3.3-4.8)	0.7 (0.4-1.0)	3.5 (2.8-4.1)	3.5 (2.8-4.1)	41.0 (39.1-42.8)	5.0 (4.2-5.8)	6.5 (5.5-7.4)
	Nurse down-triaged to low-acuity	1,912 (6.9)	0.1 (0.0-0.2)	0.0 (0.0-0.0)	0.1 (0.0-0.2)	0.8 (0.4-1.2)	5.5 (4.5-6.6)	0.2 (0.0-0.3)	0.8 (0.4-1.2)
Nurse assigned Level 3	E-Triage recommended high-acuity	3,002 (10.5)	2.7 (2.1-3.3)	0.4 (0.2-0.6)	2.4 (1.9-2.9)	3.1 (2.4-3.7)	41.3 (39.5-43.1)	4.9 (4.1-5.6)	8.0 (7.1-9.0)
	E-Triage recommended low-acuity	2,426 (8.5)	0.4 (0.2-0.7)	0.0 (0.0-0.1)	0.4 (0.1-0.6)	3.4 (2.7-4.1)	14.7 (13.3-16.1)	0.4 (0.1-0.6)	1.8 (1.3-2.3)