Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index

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Study objective: Standards for emergency department (ED) triage in the United States rely heavily on subjective assessment and are limited in their ability to risk-stratify patients. This study seeks to evaluate an electronic triage system (e-triage) based on machine learning that predicts likelihood of acute outcomes enabling improved patient differentiation.

Methods: A multisite, retrospective, cross-sectional study of 172,726 ED visits from urban and community EDs was conducted. E-triage is composed of a random forest model applied to triage data (vital signs, chief complaint, and active medical history) that predicts the need for critical care, an emergency procedure, and inpatient hospitalization in parallel and translates risk to triage level designations. Predicted outcomes and secondary outcomes of elevated troponin and lactate levels were evaluated and compared with the Emergency Severity Index (ESI).

Results: E-triage predictions had an area under the curve ranging from 0.73 to 0.92 and demonstrated equivalent or improved identification of clinical patient outcomes compared with ESI at both EDs. E-triage provided rationale for risk-based differentiation of the more than 65% of ED visits triaged to ESI level 3. Matching the ESI patient distribution for comparisons, e-triage identified more than 10% (14,326 patients) of ESI level 3 patients requiring up triage who had substantially increased risk of critical care or emergency procedure (1.7% ESI level 3 versus 6.2% up triaged) and hospitalization (18.9% versus 45.4%) across EDs.

Conclusion: E-triage more accurately classifies ESI level 3 patients and highlights opportunities to use predictive analytics to support triage decisionmaking. Further prospective validation is needed. [Ann Emerg Med. 2018;71:565-574.]

Please see page 566 for the Editor’s Capsule Summary of this article.

SEE EDITORIAL, P. 578.

INTRODUCTION

Increases in emergency department (ED) visits to more than 130 million annually in the United States have led to unprecedented levels of crowding and delays in care.1,2 Evidence linking delays to increased morbidity, mortality, and poor process measures has been established across many clinical conditions.3-10 Critically ill patients are most vulnerable to worse health outcomes because of delays.11-13

Triage often presents the first opportunity to identify critically ill patients and tends to set the trajectory for further ED care. It drives ED patient care location, queue position, and timing, and it influences provider decisionmaking (ie, resource use) up to and including final disposition.14-17 Thus, crowded EDs must maintain accurate triage systems to quickly identify and prioritize patients with critical conditions from the volumes of those with less urgent needs. Although simple in concept, the practice of triage is challenging because of limited information, time pressure, diverse medical conditions, and heavy reliance on intuition. As a result, the projected clinical course at presentation (ie, triage) is not obvious for the majority of ED patients. Almost half of adult ED visits nationally and more than 65% of ED visits at our urban and community sites were triaged to Emergency Severity Index (ESI) level 3, the ambiguous midpoint of a
5-level triage algorithm now standard in the United States.\textsuperscript{1,18-20}

Despite the ESI’s widespread adoption, it relies heavily on provider judgment, subject to high variation.\textsuperscript{21} It also poorly differentiates a large diversely ill patient group (ESI level 3), counter to the objective of triage.\textsuperscript{18,20} Inability to differentiate poses safety risks to patients critically ill and undertriaged and may influence the precision and efficiency of ED resource allocation (ie, overutilization) because low-acuity patients are overtriaged.\textsuperscript{22-25} The patient safety challenges associated with triage in crowded EDs, limitations of ESI in practice, and need for accurate risk assessment motivated us to develop an electronic health record–driven electronic triage system that leverages machine-learning capability.

Machine learning is a set of computational methods that learn patterns in data without being explicitly programmed.\textsuperscript{26,27} These methods offer advantages for predictive clinical applications because they can be designed to yield stable predictions,\textsuperscript{28,29} are able to perform variable selection as part of the model building process,\textsuperscript{29} are flexible in handling predictor data favorable for electronic health record applications,\textsuperscript{29,30} and are adept at identifying interactions in patient information, enabling them to define patient subgroups with respect to predicted outcomes.\textsuperscript{30} The last characteristic makes them useful in analyzing patients across a wide spectrum of medical conditions and illness severity germane to triage and the practice of emergency medicine in general.

The objective of this study was to use machine-learning methods to develop an electronic triage support system (e-triage) that predicts clinically important patient outcomes and facilitates differentiation of current midacuity (ESI level 3) patients. Our hypothesis was that e-triage would support improved patient differentiation compared with ESI and be adaptable to EDs’ individual populations and patient distribution objectives.

**MATERIALS AND METHODS**

**Setting and Selection of Participants**

E-triage was developed from a retrospective cohort of 172,726 adult (≥18 years) visits from an urban academic ED (60,712) and a community ED (112,014) between August 2014 and October 2015, and June 2013 and October 2015, respectively. Each ED’s annual volume varies between 60,000 and 70,000 visits per year. From the adult ED visit cohort receiving a final disposition, patients were excluded who presented with psychiatric conditions, had unknown complaint data, or had missing vital signs (Figure 1). 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.\textsuperscript{18} Patients presenting with substance abuse (eg, overdose, withdrawal) were not considered psychiatric and were included in our cohort. Institutional review board approval was obtained to perform this retrospective study.

**Methods of Measurement**

ED visit data were collected from the integrated electronic health record system at each hospital.
Data comprising outcomes, predictors, and ESI triage levels were verified by comparing characteristics to independently validated departmental reports and ad hoc electronic health record reviews during e-triage development, and by evaluation for face validity with triage nurses and ED leadership at each site.

**Outcome Measures**

The e-triage algorithm predicts critical care, emergency procedure, and inpatient hospitalization outcomes in parallel, as illustrated in Figure 2. The critical care outcome was compositely defined as either in-hospital mortality or direct admission to an ICU. An emergency procedure was defined as any surgical procedure, including cardiac catheterization, that occurred in an operating room within 12 hours of ED disposition. Both outcomes represent severe and time-sensitive medical need across a wide range of conditions treated in the ED. The hospitalization outcome was defined by any admission to an inpatient care site, including ward or direct transfer to an external acute care hospital. Patients transitioning to observation status or care areas were not considered admitted unless their observation ultimately resulted in inpatient hospitalization. The hospitalization outcome is another measure of illness severity, but also serves as a surrogate for ED resource use. Admission likelihood and resource counts per ESI definition have been substantiated as strong correlates.

Thus, by prediction of hospitalization, a resource projection for low-acuity triage designations (levels 3 to 5) was incorporated into the e-triage algorithm (Figure 2).

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. These markers were analyzed to further validate e-triage, using fully objective clinical measurements that e-triage was not designed to predict.

The e-triage algorithm generates probabilistic predictions for each patient according to clinical information routinely collected at triage: basic demographics (age and sex), arrival mode (ambulance or walk-in), vital signs (temperature, pulse rate, respiratory rate, systolic blood pressure, and oxygen saturation), primary chief complaint, and relevant (ie, active) medical history documented in the electronic health record. Vitals signs were categorized as normal and gradations of abnormal according to previous physiologic evidence as depicted in Figure 2. Separate categories for vital sign measurements on the margins (ie, near abnormal) were created to account for boundary uncertainty and measurement error.

Primary chief complaint data are fairly standardized across EDs according to reason-for-visit classifications for ambulatory care created by the Centers for Disease Control and Prevention.

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Figure 2. E-triage predictors and algorithm with an example ED risk profile. The risk profile translates predicted probabilities of critical care, emergency surgery, and hospitalization outcomes to e-triage levels. Outcome definitions: critical care outcome was compositely defined as either in-hospital mortality or direct admission to an ICU; emergency procedure outcome was defined as any surgical procedure, including cardiac catheterization, that occurred in an operating room within 12 h of ED disposition; and hospitalization outcome was defined as any admission to an inpatient care site, including ward, or direct transfer to an external acute care hospital.
and Prevention. A panel of 5 emergency physicians categorized more than 1,000 unique electronic health record–entered chief complaints across both ED populations into 48 clinically meaningful groups, using a modified Delphi technique. These groups were derived from a classification schema developed by the Agency for Healthcare Research and Quality but adjusted by the panel to meet our study objective. Postgrouping, we hypothesized that systematic differences between different EDs had the potential to influence predictor meaning in relation to outcomes. Thus, we applied a feature selection process (least absolute shrinkage and selection operator) to retain the knowledge structure from the physician panel while learning which electronic health record–entered complaints had distinct predictive value separate from their groupings. Ultimately, this process resulted in an optimal, mutually exclusive mix of clinical groupings and individual electronic health record–entered complaints used as predictors for each ED population. A similar least absolute shrinkage and selection operator approach was subsequently applied to select medical history with significant predictive value. Steps of the full-feature selection process and measures of variable importance (Figure E1) are listed in the Appendix E1 (available online at http://www.annemergmed.com).

ESI triage level was extracted from the electronic health record and used as a basis of comparison for e-triage. The ESI is used to assign patients to an acuity scale from 1 (high severity; need for immediate treatment) to 5 (low severity; nonurgent) according to provider assessment of 3 questions: whether the patient is dying, whether the patient should wait, and how many resources the patient requires. Patients who are potentially dying are assigned to level 1 (immediate treatment), those who should not wait are considered level 2 (emergency treatment), and those deemed safe to wait are stratified to level 3 (urgent treatment) through 5 (nonurgent) by anticipated resource use. Per ESI guidelines, level 1 and 2 patients (high acuity) are distinguished by requiring immediate care according to an assessment of their clinical risk. Level 3 patients (midacuity) do not meet subjective high-risk criteria, but are projected to need several resources to evaluate, including an ED bed. Many EDs group level 4 and 5 patients (low acuity) or do not use the level 5 designation. Depending on individual ED processes, these patients may be treated in separate care areas that do not require a bed.

**Primary Data Analysis**

Three distinct decision tree learning models (random forests) were developed for predicting the critical care, emergency procedure, and hospitalization outcomes for each ED population (MATLAB; Mathworks, Natick, MA). The random forest technique executes a randomized sampling process to train a set of individual decision trees (eg, 100) and aggregates output to produce a single probabilistic prediction for each outcome.

Although separate random forest models were trained for each of the 3 outcomes, they were applied in parallel to generate outcome probabilities that were mapped to a single e-triage level. For example, in Figure 2, patients with a high risk (>15%) of either the critical care or emergency procedure outcome were assigned to e-triage level 1. Patients at elevated risk (between 5% and 15%) for either the critical care or emergency procedure were assigned to level 2. Patients not meeting level 1 or 2 criteria were assigned to level 3 if they exhibited moderate risk (between 2% and 5%) of either the critical care or emergency procedure outcome or greater than 10% risk for hospitalization. Low-acuity patients with predictions below level 3 risk thresholds were assigned solely according to risk of hospitalization to level 4 (>5%) or level 5 (<5%). Risk profiles (ie, cutoff thresholds) that designate triage level groups are not static and may be adapted to individual ED populations and to objectives for risk stratification and resource allocation.

E-triage predictive performance was evaluated out of sample on test data. Random samples (bootstraps) of two thirds of observations (training sets) are used to create each tree that forms the random forest. Thus, predictions were evaluated exclusively from trees when observations fell within test sets.

E-triage was compared with ESI in its ability to differentiate critical care, emergency procedure, hospitalization, and secondary clinical outcomes of elevated troponin and lactate levels. To facilitate comparisons, the e-triage risk profile (Figure 2) was calibrated to distribute patients proportionally similar to those in the ESI group for each ED site. As common in clinical practice, low-acuity level 4 and 5 patients were grouped and denoted as level 4 and 5. The ability to discriminate both predicted and secondary outcomes was determined with the area under the receiver operator characteristic curve and graphic plots of outcome proportions by triage level. Measures of differences in classification between e-triage and ESI were reported according to 3 defined categories: agreement occurred when a patient’s e-triage and ESI levels were equivalent, up triage was defined when e-triage estimated a patient to be at higher risk than ESI (eg, e-triage level 2<ESI level 3), and down triage was defined when e-triage estimated a patient to be at lower risk than ESI (eg, e-triage level 4>ESI level 3). Additional analyses were performed to demonstrate how e-triage may be adapted to an ED’s patient distribution objectives (eg, level 3 reduction).
RESULTS

ED patient visit outcomes and predictor characteristics are displayed in Table 1. The rates of critical care (2.0% urban ED; 1.6% community ED), emergency procedures (1.4% urban ED; 1.7% community ED), and hospitalization (26% urban ED; 22.3% community ED) were similar across EDs. However, rates of secondary clinical markers for elevated troponin and lactate levels were higher for the urban ED compared with the community ED. Demographics (age and sex), the proportion of patients with vital sign abnormalities, and common complaints were comparable between EDs. However, rates of common medical history found significantly predictive were higher for the urban ED.

The distribution of e-triage levels at each site, with e-triage calibrated to match the proportions under ESI, is displayed in Figure 3. Both EDs had a majority of more than 65% of patients assigned to ESI level 3, whereas less than 20% were assigned to level 4. For high-acuity patients, the community ED was distinct in assigning less than 1% of total ED visits to ESI level 1.

Figure 3. Overall acuity distribution for e-triage, calibrated to proportionally match ESI for the urban and community ED. E-triage classification is demonstrated with stacked colored bars to indicate the original ESI triage designation for each new e-triage level group.

E-triage demonstrated an out-of-sample area under the receiver operator characteristic curve ranging from 0.90 to 0.92 for the critical care outcome, 0.73 to 0.82 for the emergency procedure outcome, and 0.82 to 0.84 for the hospitalization outcome across ED populations. Comparisons of the proportion of patients with predicted and secondary outcomes stratified by triage level are displayed in Figure 4. E-triage’s ability to detect secondary clinical outcomes was similarly equal to or greater than that of ESI (Figure 4C and D) at both study sites. The most substantial differences between triage scales were for level 1 patients in the urban ED, in which overall prevalence of elevated troponin level (>0.6 ng/mL) and lactate level (>2.4 mmol/L) was higher than in the community ED.

Table 1. ED patient visit outcomes and characteristics.

<table>
<thead>
<tr>
<th>Population</th>
<th>Urban ED</th>
<th>Community ED</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cohort size, N</td>
<td>60,712</td>
<td>112,014</td>
</tr>
<tr>
<td>Predicted outcomes, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Critical care outcome</td>
<td>2.0</td>
<td>1.6</td>
</tr>
<tr>
<td>Inhospital mortality</td>
<td>0.3</td>
<td>0.5</td>
</tr>
<tr>
<td>ICU admission</td>
<td>1.8</td>
<td>1.3</td>
</tr>
<tr>
<td>Emergency procedure outcome</td>
<td>1.4</td>
<td>1.7</td>
</tr>
<tr>
<td>Catheterization</td>
<td>0.1</td>
<td>0.2</td>
</tr>
<tr>
<td>Hospitalization (inpatient) outcome</td>
<td>26.0</td>
<td>22.3</td>
</tr>
<tr>
<td>Secondary outcomes, %</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elevated troponin</td>
<td>2.5</td>
<td>1.8</td>
</tr>
<tr>
<td>Elevated lactate</td>
<td>3.6</td>
<td>1.2</td>
</tr>
</tbody>
</table>

Demographics and arrival mode

| Age, median (interquartile range) | 44 (29–57) | 49 (33–66) |
| Sex, female, % | 52.7 | 57.9 |
| Arrival by ambulance, % | 20.4 | 25.5 |
| Temperature, °F | 0.3 | 97.3 | 2.4 | 0.2 | 97.9 | 1.9 |
| Pulse rate, beats/minute | 0.3 | 89.1 | 10.5 | 0.5 | 90.5 | 9.0 |
| Respiratory rate, breaths per minute | 0.4 | 97.0 | 2.5 | 1.2 | 96.0 | 2.9 |
| Systolic blood pressure, mmHg | 2.4 | 95.2 | 2.4 | 3.7 | 95.3 | 1.0 |
| Oxygen saturation, % | 3.2 | 96.8 | –* | 5.9 | 94.1 | – |
| Abdominal pain, % | 11.6 | 14.6 |
| Chest pain, % | 7.8 | 9.3 |
| Shortness of breath, % | 5.9 | 5.8 |
| Back pain, % | 3.1 | 3.3 |
| Headache, % | 3.1 | 2.8 |

Medical history, %

| Diabetes | 8.4 | 3.6 |
| Coronary artery disease | 4.0 | 2.0 |
| Congestive heart failure | 3.3 | 1.8 |
| Atrial fibrillation | 2.3 | 2.1 |
| End-stage renal disease | 1.7 | 0.8 |

*Dashes indicate not applicable.

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Significant differences in classification for patient visits occurred (eg, patient with ESI level 3 and e-triage level 2) despite calibration of e-triage to match the observed ESI distribution. In grouping patients as either high acuity (level 1 and 2) or low acuity (level 3 and 4), there was less agreement between e-triage and ESI for high-acuity visits (47% urban ED; 42% community ED) compared with low-acuity ones (90% urban ED; 90% community ED). Differences affecting the most patients were exhibited in the large ESI level 3 group, in which the rate of agreement was 76.6% for the urban ED and 74.7% for the community ED (Table 2). Compared with patients for whom level 3 was in agreement for e-triage and ESI, those up triaged by e-triage were at least 5 times more likely to experience the critical care outcome or emergency surgery outcome, 2 times more likely to be admitted to the hospital, and more than 2 times more likely to have elevated troponin or lactate levels (Table 2). Conversely, substantially reduced likelihood of all clinical outcomes was observed for down-triaged patients.

Although matching the overall distribution of e-triage to ESI facilitates important comparisons, a large potential value of e-triage in clinical practice is its capacity for altering distributions across triage levels to meet specific departmental targets or objectives. For example, recalibration of e-triage can facilitate reduction in the

### Table 2. Outcomes for reclassified ESI level 3 patients (majority group).

<table>
<thead>
<tr>
<th>Population</th>
<th>E-Triage Recommendation</th>
<th>Predicted Outcomes (%)</th>
<th>Secondary Outcomes (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>No. (%)</td>
<td>Critical Care</td>
</tr>
<tr>
<td>Urban ED</td>
<td>Agree</td>
<td>31,456 (76.6)</td>
<td>0.7</td>
</tr>
<tr>
<td></td>
<td>Up triage</td>
<td>4,823 (11.7)</td>
<td>3.5</td>
</tr>
<tr>
<td></td>
<td>Down triage</td>
<td>4,768 (11.6)</td>
<td>0.0</td>
</tr>
<tr>
<td>Community ED</td>
<td>Agree</td>
<td>55,383 (74.7)</td>
<td>0.3</td>
</tr>
<tr>
<td></td>
<td>Up triage</td>
<td>9,503 (12.8)</td>
<td>2.2</td>
</tr>
<tr>
<td></td>
<td>Down triage</td>
<td>9,224 (12.5)</td>
<td>0.0</td>
</tr>
</tbody>
</table>

*Agree occurred when a patient’s e-triage and ESI levels were equivalent.

†Up triage occurred when e-triage estimated a patient to be at higher risk than ESI (ie, e-triage<ESI).

‡Down triage occurred when e-triaged estimated a patient to be at lower risk than ESI (ie, e-triage>ESI).
number of patients triaged to the ambiguous midacuity (level 3) group by shifting a greater proportion of patients to low-acuity (level 4 and 5) care pathways (Figure 5). This approach includes making use of the level 5 designation. The new e-triage distribution was compared with the original ESI distribution (Figure 5A), along with the proportion of patients with critical care, emergency procedure (Figure 5B), and hospitalization (Figure 5C) predicted outcomes stratified by triage level. Such a triage level distribution may be useful in crowded EDs challenged with managing (and separating) the volumes of low-acuity patients efficiently.

LIMITATIONS

There are several limitations to this study and the e-triage tool itself. Foremost, this evaluation was based on retrospective data that solely provide evidence for the opportunity to improve triage by using e-triage. This study in no way validates the tool’s performance prospectively. In addition, retrospective data are always subject to potential error in data entry. This was mitigated through data verification and processing that included chart review by clinician team members at the urban and community ED sites.

Beyond this study, the e-triage has practical limitations. First, it is data driven and thus depends on a robust and accurate electronic health record system. Furthermore, medical history predictor(s) especially have various degrees of reliability across electronic health records and patients. This limitation should be considered in interpreting their predictive value. Another limitation of e-triage design is that although predicted outcomes are highly correlated with time-sensitive and critical care needs, there are specific clinical presentations for which this may not be the case.

For example, patients who present with opioid overdose or anaphylaxis are in need of immediate intervention, yet after initial stabilization and a short observation period may ultimately be discharged from the ED. Prospective studies designed to identify such aberrations are currently under way and may inform incorporation of additional predictor or outcome measures into the e-triage algorithm (Figure 2).

DISCUSSION

In this study, we developed a machine-learning-based triage tool (e-triage) and evaluated its performance in multiple EDs, using ESI as a comparator. E-triage demonstrated equivalent or improved identification of patients with critical outcomes (mortality, ICU admission, and emergency procedure), hospital admission, and secondary measures of elevated troponin and lactate levels.

Outcomes predicted by e-triage are simple indicators for high-severity medical need that span a broad range of conditions encountered by ED providers. Expedited ED care for patients destined for the ICU or operating room have been consistently associated with improved patient outcomes, providing strong rationale for their prediction at triage, when timing of care is first influenced.11-13,46-50 These outcomes are, however, variable by ED (eg, criteria for access to an ICU may differ by hospital) and are predicted with machine-learning methods, making e-triage inherently adaptive to local care systems, distinguishing it from existing triage tools. In contrast, the secondary outcomes evaluated, elevated troponin and lactate levels—surrogate markers for acute coronary syndrome and hypoperfusion—are less likely to vary by ED. E-triage exhibited improved identification of these outcomes as...
well, further validating its potential to support triage decisionmaking.

Although the systems compared here are both designed for ED triage, each approaches the objective differently. E-triage is driven by automated prediction of significant acute care events, whereas ESI relies on subjective (often variable) assessment of immediacy of medical need and projected resource use.21,43 These 2 approaches have overlap, but conceptual differences limit interpretation of comparative results. Yet ESI is a standard in the United States by which all new innovation in triage will be contrasted. It is within this context that we chose to draw direct comparisons to a system with which most emergency providers in the United States are familiar. Although there are significant differences between the 2 systems, the authors acknowledge that e-triage does build from core strengths of ESI. This includes using a 5-level system and integrating hospital admission as a predicted outcome, which is a strong correlate for projected ED resource use.18,22,31,32 Because hospital admission drives e-triage designations for level 3 to 5 patients (Figure 2) and comprises 85% of the total population, it is expected that agreement rates would be higher for this aggregate group (level 3 to 5) compared with the high-acuity group (level 1 and 2).

Ultimately, e-triage was developed to address an increasing challenge that has evolved with ESI: the large and diverse level 3 group. Lack of differentiation inadvertently creates safety risks and inefficiency that triage nursing staff often will mitigate through ad hoc processes. Table 2 demonstrates how a tool such as e-triage may be used to support improved differentiation of this core group with ED-specific evidence. Furthermore, e-triage enables distribution of patients that is customizable to a single ED’s systemwide objectives for risk stratification (Figure 5). This capacity may be used to distribute patients to match existing resource allocation or to discover more efficient allocation schemes (ie, patient flow pathways).

E-triage falls within a context of other health information technology efforts to improve ED triage.51-53 Previously developed triage tools are largely rule based and aimed at improving standardized triage system reliability (eg, ESI), enabling structured data capture, and facilitating institution-specific work flow.51-53 E-triage is fundamentally distinct in its use of advanced predictive analytics to drive new triage decisionmaking. The tool presented here builds from previous research that outlined a preliminary concept for e-triage using a nationally representative ED visit sample.18 Substantial advancements in the present study include derivation of the e-triage algorithm, using EDs visit data extracted from the electronic health record more applicable to use in clinical practice; introduction of a new methodological approach that leverages machine-learning capability as the predictive engine; novel use of medical history data as predictors; and evaluation against secondary markers of disease (elevated troponin and lactate levels).

E-triage is not designed to operate on its own, but rather to use data to support and enhance provider decisionmaking. This is where e-triage aligns with the overarching notion that clinical decision support paired with provider intuition can lead to improved and more consistent (less variable) decisionmaking than either alone.54 This is a focus of current prospective studies that use direct interactions between triage nurses and the electronic health record to elicit nurse rationale for triage decisions. This is geared toward learning how to create an ideal alliance between nursing expertise and health information technology.

In conclusion, heightened levels of ED crowding, consequential delays, and current triage practice standards have intensified the need for more accurate triage and improved patient differentiation. E-triage demonstrates an opportunity to apply advanced predictive analytics to large-scale electronic health record data to support triage decisionmaking and improve patient risk management in the ED. Further prospective validation is needed.

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**Author affiliations:** From Emergency Medicine, Johns Hopkins University, Baltimore, MD (Levin, Toerper, Hinson, Gardner, Dugas, Linton, Kelen); StoCastic LLC, Baltimore, MD (Levin, Toerper, Hamrock, Barnes); Decision, Operations, and Information Technologies, University of Maryland, College Park, MD (Barnes); and the National Center for Disaster Medicine and Public Health, Uniformed Services University, Bethesda, MD (Kirsch).

**Author contributions:** SL, MT, AD, TK, and GK were responsible for the original development of the triage tool evaluated in this study. SL, MT, JH, and SB contributed to the study design. SL, MT, and SB analyzed the data and provided statistical advice. EH, JH, HG, and BL contributed to understanding of implications of the tool in practice, including insights into how the ESI is used at study sites. SL drafted the article and all authors contributed to its revision. SL takes responsibility for the paper as a whole.

All authors attest to meeting the four ICMJE.org authorship criteria: (1) Substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data for the work; AND (2) Drafting the work or revising it critically for important

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† Dr. Wears died shortly before this article was accepted.
intellectual content; AND (3) Final approval of the version to be published; AND (4) Agreement to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

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REFERENCES

35. Barford C, Lauritzen MM, Danker JK, et al. Abnormal vital signs are strong predictors for intensive care unit admission and in-hospital mortality in adults triaged in the emergency department—a
DIAGNOSIS:

Auricular perichondritis. The patient was treated with oral ciprofloxacin, discharged, and instructed to follow up with ear, nose, and throat specialists. Wound cultures subsequently grew Pseudomonas aeruginosa. On completion of her antibiotic course, the patient had complete improvement in the right pinna erythema and tenderness, without any resulting deformity.

Auricular perichondritis is a potentially devastating infection of the auricular perichondrium or cartilage, excluding the lobule. There is a high misdiagnosis and mistreatment rate. The disease process results from blunt or penetrating trauma or by direct extension from otitis externa. The diagnosis is clinical, with physical examination revealing otalgia, erythema, swelling, and tenderness of the auricle, with the lobule unaffected. The most common organism responsible for perichondritis is P aeruginosa. The mainstay of treatment is with antipseudomonal antibiotics, with potential need for incision and drainage and hospitalization in the presence of necrotic cartilage. If improperly treated, the infection can propagate into a liquefactive chondritis with subsequent chondral deformities, or “cauliflower ear,” with alarming cosmetic complications.

Author affiliations: From the Department of Emergency Medicine, Inspira Medical Center, Vineland, NJ.

REFERENCES
APPENDIX E1

Feature selection process

Table E1. An example excerpt from the map of unique electronic health record–entered complaints for 3 common clinical groups.

<table>
<thead>
<tr>
<th>Clinical Groupings</th>
<th>Electronic Medical Record–Entered Complaints</th>
</tr>
</thead>
<tbody>
<tr>
<td>Abdominal pain</td>
<td>Abdominal pain, abdominal cramping, colitis, constipation, cramps, gastroesophageal reflux, flank pain, gastroparesis</td>
</tr>
<tr>
<td>Chest pain</td>
<td>Chest pain, chest tightness, chest burning, chest discomfort, lung pain, heart problem</td>
</tr>
<tr>
<td>Shortness of breath</td>
<td>Shortness of breath, airway obstruction, aspiration, breathing problem, hyperventilation, hypoxia, respiratory distress</td>
</tr>
</tbody>
</table>

The feature selection process described below is applied to full-complaint mapping to detect electronic health record (EHR)–entered complaints and medical history variables with predictive value for each outcome. Outcome probabilities were generated out of sample for each step in the process described below:

1. The baseline random forest model is developed with demographics, arrival mode, vital signs, and chief complaint clinical groupings (Table E1) exclusively.

2. Least absolute shrinkage and selection operator is applied with individual EHR-entered complaints as predictors and the outcome probabilities generated from the baseline model (step 1) as an offset. EHR-entered complaints are selected from the most regularized model (1 SD from the minimum error) to be extracted from their groupings.

3. The random forest model is updated with the chief complaint specified as the new optimal mix of clinical groupings and individual EHR-entered complaints from step 2.

4. Least absolute shrinkage and selection operator is applied to the medical history variables as predictors and the outcome probabilities generated from the updated model (step 3) as an offset. Medical history probabilities were generated out of sample for each step in the process described above.
variables selected from the most regularized model within 1 SD of the minimum error were used.

5. Original demographics, arrival mode, vital signs, optimally specified chief complaints (step 2), and medical history (step 4) are entered into the final random forest model used for e-triage.

The random forest approach enables a measure of relative importance for each predictor variable. The relative importance of predictors, including a sample of the most influential medical history variables, is available in Figure E1.