were from a single county in California and they encourage validation of these results in different populations.

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Commentary: Current TOR guidelines exist in many EMS organizations. With respect to Advanced Life Support (ALS) intervention, these guidelines call for resuscitation efforts to begin immediately and continue for up to 30 minutes. This study postulates that even those 30 minutes could pose unnecessary trauma to the patient and undue burden to the family, as well as EMS provider, for a futile outcome. Overall this is a well-done derivation of a potentially useful rule for OHCA futility. Validation is needed before this should be used to guide resuscitation policies or protocols.

☐ DID THIS PATIENT HAVE CARDIAC SYNCOPE? THE RATIONAL CLINICAL EXAMINATION SYSTEMATIC REVIEW.

Albassam OT, Redelmeier RJ, Shadowitz S, et al.
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Syncope accounts for a large proportion of Emergency Department visits each year, with an overall incidence of 0.6% per year in adults and 2-6% in elderly patients. Cardiac syncope, which accounts for 5-21% of syncope presentations in primary care and emergency settings, is transient loss of consciousness due to a reduction in cardiac output secondary to cardiopulmonary disease (i.e., mechanical/structural heart disease or arrhythmias). Distinguishing cardiac syncope from other causes, such as reflex syncope or orthostatic syncope, can be challenging.

This systematic review sought to identify the reliability of patient demographics, precipitating factors, and reported symptoms in accurately identifying the category of underlying syncope. Paired investigators independently reviewed the literature from multiple publication databases. Included studies were published in English with ≥ 10 subjects of at least 12 years of age and had valid reference standards which included cardiology consultation, non-invasive cardiac evaluation and invasive cardiac evaluation. Exclusion criteria included studies concentrated on patients with recurrent syncope, single identifiable syncopal events and patients who had previously completed invasive cardiac testing. The paired investigators used the Quality Assessment of Diagnostic Accuracy Studies tool to independently determine the quality of the publications. Consensus opinion settled any disagreements and qualitative review by a third investigator reconciled cases without consensus. The level of evidence grading system developed for the Rational Clinical Examination series was used to assign studies as being level 1, level 2 or level 3 evidence while studies graded below level 3 were excluded. Authors calculated sensitivities, specificities, likelihood ratios and the associated confidence intervals for relevant history of present illness. They also examined the reliability of combinations of findings, features useful for distinguishing syncope from seizure, and usefulness of biomarkers in evaluation of syncope.

A total of 11 studies consisting of 4,317 patients were included with four level 1 studies, two level 2 studies and five level 3 studies. Of these, 6 studies included patients presenting to the emergency department, three were patients admitted for syncope and two involved inpatient and outpatient referrals for syncope. Cardiac syncope was diagnosed in 9-58% of cases for all studies. Of included patient demographics, age at first syncope of ≥ 35 years had the greatest sensitivity for cardiac syncope (sensitivity, 91% [95% CI, 85-97%]; specificity, 72% [95% CI, 66-78%]; likelihood ratio [LR], 3.3 [95% CI, 2.6-4.1] while atrial fibrillation/flutter had the greatest specificity (sensitivity 13% [95% CI, 6-20%]; specificity, 98% [95% CI, 96-100%); LR, 7.3 [95% CI, 2.4-22]). Both heart failure and severe structural heart disease were also highly associated with cardiac syncope, exhibiting specificities of 88-94% (LR 2.7-3.4) and 84-93% (LR 3.3-4.8), respectively. While both chest pain (range of specificity 0.95-0.98) and dyspnea (specificity 95%, [95% CI, 80-99%) prior to the syncopal event conferred higher likelihood of cardiac syncope, preceding palpitations had inconsistent correlation. Cyanosis during loss of consciousness was highly specific for cardiac syncope (sensitivity 8% [95% CI, 2-14%]; specificity, 99% [95% CI, 98-100%]; LR, 6.2 [95% CI, 1.6-24]. Although the absence of prodromal symptoms is classically associated with cardiac syncope, no association for higher or lower likelihood was exhibited. Preceding pallor and injury after the event also failed to confer higher or lower likelihood of cardiac syncope.

Cardiac syncope was less likely in cases of preceding mood changes, cold feeling, headache, and abdominal discomfort, as well as with mood changes after the event or amnesia to behavior preceding the syncopal event. Patients with normal EKG findings and no history of heart disease were less likely to have experienced cardiac syncope while those with one or both had increased likelihood (sensitivity 88% [95% CI, 82-94%]; specificity, 61% [95% CI, 51-71%]; LR, 0.20 [95% CI, 0.12-0.33]). The Evaluation of Guidelines in Syncope Study (EGSYS) score (range -2 to 12) was prospectively validated in 2 studies and cardiac syncope was more likely for an EGSYS score ≥ 3 (sensitivity 89-91%; specificity 69-73%; LR 0.12-0.17). A vasovagal score (range 14 to 6) did well in an initial level 3 study but failed validation in a subsequent study with combined data demonstrating a score less than -2 confers increased risk of cardiac syncope (n = 703; sensitivity 0.32-0.91%; specificity 0.81-0.89%; LR 1.7-8.6). A level 3 study also examined features to distinguish seizure versus syncope. Features most helpful for indicating syncope were prolonged sitting/standing (LR 20, [95% CI, 5.3-100]), dyspnea (LR 13 [95% CI,3.0-50]) and palpitations (LR 8.3 [95% CI,3.2-25]). This same study also showed cardiac disease conferred the greatest risk for cardiac syncope (LR 13 [95% CI, 3.2-50]). With regards to biomarkers, a specificity of 95% for cardiac syncope was seen with a high-sensitivity troponin T threshold of 42ng/L (LR, 5.1 [95% CI, 3.6-7.1]) and a high-sensitivity troponin I of 31.3ng/L (LR 5.4 [95% CI, 3.9-7.6]). Syncope was ruled out for high-sensitivity troponin T < 5ng/L (LR, 0.15 [95% CI, 0.08-0.31]) or high-sensitivity troponin I < 2.2 ng/L (LR, 0.18 [95% CI, 0.10-0.35]). A 95% specificity for cardiac syncope required an N-terminal pro-B-type natriuretic peptide (NT-proBNP) level > 1966pg/mL (LR, 5.8 [95% CI, 4.2-8.1]) while normal levels had low likelihood of cardiac etiology (range of LR, 0.06-0.21). The NT-proBNP level is useful in about 36% of patients.

The authors concluded that their review suggests that cardiac syncope can be accurately identified using clinical examination. There are some limitations to the review, including the risk of misclassification bias in some studies which may overestimate sensitivities and specificities. Additionally, exclusion of patients with unexplained syncope in some studies may have also increased sensitivities and specificities reported. Additionally, the findings from these studies are not generalizable to all clinicians. Some studies have shown promise for the use of multivariable clinical prediction rules, but further research is needed. Features such as palpitations, pallor, diaphoresis, absence of prodromal symptoms and injury are classically associated with cardiac syncope but may be unreliable based on the studies reviewed. The reviewers conclude that cardiac markers should not be used routinely but may be beneficial in some populations, which is consistent with recommendations by European Society of Cardiology and American College of Cardiology/American Heart Association.

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Comment: This review provides further support that clinicians can use the history and physical examination to determine an appropriate workup in patients presenting with syncope. The combination of low risk features with a normal EKG confers low overall risk of cardiac syncope. The patient populations studied were not all emergency department patients which could affect generalizability. However, an understanding of evidence-based high- and low-risk features allows physicians to pursue patient specific workups and dispositions.

☐ EMERGENCY DEPARTMENT TRIAGE PREDICTION OF CLINICAL OUTCOMES USING MACHINE LEARNING MODELS.

Yoshihiko R, Tadahiro G, Mohammad KF, et al.
Critical Care 2019;23(1):64

The practice of emergency medicine relies on the application of a triage system to determine which patients are most ill and require evaluation and treatment more urgently than others. The most widely used conventional model is the Emergency Severity Index (ESI). The authors of this study used machine learning models and compared their predictive performance to that of the conventional ESI method in order to determine which may more accurately predict clinical outcomes flowing triage in the ED.

The study used emergency department data from the 2007-2015 National Hospital and Ambulatory Medical Care Survey (NHAMCS). This survey collects data from general and short stay hospitals, and excludes federal, military, and Veterans Affairs (VA) hospitals. The study identified all ED visits in the data set from 2007-2015. Exclusion criteria included those who were deceased on arrival, patients who left without being seen, patients who left against medical advice (AMA), and patients with missing information or data inconsistencies. Routine ED triage information were used as predictors for the learning models, including age, sex, method of arrival, vital signs, chief complaint(s), and comorbidities. The primary outcome was a critical care outcome, defined as either direct admission to a critical care unit or in-hospital death. The secondary outcome was hospitalization, either at the original hospital or transfer to an acute care hospital. The authors used 70% randomly selected samples of the data set for a training model. The reference model utilized ESI as a predictor of clinical outcomes. For comparison, four machine learning models were developed: Lasso regression, random forest, gradient boosted decision tree, and deep neural network. The remaining 30% of samples were used in a test set to predict the performance of each model using area under receiver-operating characteristics curve (AUC), net reclassification improvement, and confusion matrix results (i.e sensitivity, specificity, positive predictive value, and negative predictive value).

During the 2007-2015 time period, 209,800 adult ED visits were recorded in the NHAMCS. A total of 74,330 patients were excluded due to the previously listed exclusion criteria, leaving a total of 135,470 visits to be analyzed. Characteristics between the analyzed and non-analyzed cohorts were similar. Regarding prediction of a critical care outcome, all four machine learning models demonstrated a significantly higher AUC) (all p<0.001). The reference model resulted in an AUC of 0.74 [95% CJ 0.72-0.75], , while the AUC for the machine learning models ranged from 0.84-086. All machine learning models had a higher sensitivity (0.75-0.86) for a critical care outcome than the reference model (0.50). The reference model did have a higher specificity than the machine learning models for a critical care outcome (0.86 vs 0.68-.077). The ESI model correctly predicted critical care outcomes in ESI level 1 and 2 patients (49.6% of all critical care outcomes), but also over-triaged a large number of patients into these two categories, as well as under-triaged critical care patients in levels 3-5 (under triaging 50.4% of critical care patients). In contrast, the machine learning models correctly identified 71.3-81.6% of critical care outcomes in ESI levels 3-5. In regards to hospitalization, all machine learning models had a significantly higher AUC (p<0.001). Regarding hospitalization, the reference model had a higher sensitivity (0.87 [95% CI 0.86-0.87]) than the highest computer learning model, 0.71 [95% CI 0.70-0.72]. However, machine learning models had a higher specificity (0.71-0.76) as compared to the reference model (0.42) with regards to hospitalization. The reference model over-triaged many patients and failed to predict hospitalization for patients with a lower ESI level (3-5), ultimately under-triaging 13.4% of patients. The machine learning models successfully predicted hospitalization outcomes in 64.2-72.4% of patients triaged to a lower ESI.

The authors conclude that the machine learning methods were statistically superior to the conventional ESI method in their ability to predict critical care and hospitalization outcomes. The authors highlight that in particular the machine learning models have a higher sensitivity for critical care outcomes with less under-triaging of patients with regard to a critical care outcome, and a higher specificity for hospitalization outcomes with less over-triaging. The authors note limitations that include similar possible selection bias, ascertainment bias