References / Literature Review and Grading

American Academy of Emergency Medicine (AAEM) Clinical Practice Statement
CAN APPLICATION OF ARTIFICIAL INTELLIGENCE IMPROVE ED TRIAGE PERFORMANCE?
(4/21/2023)

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Relevant Papers (38 papers) Chosen for Review final

	Publication	Grade	Quality	Comments	Supportive
1	Raita Y, Goto T, Faridi MK, Brown DFM, Camargo CA Jr, Hasegawa K. Emergency department triage prediction of clinical outcomes using machine learning models. Crit Care. 2019 Feb 22;23(1):64	D	Outstanding	Retrospective data analysis, data of 135,470 adult ED visits (2007-2015), only routinely available data at current ED triage setting. Machine learning triage models demonstrated **<u>superior performance</u>** in predicting critical care and hospitalization outcome (CC outcome – DNN AUC 0.86 vs reference AUC 0.74, Hosp. outcome DNN AUC 0.81 vs reference AUC 0.69).	YES
2	Fernandes M, Vieira SM, Leite F, Palos C, Finkelstein S, Sousa JMC. Clinical Decision Support Systems for Triage in the Emergency Department using Intelligent Systems: a Review. Artif Intell Med. 2020	A	Outstanding	This systematic review and meta-analysis of literature - 6 digital libraries, 62 papers were included, with clinical decision support system (CDSS) used and designed based on intelligent technique (AI) using information available at triage only. The main contributions of the selected papers were **<u>improvement of patient's prioritizations</u>**, prediction of need for critical care, hospital or ICU admission, ED LOS and mortality.	YES
3	Goto T, Camargo CA Jr, Faridi MK, Freishtat RJ, Hasegawa K. Machine Learning-Based Prediction of Clinical Outcomes for Children During Emergency Department Triage. JAMA Netw Open. 2019 Jan 4;2(1)	D	Outstanding	Retrospective analysis of HER data of 52,037 children who presented to ED, Data used: only data available at ED triage setting. Application of ML approaches to ED triage **<u>improved the discriminative ability</u>** to	YES

				predict clinical and disposition outcome compared with the conventional triage approach (Critical Care outcome prediction ability: reference 0.78 vs AI-based models: 0.84-0.85; Hosp. outcome prediction ability: ref. 0.73 vs AI-based models: 0.78-80).	
4	Hong WS, Haimovich AD, Taylor RA. Predicting hospital admission at emergency department triage using machine learning. PLoS One. 2018 Jul 20;13(7)	D	Outstanding	A retrospective study design, analysis of 560.486 adult patients visited ED (all visited adult 2014-2017) from EHR, 972 variables extracted from EHR, with the aim to predict hospital admission at the time of ED triage. In conclusion: addition of historical information (from EHRs) improved predictive performance compared to using triage information alone.	YES
5	Cho A, Min IK, Hong S, Chung HS, Lee HS, Kim JH. Effect of Applying a Real-Time Medical Record Input Assistance System With Voice Artificial Intelligence on Triage Task Performance in the Emergency Department: Prospective Interventional Study. JMIR Med Inform. 2022 Aug 31;10(8)	C	Outstanding	Prospective interventional study, at Level 2 ED at the tertiary hospital, 1063 cases used for study analysis. The aim of the study was: to investigate the use of -voice-AI-based real-time medical record input system (RMIS-AI) and to compare it with manual methods for ED triage tasks. In conclusion: RMIS-AI system improves the promptness in performing triage tasks as compared to using the manual input method (the median time: RMI-AI: 204 sec vs manual: 231 sec) but accuracy was inferior for most fields in comparison to manual input	YES
6	Soltan AAS, Yang J, Pattanshetty R, Novak A, Yang Y, Rohanian O, Beer S, Soltan MA, Thickett DR, Fairhead R, Zhu T, Eyre DW, Clifton DA; CURIAL Translational Collaborative. Real-world evaluation of rapid and laboratory-free	C	Outstanding	Multicentre validation and prospective evaluation study of AI-based triage system to rapidly screen COVID-19 patients using routine clinical data available at triage (within to 1 hour of arrival to hospital). Cohort tested: 72.223 patients, conclusions: use of AI-based	YES

	COVID-19 triage for emergency care: external validation and pilot deployment of artificial intelligence driven screening. Lancet Digit Health. 2022 Apr;4(4):			triage resulted in improvements of triage sensitivity (superior NPV), to safely stream COVID-19 free patients.	
7	Liu Y, Gao J, Liu J, Walline JH, Liu X, Zhang T, Wu Y, Wu J, Zhu H, Zhu W. Development and validation of a practical machine-learning triage algorithm for the detection of patients in need of critical care in the emergency department. Sci Rep. 2021 Dec 15;11(1)	C/D	Adequate	Retrospective data analysis of EHR data with prospective cohort arm (22,272 records), to develop and validate ML-based triage algorithm. In conclusion: AI based model **showed better performance** (AI-AUC 0.875 vs reference model-AUC 0.843). In prospective arm: AI-model mis-triage rate was lower than reference (0.9% vs 1.2%).	YES
8	Sterling NW, Brann F, Patzer RE, Di M, Koebbe M, Burke M, Schrager JD. Prediction of emergency department resource requirements during triage: An application of current natural language processing techniques. J Am Coll Emerg Physicians Open. 2020 Oct 14;1(6):1676-1683	D	Outstanding	Retrospective cohort study of all consecutive ED encounters (265,572 pts) – 3 ED centres, with the aim to predict the ED resource requirements during triage using NL processing techniques. In conclusion: ML of nursing triage notes combined with clinical data available at ED presentation can help predict ED resources.	YES
9	Choi DH, Hong KJ, Park JH, Shin SD, Ro YS, Song KJ, Kim KH, Kim S. Prediction of bacteremia at the emergency department during triage and disposition stages using machine learning models. Am J Emerg Med. 2022 Mar;53:86-93.	D	Outstanding	Retrospective cohort study, one hospital ED, using data of all adult ED encounter Jan 2016-Dec 2018 with 2 sets of blood culture taken in the ED, with the aim to develop and validate ML model to predict bacteriemia. In conclusion: ML (XGB)-triage based model could be used to identify patients with a low risk of bacteriemia immediately after initial ED triage.	YES
10	Jiang H, Mao H, Lu H, Lin P, Garry W, Lu H, Yang G, Rainer TH, Chen X. Machine learning-based models to support decision-making in emergency department	D	good	Retrospective cross – sectional study of patient’s data from ED information system, presented to ED, aged >14 yrs., with suspected CVD, to study performance of ML models to assist in decision making at ED	YES

	triage for patients with suspected cardiovascular disease. Int J Med Inform. 2021 Jan;145			triage level. In conclusion: the study showed that ML models **were successfully able to support decision-making** of triage for patients with susp. CVD (AUC 0.937, 0.921, 0.919, 0.908 for all ML models).	
11	Xie F, Ong MEH, Liew JNMH, Tan KBK, Ho AFW, Nadarajan GD, Low LL, Kwan YH, Goldstein BA, Matchar DB, Chakraborty B, Liu N. Development and Assessment of an Interpretable Machine Learning Triage Tool for Estimating Mortality After Emergency Admissions. JAMA Netw Open. 2021 Aug 2;4(8):	D	Outstanding	Retrospective cohort study of all ED patients (2009-2016) with the aim to develop ML tool (based on ED triage data) estimating risk of death. In conclusion: all ML tools (scores) **had better prediction performance** then existing triage scores	**YES**
12	Roquette BP, Nagano H, Marujo EC, Maiorano AC. Prediction of admission in pediatric emergency department with deep neural networks and triage textual data. Neural Netw. 2020 Jun;126:170-177	D	Adequate	Retrospective cohort study of 499,853 patient's presented to paediatric ED using unstructured and structured data to develop predictive model for admission. In conclusion: DNN model (text processing) developed achieved AUC 0,892 in the text data	YES
13	Patel SJ, Chamberlain DB, Chamberlain JM. A Machine Learning Approach to Predicting Need for Hospitalization for Pediatric Asthma Exacerbation at the Time of Emergency Department Triage. Acad Emerg Med. 2018 Dec;25(12):1463-1470.	D	Outstanding	Retrospective analysis of EHR data of 29,392 asthma exacerbation patients age 2-18 (2012-2015), 2 urban pediatric Eds - To compare the performance of 4 machine learning approaches for early prediction of the need for hospital admission in pediatric asthma, in conclusions: ML based model - Pediatric Risk of Admission (PRISA) score – **similar to reference performance** (AUC 0.85) – incorporated additional data beyond triage (including worse vital signs, laboratory results)	YES
14	Yao LH, Leung KC, Tsai CL, Huang CH, Fu LC. A Novel Deep Learning-Based	D	Outstanding	Retrospective study from open data set (2009-2016) – 1 set of 118,602 US ED pts + set of 745,441 Taiwan ED pts –	YES

	System for Triage in the Emergency Department Using Electronic Medical Records: Retrospective Cohort Study. J Med Internet Res. 2021 Dec 27;23(12):			study aim: to develop DL-based triage system using pt's ED EHR data to predict clinical outcome after ED admission. Results: DL-model **achieved better performance** then traditional methods.	
15	Kim D, Oh J, Im H, Yoon M, Park J, Lee J. Automatic Classification of the Korean Triage Acuity Scale in Simulated Emergency Rooms Using Speech Recognition and Natural Language Processing: a Proof of Concept Study. J Korean Med Sci. 2021 Jul 12;36(27	D	Outstanding	Prospective and preliminary simulation study with retrospective data from ED encounters to assess ML-based triage system composed of a speech recognition model and NLP. In conclusion: authors demonstrated the **potential** of an autonomic triage classification system using speech recognition and NLP.	YES
16	Klug M, Barash Y, Bechler S, Resheff YS, Tron T, Ironi A, Soffer S, Zimlichman E, Klang E. A Gradient Boosting Machine Learning Model for Predicting Early Mortality in the Emergency Department Triage: Devising a Nine-Point Triage Score. J Gen Intern Med. 2020 Jan;35(1):220-227	D	Good	Retrospective study, data of all adult patients admitted to ED (Jan 2012-Dec 2018), 799,522 cases, with the aim to evaluate ML-model for predicting mortality at the triage level. In conclusion: ML-based model (gradient boosting) shows **high predictive ability** for screening patients at risk of early death (AUC 0.962 for early mortality).	YES
17	Zhang X, Kim J, Patzer RE, Pitts SR, Chokshi FH, Schrager JD. Advanced diagnostic imaging utilization during emergency department visits in the United States: A predictive modeling study for emergency department triage. PLoS One. 2019 Apr 9;14(4):	D	Good	Retrospective study of survey data from US Database (2009-2014), 139,150 adult ED visits, with the aim to develop AI-based model to predict utilization of advanced diagnostic imaging (ADI) during ED encounter. In conclusion: patient information available at ED triage can **accurately predict** the eventual use of ADI.	YES
18	Kim J, Chang H, Kim D, Jang DH, Park I, Kim K. Machine learning for prediction of septic shock at initial triage in emergency department. J Crit Care. 2020 Feb;55:163-170	D	Outstanding	Single-center observational study on EHRs database of ED visits with susp. Infection (2008-2016) with the aim to assess performance of ML-based triage tool in screening patients with septic shock in ED. In conclusion: all ML-	YES

				classifiers **outperformed clinical scores** (qSOFA, MEWS) in screening septic shock at ED triage.	
19	Kim D, Hwang JE, Cho Y, Cho HW, Lee W, Lee JH, Oh IY, Baek S, Lee E, Kim J. A Retrospective Clinical Evaluation of an Artificial Intelligence Screening Method for Early Detection of STEMI in the Emergency Department. J Korean Med Sci. 2022 Mar 14;37(10	D	Good	Single-center retrospective study of ED pts susp. of having STEMI (Jan 2011-Jun 2021), 80 pts, with the aim to access AI-assisted CCL activation. In conclusion: AI interpretation of initial ECG **was non-inferior** to joint clinical evaluation by Eps and cardiologists in screening STEMI in ED.	YES
20	Dyer T, Chawda S, Alkilani R, Morgan TN, Hughes M, Rasalingham S. Validation of an artificial intelligence solution for acute triage and rule-out normal of non-contrast CT head scans. Neuroradiology. 2022 Apr;64(4):735-743.	D	Good	Retrospective validation study, of 390 CT head scans, with the aim to validate AI-based algorithm to triage patients presenting with ICH/acute infarct. In conclusion: the algorithm showed AUC of 0.988, 0.933, and 0.939 (for ICH, AI, nl respectively) suggesting that AI-based model can provide **effective trigae** of ICH and acute infarct.	YES
21	Chang YH, Shih HM, Wu JE, Huang FW, Chen WK, Chen DM, Chung YT, Wang CCN. Machine learning-based triage to identify low-severity patients with a short discharge length of stay in emergency department. BMC Emerg Med. 2022 May 20;22(1):88	D	Outstanding	Retrospective study of ED datasets - of adult non-trauma ED patients with TTAS (Taiwan Triage and Acuity Scale) level 3, 44,775 patients, with the aim to establish a ML model for prediction of low-severity patients with short ED DLOS. In conclusion: authors developed a ML-modal using triage information alone to predict which patients have low severity with short DLOS.	YES
22	Yu JY, Xie F, Nan L, Yoon S, Ong MEH, Ng YY, Cha WC. An external validation study of the Score for Emergency Risk Prediction (SERP), an interpretable machine learning-based triage score for the emergency department. Sci Rep. 2022 Oct 19;12(1):17466	D	Outstanding	Retrospective cohort study, of 285,523 ED visits (2016-2020) aimed to validate the SERP score (ML-based ED triage tool – score for Emergency Risk Prediction) on the different population. In conclusion: SERP was superior to other traditional scores for in-hospital and 30-day mortality (SERP	YES

				AUC 0.821-0.803 vs KTAS AUC 0.679-0.729).	
23	Tu KC, Eric Nyam TT, Wang CC, Chen NC, Chen KT, Chen CJ, Liu CF, Kuo JR. A Computer-Assisted System for Early Mortality Risk Prediction in Patients with Traumatic Brain Injury Using Artificial Intelligence Algorithms in Emergency Room Triage. Brain Sci. 2022 May 7;12(5):612.	D	Outstanding	Retrospective cohort study of 18,249 adult TBI patient's EHRs (2010-2019) with the aim to develop ED triage AI-based prediction model using EHRs data. In conclusion: AI-based triage system (using only triage information) can provide a real-time prediction on further ED management (AI-based predictive models AUC: 0.851-0.925).	YES
24	Desai A, Zumbo A, Giordano M, Morandini P, Laino ME, Azzolini E, Fabbri A, Marcheselli S, Giotta Lucifero A, Luzzi S, Voza A. Word2vec Word Embedding-Based Artificial Intelligence Model in the Triage of Patients with Suspected Diagnosis of Major Ischemic Stroke: A Feasibility Study. Int J Environ Res Public Health. 2022 Nov 19;19(22):15295	D	Good	Retrospective cohort study of data of clinical notes (Jan 2015-March 2021) of 648 MIS with the aim to assess word Embedding-based AI-triage model for pts with susp. MIS. In conclusion: tested AI-algorithm (Word2vec model) successfully identified 83.9% of them, with AUC 95.1%, revealing potential for early detection of MIS at triage using AI-tool.	YES
25	Sánchez-Salmerón R, Gómez-Urquiza JL, Albendín-García L, Correa-Rodríguez M, Martos-Cabrera MB, Velando-Soriano A, Suleiman-Martos N. Machine learning methods applied to triage in emergency services: A systematic review. Int Emerg Nurs. 2022 Jan;60:101109	A	Good	A systematic review/meta-analysis of 11 articles with the aim to analyse the effectiveness of ML systems in ED triage. In conclusions: ML with triage data input solidly predict outcomes like mortality, critical needs or need for hospitalization with more accuracy than other conventional scale like ESI.	YES
26	Kwon JM, Lee Y, Lee Y, Lee S, Park H, Park J. Validation of deep-learning-based triage and acuity score using a large national dataset. PLoS One. 2018 Oct 15;13(10):e0205836. doi: 10.1371/journal.pone.0205836	D	Outstanding	Retrospective observational cohort study, national database (Korean) – 151 EDs, 11,656,559 patients, with the aim to validate DL-based Triage and Acuity Score (DTAS). In conclusion: study showed that DTAS predicts in-hospital mortality, critical care and hospitalization more accurately (measured by AUC) than existing triage scores.	YES

27	Sung SF, Hung LC, Hu YH. Developing a stroke alert trigger for clinical decision support at emergency triage using machine learning. Int J Med Inform. 2021 Aug;152:104505.	D	Outstanding	Retrospective cohort study of 1361 ED patients admitted with acute stroke symptoms to ED, aim of the study: to develop a stroke-alert ML-based trigger to identify potential patients with suspected stroke at ED triage. In conclusions: ML tool significantly improved the performance of prediction model for identification of patients with suspected stroke.	YES
28	Ivanov O, Wolf L, Brecher D, Lewis E, Masek K, Montgomery K, Andrieiev Y, McLaughlin M, Liu S, Dunne R, Klauer K, Reilly C. Improving ED Emergency Severity Index Acuity Assignment Using Machine Learning and Clinical Natural Language Processing. J Emerg Nurs. 2021 Mar;47(2):265-278	D	Good	Retrospective study of data from EHRs (147,052 ED encounters) to determine if these data can be used with NLP and ML algorithms (KATE) to produce accurate ESI prediction model. In conclusion: KATE model provided a triage acuity assignment more accurate than conventional one.	YES
29	Chang H, Yu JY, Yoon S, Kim T, Cha WC. Machine learning-based suggestion for critical interventions in the management of potentially severe conditioned patients in emergency department triage. Sci Rep. 2022 Jun 22;12(1):	D	Good	Retrospective observational study of 137,883 ED patients (data from EHRs) to predict early critical interventions (as a ML based recommendations). In conclusions: AUC for all critical interventions were high enough (0.899-0.945) to suggest early interventions for EPs.	YES
30	Yun H, Park JH, Choi DH, Shin SD, Jang MJ, Kong HJ, Kim SW. Enhancement in Performance of Septic Shock Prediction Using National Early Warning Score, Initial Triage Information, and Machine Learning Analysis. J Emerg Med. 2021 Jul;61(1):1-11	D	Outstanding	Retrospective study of all adult ED encounters with susp. infections (2014-2018), 41,687 patients, with the aim to develop and validate NEWS-based ML prediction model for detecting septic shock early. In conclusion: addition of initial triage information to the model improved performance (measured by AUC).	YES
31	O'Connell GC, Walsh KB, Smothers CG, Ruksakulpiwat S, Armentrout BL, Winkelman C, Milling TJ, Warach SJ, Barr TL. Use of deep artificial neural	D	Outstanding	Retrospective cohort study of 160 patients with stoke/stroke mimics, with the aim to determine if ML-model can help identify stroke during ED triage. In conclusion: changes in CBC + diff in ML-based	YES

	networks to identify stroke during triage via subtle changes in circulating cell counts. BMC Neurol. 2022 Jun 3;22(1):206			model could support clinicians in triage decisions about stroke patients	
32	Nguyen M, Corbin CK, Eulalio T, Ostberg NP, Machiraju G, Marafino BJ, Baiocchi M, Rose C, Chen JH. Developing machine learning models to personalize care levels among emergency room patients for hospital admission. J Am Med Inform Assoc. 2021 Oct 12;28(11): 2423-2432	D	Outstanding	Retrospective cohort study of EHRs data (all adult ED patients 2015-2019), with the aim to develop a AI-prediction model for level of care (ICU vs non-ICU). In conclusion: ML-models developed achieved better performance (by AUC) than benchmarking model (ESI).	YES
33	Stella P, Haines E, Aphinyanaphongs Y. Prediction of Resuscitation for Pediatric Sepsis from Data Available at Triage. AMIA Annu Symp Proc. 2022 Feb 21;2021:1129-1138.	D	Outstanding	Retrospective cohort study of EHRs of 26,564 pediatric ED encounters, to develop AI-based models to predict resuscitation for pediatric sepsis patients. In conclusion: AI-based model developed outperformed existing rule-based sepsis alerts in predicting need for resuscitation.	YES
34	Artificial Intelligence-Based Triage for Patients with Acute Abdominal Pain in Emergency Department; a Diagnostic Accuracy Study. Farahmand S, et al. Adv J Emerg Med. 2017	C	Good	Prospective accuracy study of 215 patients admitted to ED with acute abdominal pain, the study aim was to evaluate the application of AI-based model to estimate ESI-verison-4 without estimate of required resources. In conclusion: tested AI-based model achieved acceptable level of accuracy.	YES
35	Wang YC, Chen KW, Tsai BY, Wu MY, Hsieh PH, Wei JT, Shih ESC, Shiao YT, Hwang MJ, Chang KC. Implementation of an All-Day Artificial Intelligence-Based Triage System to Accelerate Door-to-Balloon Times. Mayo Clin Proc. 2022 Dec;97(12):2291-2303	D	Outstanding	Single-center retrospective cohort study of 154 consecutive STEMI patients to implement AI-based system to facilitate ED triage chest paint pts. In conclusion: Implementation of AI-based triage system significantly reduced D2B time for STEMI patients.	YES
36	Hwang S, Lee B. Machine learning-based prediction of critical illness in children visiting the emergency department. PLoS One. 2022 Feb	D	Outstanding	Cross-sectional observational study of national dataset of 2,621,710 children under 15 yrs to develop ML-based model to predict clinical	YES

	17;17(2			course. In conclusion: ML-based model achieved superior performance than conventional triage system (AUC for critical outcome: 0.991)	
37	Levin S, Toerper M, Hamrock E, Hinson JS, Barnes S, Gardner H, Dugas A, Linton B, Kirsch T, Kelen G. Machine-Learning-Based Electronic Triage More Accurately Differentiates Patients With Respect to Clinical Outcomes Compared With the Emergency Severity Index. Ann Emerg Med. 2018 May;71(5):	D	Outstanding	Multisite, retrospective, cross-sectional study of 172,726 ED visits to evaluate ML-based ED triage system. In conclusion: E-triage system (ML-based) more accurately classifies ESI 3 patients	YES
38	Rendell K, Koprinska I, Kyme A, Ebker-White AA, Dinh MM. The Sydney Triage to Admission Risk Tool (START2) using machine learning techniques to support disposition decision-making. Emerg Med Australas. 2019 Jun;31(3):429-435	D	Outstanding	Retrospective study of data of 1,721,294 ED visits, to develop and refine an ED in-patient admission model using ML. In conclusion: ML-models demonstrated similar performance to LR for ED disposition prediction model.	YES

Table 1: Evidence Grade

Table 1. The Definitions of the Grades of Evidence of the Articles	
Grade	Definition
A	Randomized clinical trials or meta-analyses (i.e., multiple clinical trials) or randomized clinical trials (i.e., smaller trials), directly addressing the review issue
B	Randomized clinical trials or meta-analyses (i.e., multiple clinical trials) or randomized clinical trials (i.e., smaller trials), indirectly addressing the review issue
C	Prospective, controlled, nonrandomized, cohort studies
D	Retrospective, nonrandomized, cohort or case-control studies
E	Case series, animal/model scientific investigations, theoretical analyses, or case reports
F	Rational conjecture, extrapolations, unreferenced opinion in literature, or common practice

Table 2: Article Quality Definitions

Table 2. The Definitions of the Quality Ranking Scores of the Articles			
Ranking	Design Consideration Present	Methodology Consideration Present	Both Considerations Present
Outstanding	Appropriate	Appropriate	Yes, both present
Good	Appropriate	Appropriate	No, either present
Adequate	Adequate with possible bias	Adequate	No, either present
Poor	Limited or biased	Limited	No, either present
Unsatisfactory	Questionable/none	Questionable/none	No, either present

Table 3. Definitions for Recommendations

Level of Recommendation	Criteria for Level of Recommendation	Mandatory Evidence
Class A (recommended with outstanding evidence)	Acceptable	Level A/B grade
	Safe	Outstanding Quality
	Useful	Robust
	Established/definitive	All Positive
Class B (acceptable & appropriate with good evidence)	Acceptable	Level A/B grade lacking
	Safe	Adequate to good quality
	Useful	Most evidence positive
	Not yet definitive	No evidence of harm
Class B1	Standard approach	Higher grades of evidence
		Consistently positive
Class B2	Optional or alternative approach	Lower grades of evidence
		Generally, but not consistently, positive
Class C (not acceptable or not appropriate	Unacceptable	No positive evidence
	Unsafe	Evidence of harm
	Not useful	
Class indeterminate	Minimal to no evidence	Minimal to no evidence

(unknown)		