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ORIGINAL PAPER

An AI-Enabled Dynamic Risk Stratification for Emergency Department Patients with ECG and CXR Integration

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Abstract

Emergency department (ED) triage scale determines the priority of patient care and foretells the prognosis. However, the information retrieved from the initial assessment is limited, hindering the risk identification accuracy of triage. Therefore, we sought to develop a 'dynamic' triage system as secondary screening, using artificial intelligence (AI) techniques to integrate information from initial assessment data and subsequent examinations. This retrospective cohort study included 134,112 ED visits with at least one electrocardiography (ECG) and chest X-ray (CXR) in a medical center from 2012 to 2022. Additionally, an independent community hospital provided 45,614 ED visits as an external validation set. We trained an eXtreme gradient boosting (XGB) model using initial assessment data to predict all-cause mortality in 7 days. Two deep learning models (DLMs) using ECG and CXR were trained to stratify mortality risks. The dynamic triage levels were based on output from the XGB-triage and DLMs from ECG and CXR. During the internal and external validation, the area under the receiver operating characteristic curve (AUC) of the XGB-triage model was >0.866; furthermore, the AUCs of DLMs using ECG and CXR were >0.862 and >0.886, respectively. The dynamic triage scale provided a higher C-index (0.914-0.920 vs. 0.827-0.843) than the original one and demonstrated better predictive ability for 5-year mortality, 30-day ED revisit, and 30-day discharge. The AI-based risk scale provides a more accurate and dynamic stratification of mortality risk in ED patients, particularly in identifying patients who tend to be overlooked due to atypical symptoms.

Keywords Artificial intelligence · Electrocardiogram · Chest X-ray · Deep learning · Triage scale · Emergency department

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Introduction

Emergency department (ED) triage determines the urgency of a patient's medical condition and rates the priority of care when the patient presents to the ED [1, 2]. Adequately allocating medical resources to critically ill patients through triage could mitigate mortality, while delays in timely intervention from EDs are associated with mortality [3, 4]. Several ED triage scales have been designed to prioritize patient acuities [5–8]. An exemplary system widely used in Taiwan is the Taiwan Triage and Acuity Scale (TTAS), a five-level model adapted from the Canadian Triage and Acuity Scale, incorporating chief complaints and other specific modifiers [7, 8]. However, despite these systems being rooted in substantial medical expertise, these systems largely hinge on evaluating patients' present symptoms and vital signs.

Previous studies have shown that a substantial proportion of ED patients with lower acuity triage levels still deteriorate prematurely or die unexpectedly [9]. The currently available triage systems have shown variable validity in mortality prediction, with some triage systems predicting ED mortality better than in-hospital mortality or hospitalization [1, 10]. Several early warning scores, such as the Rapid Emergency Medicine Score (REMS) [11] and Triage Early Warning Score (TREWS) [12], have been proposed to predict in-hospital mortality; however, these models are limited to using parameters available at the ED triage. In contrast, certain machine-learning (ML) models that use triage data have shown the potential to predict in-hospital cardiac arrest. Nevertheless, these prediction models are also constrained using variables collected solely at the ED triage [13, 14].

Electrocardiography (ECG) and chest X-ray (CXR) are the two most popular tests in ED and are often used for further differential diagnosis. Widespread applications of deep learning models (DLMs) on ECG and CXR [15], AI-enabled ECG [16] and CXR [17] have been validated to extract mortality risk and further enable risk stratification. Studies have yet to integrate them into the ED triage scale for universal ED visits. ECG and CXR can identify characteristics of acute diseases, such as silent ST-segment elevation myocardial infarction [18], aortic dissection, and massive pulmonary thromboembolism. Therefore, a triage system that dynamically incorporates critical information from these follow-up examinations once results are available could better detect risky ED patients and help physicians promptly reassess patients.

This study aimed to develop three AI models using information obtained from triage, ECG, and CXR to identify patients at risk of in-hospital mortality after ED visits. Moreover, we integrated and established an AI-enabled "dynamic" triage scale and explored its performance in mortality risk stratification. This dynamic ED triage scale may serve as secondary triage to improve safety and quality of care for patients admitted from

Methods

Data source

The records of ED visits were retrieved from two hospitals, Hospital A and Hospital B, from Apr 2012 to Feb 2022. The study flow charts and dataset generation are shown in Fig. 1. Hospital A, an academic medical center, provided 614,078 ED visits from 295,748 patients, including 138,122 visits (22.5%) with at least 1 ECG and CXR examination. Meanwhile, a community hospital, Hospital B, provided 161,213 ED visits from 59,288 patients, including 46,101 visits (28.6%) with at least 1 ECG and CXR examination. The visits from Hospital A were randomized by patients into three independent groups for the development set, tuning set, and internal validation set. The visits from Hospital B served as the external validation set. Details are provided in the Online Supplemental material etext 1.

Data annotation and variables

Each patient involved with an ED visit who had died 7 days after entering the ED was annotated as a case, and the others were annotated as controls. Since ED visits might have more than 1 ECG/CXR in the development set, we applied the same annotation to all ECG/CXR records for each ED visit. Patient status (dead/alive) was captured through the electronic medical record (EMR). Although death could be at other hospitals, which our EMR would not capture, the proportion might be scarce since only 0.16% of readmissions occurred at a different hospital [19]. We additionally collected specific resuscitative interventions as surrogate endpoints for ED visits who survived beyond 7 days. The ECG signals, CXR images, and relevant clinical information were recorded. The relevant clinical information, including physiological status and chief complaints recorded by triage nurses. Details are provided in the Online Supplemental material etext 2.

For ED visits of original triage scale level 2 to 5 where the patient died within 7 days, we analyzed their cause of death. We further classified them as expected and unexpected events as reviewed by two independent investigators. The expected death was defined as those diagnosed with a terminal illness or condition that is likely to deteriorate and not expected to improve. The secondary outcomes of interest included 5-year mortality, 30-day ED revisit, and 30-day discharge. For mortality, we used the last known live hospital encounter as the censored event to verify that the censored patients survived at the end of follow-up.

Moreover, we stratified each ED visit into admitted visits and nonadmitted visits. For the 30-day ED revisit, there

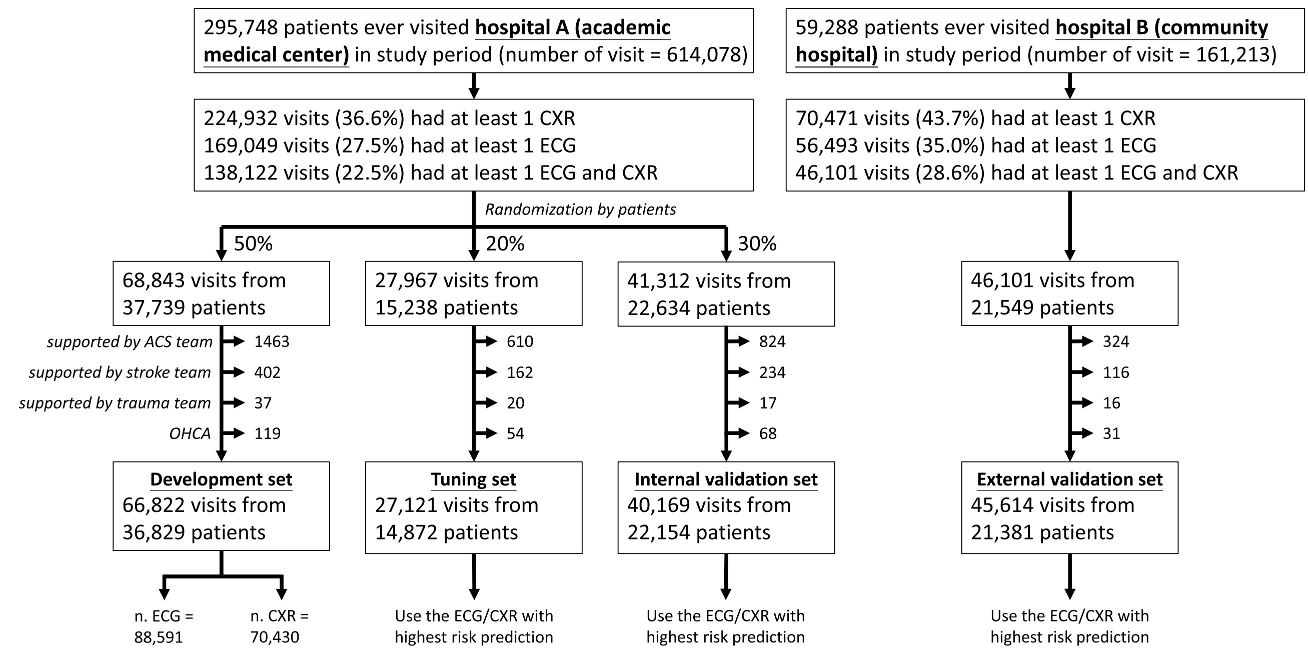

Fig. 1 Study flow charts and dataset generation. Schematic of the dataset creation and analysis strategy, devised to ensure a robust and reliable dataset for training, validating, and testing of the network. Once a patient's data were placed in one of the datasets, that individual's data were used only in that set, avoiding 'cross-contamination' among the training, validation, and test datasets. The details of the flow chart and how each dataset was used are described in the Methods

were only nonadmitted visits in this analysis. For the 30-day discharge, we analyzed the odds of discharge by the length of inpatient stay without death in the admitted visits, calculated from the admission date to the discharge date. Cases of in-hospital death were censored data in this analysis.

Model development

We used the eXtreme gradient boosting (XGB) model to integrate the original triage information for predicting death within 7 days, and this model had a logistic output for binary classification. This model was trained by data in the development set, and the hyperparameters were selected based on the model performance in the tuning set. The DLM for ECG was used to predict the likelihood of death based on a convolutional neural network with 82 trainable layers, described in our previous study [20]. The training details of the DLM for CXR were revised from a previous study which was a 121-layer DenseNet [21]. The details for the above models are provided in the Online Supplemental material etext 3.

Statistical analysis

The receiver operating characteristic (ROC) curve and AUC were applied to measure model performance. The operating point was selected based on the maximum of Youden's index for detecting HT in the tuning set, and internal and external validation shared the same operating point to calculate the corresponding sensitivity, specificity, positive predictive value, and negative predictive value. We also used multivariable Cox proportional hazard models to analyze the relationship between AI prediction and outcomes of interest. Sex- and age-adjusted hazard ratios (HRs) and 95% conference intervals (95% CIs) were used for comparison, and Kaplan−Meier curve analysis was used for visualization. The Spearman correlation coefficient was used to measure the relationship between each AI prediction, and the polychoric correlation coefficient (r) was used to quantify the relationship between two ordinal variables. The statistical analysis was carried out using the software environment R version 3.4.4 with a significance level of $p < 0.05$.

Results

The baseline characteristics of the ED visits

The patient characteristics of each dataset are shown in Table 1. The proportions of patients who died within 7 days were 1.7%, 1.8%, 1.9%, and 1.4% in the development, tuning, internal validation, and external validation sets, respectively. A higher proportion of original triage level 1 (8.7-9.1%) was presented in Hospital A than in

Hospital B (5.3%), while a lower proportion of patients were discharged from Hospital A (49.8-50.6%) compared to Hospital B (51.6%). These results indicate that the ED visits in the internal validation set had higher severity than the external validation set. Online Supplemental material eTable 1 shows the detailed ED triage assessment in each dataset.

The performance for 7-day death prediction

Figure 2A shows the risk of death within 7 days stratified by the original triage scale. In the internal validation set, the original triage level 1 group had a significantly higher incidence of all-cause mortality at 7 days (11.0%) compared to level 2 (1.9%) and levels 3/4/5 groups (0.4%),

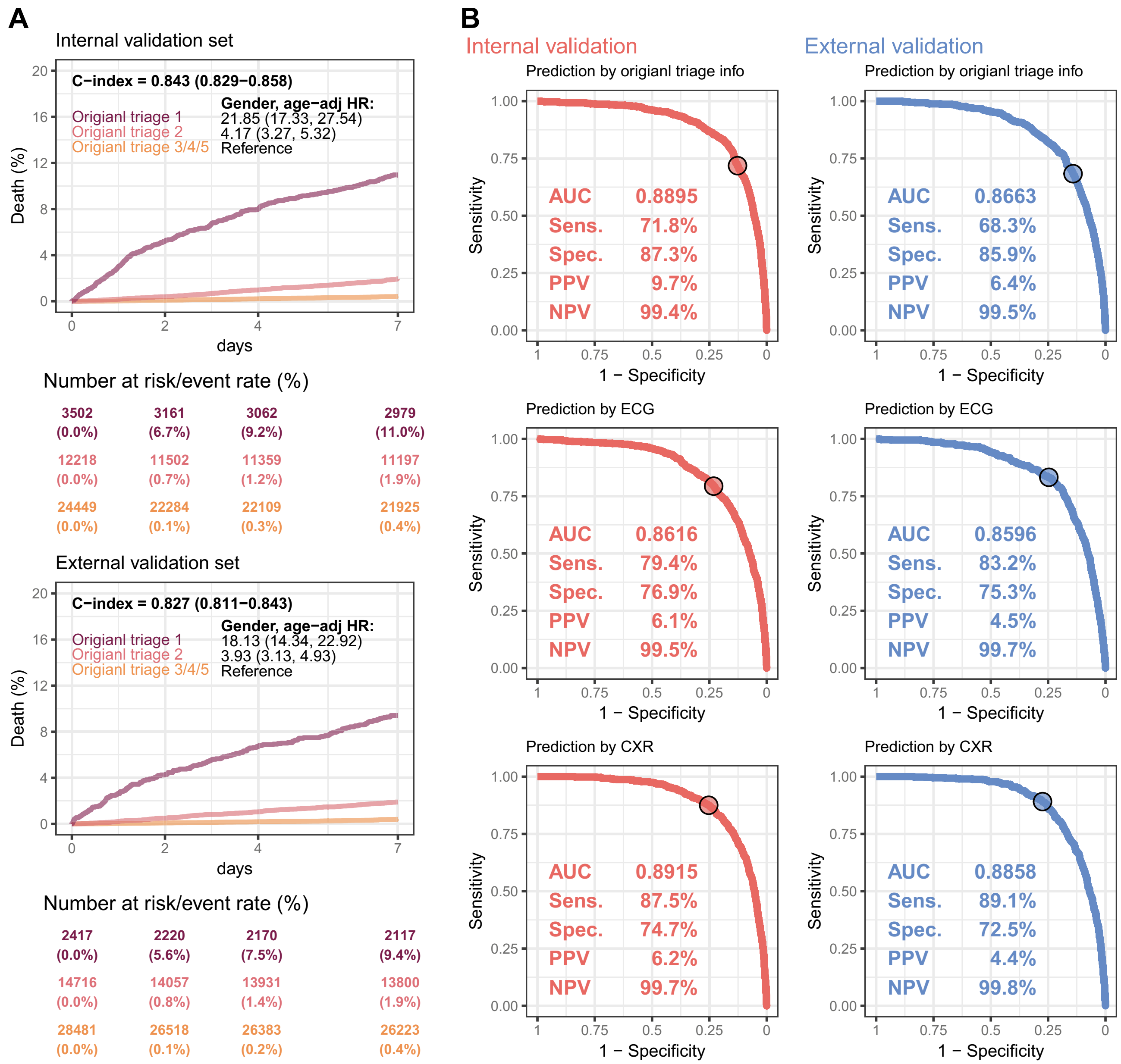

Fig. 2 Summary of model performance for predicting all-cause mortality within 7 days in the internal and external validation sets. **A** Kaplan–Meier curve analysis for the original triage scale. The analyses were conducted in both the internal and external validation sets. The table shows the at-risk population and cumulative risk for the given time intervals in each risk stratification. **B** ROC curves of the risk prediction based on the AI model using the information at triage, electrocardiogram (ECG), and chest X-ray (CXR). The operating point was selected based on the maximum of Youden's index in the tuning set and was presented using a circle mark. The area under the ROC curve (AUC), sensitivity (Sens.), specificity (Spec.), positive predictive value (PPV), and negative predictive value (NPV) were calculated. The cases are the patients who died within 7 days, and the controls are those who were alive for more than 7 days. Patients missing within 7 days were excluded from this analysis

with an adjusted HR of 21.85 (95% CI: 17.33-27.54). This trend was also present in the external validation set. The C-indices were 0.843 and 0.827 in the internal and external validation sets.

The original triage scale attained AUCs of 0.808/0.772 in the internal/external validation sets, and the XGB model further enhanced accuracy by utilizing other features, shown in Online Supplemental material eFig. 1A. Also, Online Supplemental material eFig.1B shows the prediction by the XGB model that provided further risk stratification independent of the original triage scale. As shown in Fig. 2B, the XGB model using triage information achieved AUCs of 0.8896/0.8663 in the internal/external validation sets for predicting death within 7 days, implying the ultimate accuracy in predicting short-term death initially at triage.

While the XGB model demonstrated good risk stratification, it was restricted to original triage information. The DLM with ECG achieved AUCs of 0.8616/0.8596 in internal/external validation, while the CXR AUCs were 0.8915/0.8858 (Fig. 2B), indicating the significance of additional information beyond original triage for death prediction. Of note, all AI predictions provided a better predictive ability for mortality within 7 days than the original triage scale.

The generation of a dynamic triage scale

Online Supplemental material eFig. 2 displays the HRs in the stratified analysis by the original triage scale, XGB model with original triage information, and DLM with ECG and CXR regarding mortality within 7 days. These results were all lower compared to the naïve analysis (Fig. 2A), and the ability of risk stratification was lower in the ED visits with original triage level 1 compared to the ED visits with original triage levels 2-5. This phenomenon implied the repetitiveness of the information in the original triage scale and AI predictions, and Online Supplemental material eFig. 3 validated this conjecture with Spearman correlation coefficients of 0.339-0.650. Notably, the XGB model with original triage information had a stronger correlation than the DLMs with ECG/CXR to the original triage scale, highlighting the significance of non-triage data. Moreover, the correlations in these three AI models ranged from 0.599 to 0.689.

However, the models can still effectively identify abundant high-risk patients, significantly impacting risk stratification. Figure 3A summarizes the stratification by the original triage scale and AI predictions. We combined HR-matching subgroups marked by the same color and proposed a new triage scale - the dynamic triage scale - which involves extra assessments beyond the triage station. For ED visits with an original

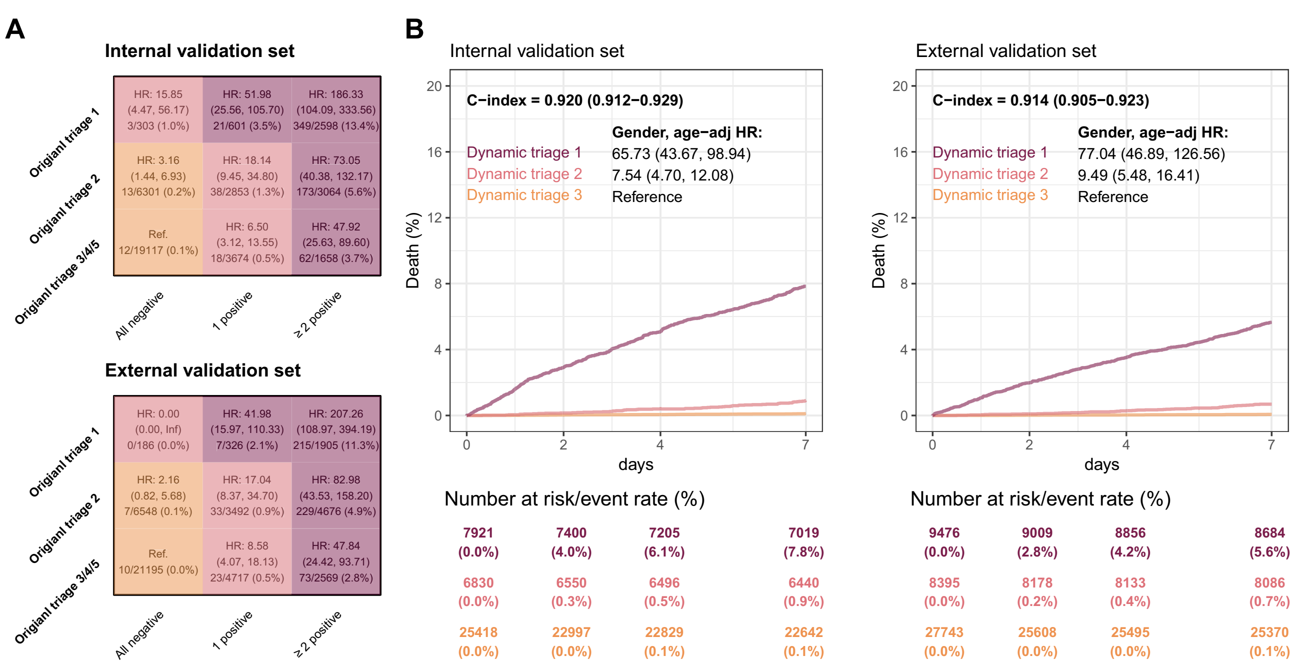

Fig. 3 Integration analysis of the AI model using information at triage, electrocardiogram (ECG), and chest X-ray (CXR). **A** The risk matrix of patients with different conditions. The HRs are adjusted by sex and age, and the proportions below are the patients who died within 7 days in each group. We regrouped them into three triage levels: dynamic triage 3 (All negative, light orange), dynamic triage 2 (1 positive, light purple), and dynamic triage 1 (≥ 2 positive, dark purple). **B** Kaplan–Meier curves for each dynamic triage level on 7-day death. The analyses are conducted in both the internal and external validation sets. The table shows the at-risk population and cumulative risk for the given time intervals in each risk stratification

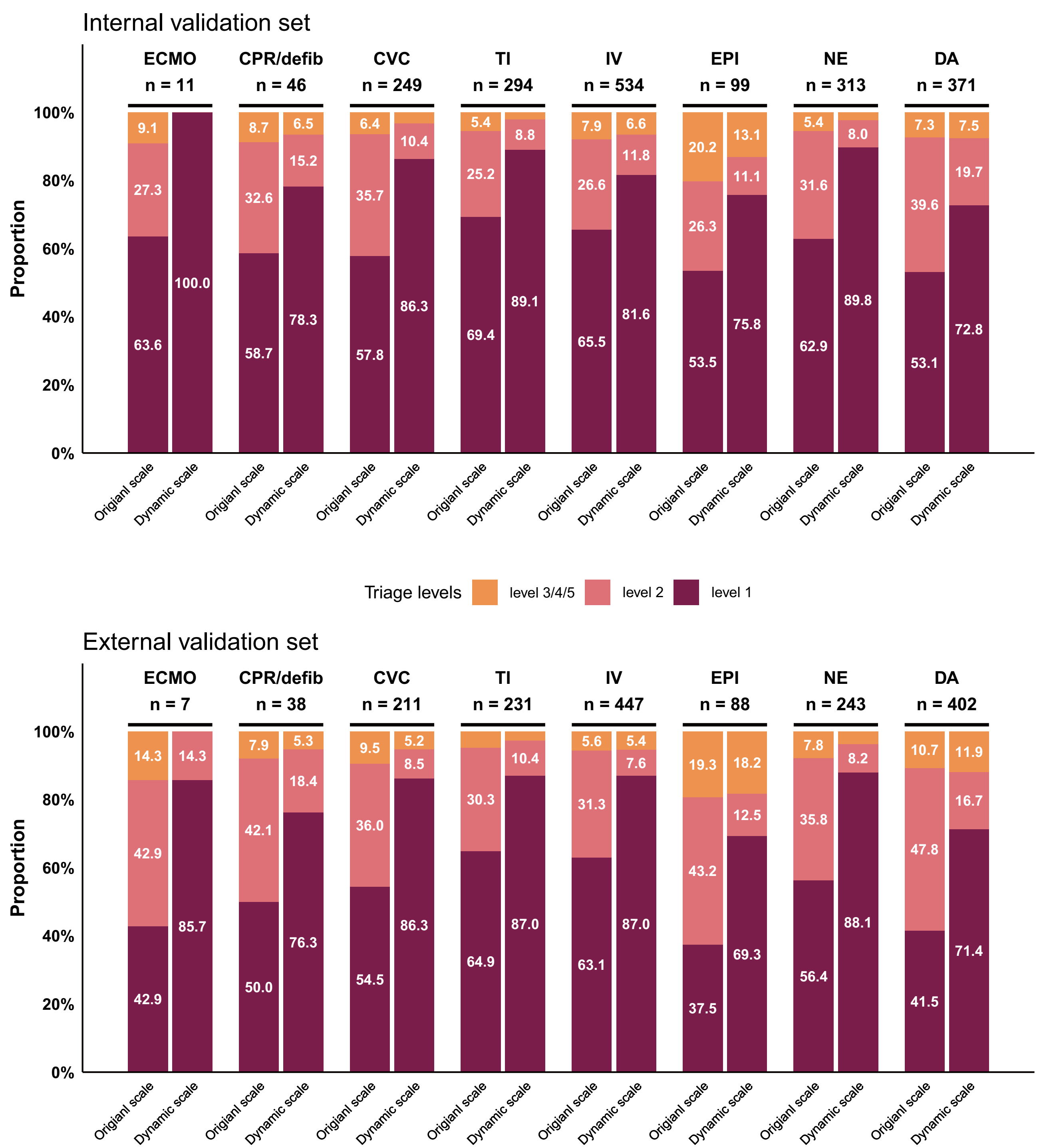

Fig. 4 Proportions of resuscitative measures stratified by original and dynamic triage scales for patients alive within 7 days. Proportions of resuscitative measures stratified by original and dynamic triage scales for patients alive within 7 days. Abbreviations: ECMO, extracorporeal membrane oxygenation; CPR/defib, cardiopulmonary resuscitation/defibrillation; CVC, central venous catheter; TI, tracheal intubation; IV, invasive ventilation; EPI, epinephrine; NE, norepinephrine; DA, dopamine

triage scale of level 1, the three AI models consistently predicted that negative results were defined as a "dynamic triage scale of level 2", and ≥1 positive result was defined as a "dynamic triage scale of level 1". For lower levels of the original triage scale (levels 2-5), negative results were defined as "dynamic triage scale of level 3", with one positive result defined as "dynamic triage scale of level 2", and ≥2 positive results defined as "dynamic triage scale of level 1". Online

Supplemental material eFig. 4 displays a stratified analysis by the original triage scale, XGB model with triage data, and DLM with ECG and CXR, regarding mortality within 7 days. We observed that detailed combinations of conditions may not be crucial for every triage scale, but the models can still effectively identify a large number of high-risk patients, which can greatly impact risk stratification.

Using the proposed dynamic triage scale, the dynamic triage level 1 and the dynamic triage level 2 groups had a 65.73-77.04- and a 7.54-9.49-fold risk of death within 7 days, respectively, compared to the dynamic triage level 3 group (Fig. 3B). Online Supplemental material eFig. 5 shows the comparison between the original triage scale and the proposed dynamic triage scale regarding risk stratification ability. Notably, dynamic triage level 3 had a lower 7-day mortality rate (0.1%) than the original triage scale level 3 (0.4%), with a similar number of patients in both. Likewise, the number of patients in dynamic triage level 1A (original triage level 1 with ≥2 positive AI findings) and original triage level 1 became similar, demonstrating the effectiveness of dynamic triage. It illustrated dynamic triage scale could improve risk stratification without increasing ED loading.

Further application of the dynamic triage scale

Figure 4 shows the proportions of eight resuscitative events identified by original and dynamic triage for ED visits in which the patient survived for 7 days. The dynamic triage scale found more critically ill patients requiring resuscitative

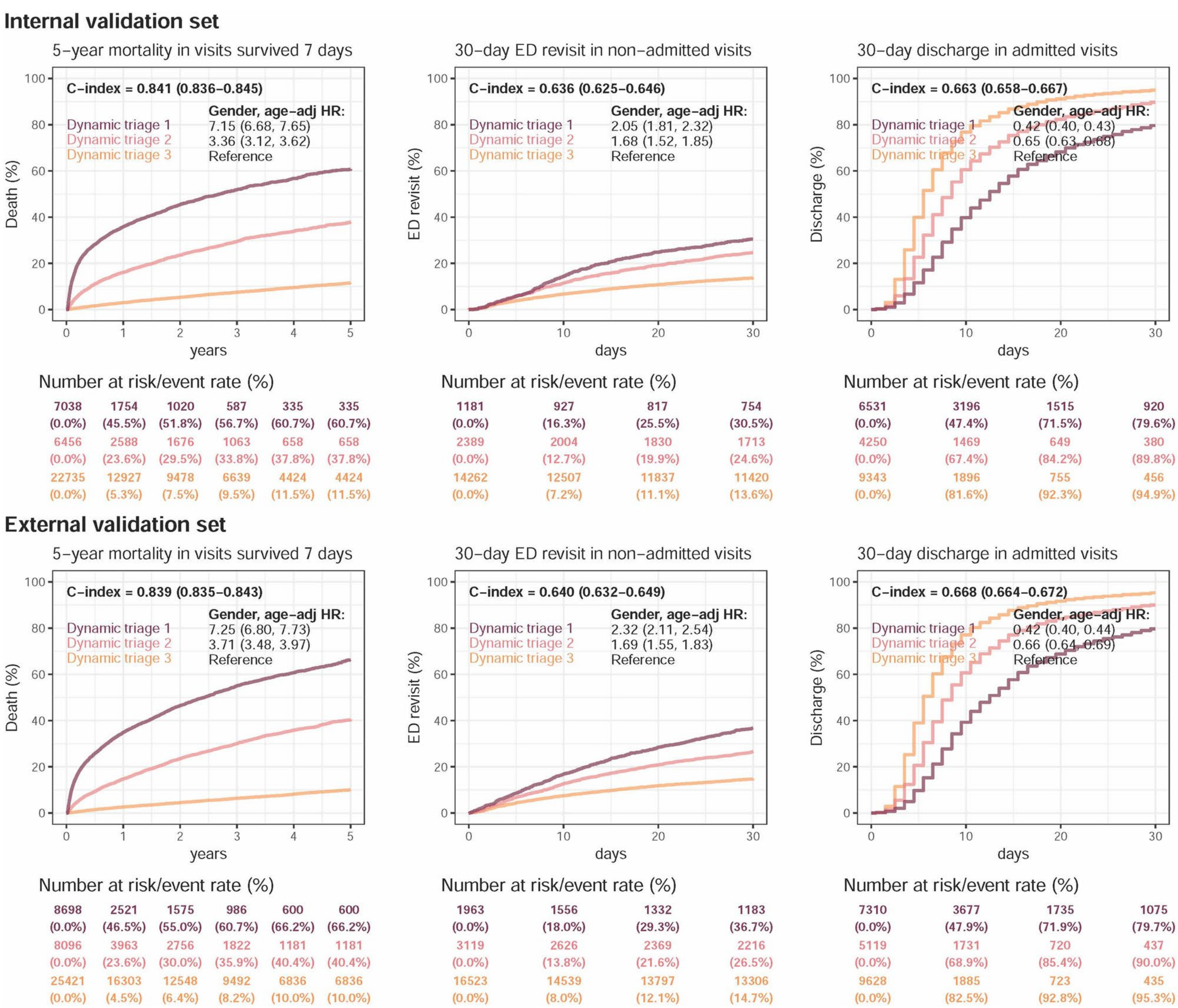

Fig. 5 Kaplan–Meier curves for each dynamic triage level on 5-year all-cause mortality, 30-day ED revisit, and 30-day discharge. The analyses are conducted in both internal and external validation sets. The table shows the at-risk population and cumulative risk for the given time intervals in each risk stratification

interventions than the original scale. For ED visits with an original triage level of 2-5, Online Supplemental material eFig. 6 showed a mild association between the severity of the dynamic triage scale and expected death defined by physicians. The polychoric correlation coefficients of 0.451/0.301 highlight the need for human-machine cooperation. The detailed cause-related death stratified by the dynamic triage scale is shown in Online Supplemental material eFig. 7. As the severity of the dynamic triage scale increased from 3 to 1, the proportion of respiratory and oncological disease-related deaths increased significantly.

The median follow-up time for the internal and external validation sets is 1.85 years (interquartile range: 0.55–3.76 years) and 2.28 years (interquartile range: 0.79–4.45 years), respectively. Figure 5 depicts the long-term follow-up analysis of ED visits that patients survived for 7 days. The severe dynamic triage scale was prone to a higher risk of all-cause mortality [adjusted HRs = 7.15-7.25 (level 1 vs. levels 3) and 3.36-3.71 (level 2 vs. levels 3)]. The dynamic triage scale also assesses the risk of revisits within 30 days for nonadmitted ED visits, with higher risk seen in levels 1 and 2 compared to level 3 [adjusted HRs = 2.05-2.32 (level 1) and 1.68-1.69 (level)]. For admitted ED visits, dynamic triage levels 1 (adjusted HRs = 0.42) and 2 (adjusted HRs = 0.65-0.66) were prone to delayed discharge in 30 days compared to dynamic triage level 3, highlighting the worth of the dynamic triage scale for assessing risk in discharged ED patients.

Discussion

This study developed three AI models of ED triage using the information at triage, ECG, and CXR. This AI-enabled dynamic triage scale was proposed by integrating inputs from these three sources to stratify the risk of ED patients. ED triage is implemented to appraise both the "acuity" and "severity" of patients. While original triage systems evaluate patient acuity based on initial assessments, our dynamic triage system primarily focuses on and is superior to mortality risk stratification. It is a beneficial secondary triage tool to enhance risk awareness among healthcare providers in crowded EDs.

AI interventions, such as radiographic imaging analysis and prediction-based diagnoses [22–29], show promising in improving emergency care. Our DLMs, which use ECG and CXR, have achieved AUCs comparable to those in previous studies for stratifying mortality risk [16, 17]. Intelligent triage systems for prognosis prediction often use information recorded at triage, such as age, gender, vital signs, and chief complaints, to predict prognosis [29]. In a previous study using these variables, an AUC of 0.86 was achieved on admission to the intensive care unit or in-hospital death [30]. That is similar to our XGB model, with an AUC of 0.87-0.89. However, the limited availability of most examinations at the initial triage has hindered the performance of AI models for predicting prognosis. Therefore, the novelty of this study lies in integrating ECG, CXR, and triage information into a triage system. This dynamic triage scale achieved a high C-index (0.914-0.920) through information integration and is significantly better than the original triage scale (0.827-0.843) and the AI model that only used triage information (AUC = 0.890/0.866).

We reviewed 691 ED visits that were originally triaged as levels 2 to 5 and resulted in death within 7 days, with 75 cases (10.9%) being unexpected. Among the unexpected deaths, we identified 18 probably preventable cases, including 11 of cardiovascular origin and 6 of pulmonary origin (data not shown). AI models identified 12 cases (66.7%) as having a dynamic triage scale of level 1 and 3 cases (16.7%) as having a dynamic triage scale of level 2 (selected cases shown in Online Supplemental material eFigs. 8-9). AI could aid in early intervention to prevent tragic events such as sudden in-hospital cardiac arrest, generally attributed to cardiovascular and respiratory etiologies [31]. False positives with a dynamic triage scale level 1, which predicts long-term outcomes, may still benefit from clinically relevant predictions. Additionally, the false-positive predictions by DLM have been validated and linked to poor prognoses, serving as an objective assessment for inpatient management [32–34].

AI models in EDs can cause alert fatigue via frequent alarms with individual warning systems [35]. While AI-enabled ECG [36] and CXR [37] support risk prediction, an integrated and precise clinical decision support system may be a better secondary triage tool in EDs, as clinicians often override medical alerts [38]. The mortality analysis shows a high correlation between physicians' expectations and our dynamic triage scale, indicating its high consistency and acceptability in clinical practice. The number of people in dynamic triage level 3 is comparable to the original triage scale levels 3/4/5. However, the 7-day mortality rate is notably lower in our dynamic triage level 3 (0.1%) than in the original triage levels 3/4/5 (0.4%), suggesting that our AI-based triage system could enhance efficiency in the ED. Our dynamic triage system has been designed to include original triage data along with the results from CXRs and ECGs when they are available. Furthermore, the system is discretionary for clinicians, allowing them to arrange ECG or CXR tests as they deem fit.

Certain limitations of this study should be mentioned. Firstly, this study only retrospectively validated established DLMs and proposed an improved dynamic risk tool. Clinical benefits should be confirmed through prospective trials.

Secondly, ECG/CXR examinations were not restricted by time, with some patients receiving these tests more than two hours after ED admission. However, since most patients were triaged before complete data was available, this AI dynamic triage tool is only intended as decision support for secondary triage rather than to replace clinical judgment. Thirdly, the black box limitation of DLM may make it challenging for physicians to differentiate high-risk from low-risk patients. Nevertheless, physicians can reevaluate patients and offer high-intensity care to lower mortality risk [3]. Finally, our study, conducted in a tertiary medical center with rare patient transfers and untracked outcomes post-discharge, affects the generalizability. However, the significance of our findings remains. Future research should address these gaps for broader applicability.

This study developed an AI-enabled dynamic ED triage scale to objectively and accurately stratify patient risk, benefiting asymptomatic urgent patients initially triaged at a non-urgent level. Using an AI-assisted ECG recommendation system to expedite ECG acquisition and prediction input improves the efficiency of dynamic triage [39]. These features support the implementation of the dynamic triage scale and enhance the quality of care in fast-paced EDs. Future studies should include more medical examinations in the dynamic triage model to improve its predictability and the quality of care in the ED.

Supplementary Information The online version contains supplementary material available at https://doi.org/10.1007/s10916-023-01980-x.

Author contribution All authors participated in designing the study, generating hypotheses, interpreting the data, and critically reviewing the paper. YHJC and SJC wrote the first draft, and CSL, WHF, CCL, and CHW contributed substantially to writing subsequent versions. YHJC designed and conducted statistical analyses with support from CL and DJT. All authors had full access to all the data in the study and accepted responsibility for the decision to submit for publication. YHJC and SJC verified all the data used in this study. The corresponding author (SJC) attests that all listed authors meet authorship criteria and that no others meeting the criteria have been omitted.

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Data availability statement The data analyzed in this study is not publicly available due to privacy and security concerns. The data may be shared with a third party upon execution of data sharing agreement for reasonable requests, such requests should be addressed to J.Y.H.C. (e-mail: jamiechen@mail.ndmctsgh.edu.tw) or S.J.C.

Declarations

Ethics approval The Tri-Service General Hospital, Taipei, Taiwan, conducted the ethical review of this study (IRB No. C202105049). The institutional review board agreed to waive individual consent since the data were collected retrospectively and analyzed on the intranet.

Conflict of interest The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript; or in the decision to publish the results.

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