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Construction and evaluation of a triage assessment model for patients with acute non-traumatic chest pain: mixed retrospective and prospective observational study

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Abstract

Background Acute non-traumatic chest pain is one of the common complaints in the emergency department and is closely associated with fatal disease. Triage assessment urgently requires the use of simple, rapid tools to screen patients with chest pain for high-risk condition to improve patient outcomes.

Methods After data preprocessing and feature selection, univariate and multiple logistic regression analyses were performed to identify potential predictors associated with acute non-traumatic chest pain. A nomogram was built based on the predictors, and an internal evaluation was performed using bootstrap resampling methods. The model was also externally validated in this center. Furthermore, the model results were risk-stratified using the decision tree analysis to explore the corresponding triage level. Subsequently, we developed an online visualization tool based on the model to assess the risk of high risk in patients with chest pain.

Results Multiple logistic regression analysis showed that age, smoking, coronary heart disease, hypertension, diabetes, hyperlipidemia, pain site, concomitant symptoms, and electrocardiograph, all of which are independent predictors of high-risk chest pain patients. The AUC of our model in the development and validation groups was 0.919 (95%CI: 0.891 ~ 0.974) and 0.904 (95%CI: 0.855 ~ 0.952). Moreover, our model demonstrated better outcomes in terms of accuracy/sensitivity in both cohorts (81.9%/85.2% and 94.8%/78.5%). The calibration curve shows a high degree of agreement between the predicted and actual probabilities. Decision curve analysis clarified that our model had higher net gains across the entire range of clinical thresholds. Afterward, we developed an online tool, which is used in the triage link to facilitate nurses to screen people with high-risk chest pain.

Conclusion We proposed an accurate model to predict the high-risk populations with chest pain, based on which a simple and rapid online tool was developed and provided substantial support for its application as a decision-making tool for the emergency department.

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Keywords Chest pain, Triage, Risk prediction model, Risk stratification

Introduction

Chest pain is one of the most frequent causes of emergency department (ED) consultation worldwide and the prevalence of acute non-traumatic chest pain in the general population is 20%~40% [1]. It represents approximately 6 to 9 million visits per year in the USA [2, 3]. It is closely associated with acute coronary syndrome, acute aortic syndrome, acute pulmonary embolism, and others [4]. Therefore, early assessment of patients with chest pain can significantly reduce mortality rates and improve patient outcomes.

The first step toward better chest pain care in the ED is to rapidly recognize high-risk conditions in patients and triage to centers capable of delivering the appropriate treatment. In addition, effective evaluation is important to accurately triage patients with chest pain. However, the classification of chest pain in the existing triage guidelines lacks comprehensive quantitative indicators to guide the classification, and triage nurses need to evaluate the patient's condition based on clinical experience [5]. Because chest pain is often associated with critical illness, triage nurses often grade them to a higher level, which can easily lead to patients with mild conditions occupying emergency resources, resulting in a waste of resources [6].

Previous studies have consistently demonstrated the superiority of risk-scoring systems over clinical judgment in risk prediction [7]. The risk score is a powerful tool to improve the accuracy of assessment. Based on this, some medical teams have developed scores such as HEART, TIMI, GRACE, and other scores for the evaluation of patients with chest pain, which have a good predictability of high-risk risk, mainly to evaluate the prognosis and discharge of patients in the ward or rescue room [8]. However, these scores are rarely used in triage assessment, the possible reason is the current clinical prediction models suitable for chest pain assessment mostly cover biomarker detection, which makes it difficult to meet the assessment time limit of triage [9]. Although some researchers have developed EDACS for the triage environment, which has a great reference ability for chest pain evaluation, the scoring rules are complex, and the risk stratification is not linked with the triage rank [10]. Early evaluation and appropriate triage of patients with chest pain remain challenging for ED nurses. These challenges affect nurses in providing accurate and timely triage responses to patients, sometimes leading to sudden events such as cardiac arrest [11].

A chest pain assessment tool that can be applied to the triage process is an important channel to help standardize effective triage, considering that China has a large population base, the assessment tool should align with the characteristics of simple use and intuitive results. Therefore, we aim to develop and validate a nomogram of triage assessment based on clinical risk factors in patients with chest pain. Combined with the key clinical risk factors and chest pain characteristics, the figure realizes the individualized prediction of patients, which is conducive to assisting triage nurses to achieve accurate classification, optimizing the triage process of chest pain, and rationally allocating emergency resources.

Methods

Design and setting

This study is a mixed retrospective and prospective observational study performed in the Fujian Provincial Emergency Center (ED of Fujian Provincial Hospital). By using the National Emergency Triage Guidelines of China, all patients presenting to the ED are initially triaged by nurses. The Triage Guidelines classify patients into 4 levels [12], the higher the level, the sicker the patient. Two independent datasets were used in this study. We collected data of clinical data related to chest pain through an electronic medical record system from January 2020 to December 2021 for all consecutive adult patients who presented with chest pain in the Fujian Provincial Hospital, as a development cohort for retrospective analysis. A prospective observational study was conducted in the independent validation cohort, including patients with chest pain at the Fujian Provincial Hospital from March 2022 to July 2022.

Study participants

Inclusion criteria: Age ≥ 18 years; "Chest discomfort" is the main complaint of patients; The onset time was within 24 h; Patients who are not the result of trauma.

Exclusion criteria: Patients with cardiac arrest and consciousness; Doctors diagnose patients with serious diseases such as stroke, malignancy, systemic inflammatory response syndrome, and organ failure; Group chest pain events due to a public emergency; The medical records are incomplete. The patient refused to sign the informed consent form or request for withdrawal during the second phase.

Table 1 Clinical and demographic data for the development cohort and validation cohort

Features	Development cohort		Statistics	*P*	Validation cohort		Statistics	*P*
	Non-high risk (*n* = 270)	High risk (*n* = 135)			Non-high risk (*n* = 86)	High risk (*n* = 56)		
Age, y	59.93 ± 15.28	64.64 ± 11.91	-3.142	0.002	62.20 ± 16.94	69.98 ± 13.04	-2.921	0.004
Gender			2.314	0.163			3.060	0.107
Female	66(24.4)	24(17.8)			26(51.0)	25(65.9)		
Male	204(75.6)	111(82.2)			60(49.0)	31(34.1)		
Smoking	90(33.3)	78(57.8)	22.154	< 0.001	17(19.8)	13(23.2)	0.242	0.676
Obesity	18(6.7)	8(5.9)	0.082	0.833	7(8.1)	6(10.7)	0.270	0.767
Hypertension	155(57.4)	98(72.6)	8.852	0.003	42(48.8)	41(73.2)	8.299	0.004
Diabetes	67(24.8)	58(43.0)	13.892	0.003	12(14.0)	28(50.0)	21.779	< 0.001
Hyperlipemia	65(24.1)	54(40.0)	11.001	0.001	10(11.6)	21(37.5)	13.303	< 0.001
Stroke	19(7.0)	16(11.9)	2.643	0.132	5(5.8)	6(10.7)	1.14	0.130
Myocardial infarction	22(8.1)	15(11.1)	0.952	0.362	3(3.5)	0(0)	1.996	0.278
Coronary heart disease	73(27.0)	60(44.4)	12.365	0.001	23(26.7)	35(62.5)	17.946	< 0.001
Family history of coronary heart disease	5(1.9)	4(3.0)	0.511	0.724	1(1.2)	0(100)	0.656	1.000
Peripheral vascular disease	28(10.4)	24(17.8)	4.413	0.041	9(10.5)	17(30.4)	8.972	0.004
Chronic renal disease	5(1.9)	1(0.7)	0.761	0.668	2(2.3)	3(5.4)	-	0.383
Heart failure[a]	17(6.3)	19(14.1)	6.723	0.015	3(3.5)	2(3.6)	-	1.000
External stimulation	39(14.4)	16(11.9)	0.515	0.540	13(15.1)	7(12.5)	0.192	0.806
Site of chest pain[a]			30.543	< 0.001			12.349	0.015
Front	117(43.3)	29(21.5)			47(54.7)	19(33.9)		
Left	12(4.4)	19(14.1)			4(4.7)	0(0)		
Praecordia	72(26.7)	49(36.3)			24(27.9)	26(46.4)		
Right	13(4.8)	10(7.4)			2(2.3)	0(0)		
Thoracnal	42(15.6)	26(19.3)			8(9.3)	8(14.3)		
Under the sword	14(5.2)	2(1.5)			1(1.2)	3(5.4)		
Type of chest pain[a]			10.173	0.101			6.818	0.320
Choking sensation	72(26.7)	22(16.3)			20(23.3)	9(16.1)		
Stuffy pain	144(53.3)	83(61.5)			49(57.0)	27(48.2)		
Stabbing	8(3.0)	3(2.2)			4(4.7)	7(12.5)		
Rip feeling	7(2.6)	2(1.5)			3(3.5)	1(1.8)		
Press	25(9.3)	21(15.6)			6(7.0)	8(14.3)		
Angina	12(4.4)	3(2.2)			3(3.5)	3(5.4)		
Knife cutting	2(0.7)	1(0.7)			1(1.2)	1(1.8)		
Simultaneous phenomenon[a]			58.600	< 0.001			36.71	< 0.001
No	127(47.0)	21(15.6)			45(52.3)	10(17.9)		
Only atypical symptoms	85(31.5)	40(29.6)			31(36.0)	14(25.0)		
Radiating pain	34(12.6)	32(23.7)			5(5.8)	9(16.1)		
Both have	24(8.9)	42(31.1)			5(5.8)	23(41.1)		

Table 1 (continued)

Features	Development cohort		Statistics	*P*	Validation cohort		Statistics	*P*
	Non-high risk (*n* = 270)	High risk (*n* = 135)			Non-high risk (*n* = 86)	High risk (*n* = 56)		
Temperature, °C	36.56 ± 0.39	36.47 ± 0.348	2.087	0.038	36.589 ± 0.27	36.49 ± 0.33	2.006	0.047
Heart rate, beats/min	84.23 ± 25.40	81.55 ± 20.80	1.060	0.290	84.814 ± 14.7	85.339 ± 16.01	-0.201	0.841
Respiratory rate, beats/min	19.55 ± 1.49	19.44 ± 1.81	0.679	0.497	19.465 ± 1.93	19.267 ± 2.01	0.585	0.560
Systolic pressure, mmHg	140.75 ± 27.95	139.27 ± 27.87	0.503	0.615	130.314 ± 26.7	142.517 ± 25.95	-0.269	0.008
Oxygen saturation, %	97.67 ± 2.36	97.01 ± 2.37	2.679	0.008	97.291 ± 1.55	97.089 ± 1.32	0.798	0.426
Conscious state[a]			-	0.603			-	0.394
Alert	268(99.3)	133(98.5)			86(100)	55(98.2)		
V / P / U	2(0.7)	2(0.5)			0(0)	1(0.8)		
Numerical rating scale			9.115	0.010			22.295	< 0.001
0〜3	124(45.9)	45(33.3)			40(46.5)	10(17.9)		
4〜7	134(49.6)	76(56.3)			44(51.2)	33(58.9)		
8〜10	12(4.4)	14(10.4)			2(2.3)	13(23.2)		
Electrocardiogram findings			37.261	< 0.001			23.017	< 0.001
Normal	123(45.6)	22(16.3)			30(34.9)	7(12.5)		
Nonspecific abnormalities	66(24.4)	38(28.1)			35(40.7)	13(23.2)		
Ischemia	81(30.0)	75(55.6)			21(24.4)	36(64.3)		
Reperfusion therapy	45(16.7)	21(15.6)	0.081	0.887	9(10.5)	9(16.1)	0.963	0.439
Self-medication	69(25.6)	35(25.9)	0.006	1.000	29(33.7)	12(21.4)	2.495	0.132

[a]Fisher's test

Potential predictive variables

We analyzed case data and previous literature reviews, combined with information routinely provided during the ED triage process, and we included a total of 28 potential predictor variables. The information included: (1) Demographic data: age, gender; (2) Risk factors: history of smoking in any form, coronary heart disease, diabetes, hypertension, hyperlipidemia, obesity, etc.; (3) ED manifestations: nature, location, vital signs, mental status and numerical rating scale at triage; (4) Initial evaluation: electrocardiogram findings (including normal, non-specific abnormalities, ischemic changes); (5) history of drug therapy: self-medication nitroglycerin and reperfusion therapy for chest pain. To ensure the quality of the data, we manually extracted the clinical information and results of all patients from electronic medical records (EHR). One screened participants from EHR based on inclusion and exclusion criteria, and the other was blinded to clinical outcomes, having all available ED records reviewed for a complete assessment. After data collection, raw data were preprocessed and those with missing data and outliers were excluded from the study.

Endpoint

The primary endpoint was the occurrence of high risk in chest pain patients (HEART PATHWAY ≥ 7). In this study, the chest pain risk score-HEART PATHWAY proposed by the Guideline for the Evaluation and Diagnosis of Chest Pain [13] was used as an evaluation reference for high-risk chest pain. Patients with chest pain have a wide spectrum of symptoms, and clinicians evaluate patients primarily based on chest pain risk score results before undergoing imaging tests. Therefore, to improve the coherence between triage classification and physician assessment, we used HEART PATHWAY scoring criteria to classify high-risk patients, so that the nomogram developed in this study can better classify patients with chest pain and correspond to the prioritization of patient visits.

Model construction and statistical analysis

Firstly, descriptive statistical analyses were performed using absolute and relative frequencies of categorical variables and arithmetic mean and standard deviation (SD) of continuous variables. Subsequently, univariate analysis of 28 potential predictors was performed using Pearson's chi-square test and Student's t-test. We selected the predictor variables that showed a clear effect on the outcome. Among these variables, we performed a multivariate logistic regression analysis, constructed the model, and drew the nomogram based on the regression results. A P value < 0.05 was regarded as statistically significant.

Model evaluation and risk stratification

The receiver operating characteristic (ROC) curve was used to evaluate the model's predictive performance, and the calibration curve and decision curve analysis (DCA) were used to evaluate the model's predictive consistency and clinical utility. The above model evaluation methods are all using Bootstrap Aggregating, which can help us avoid the risk of overfitting while improving the stability and accuracy of the model. After constructing the model, decision tree analysis was used to make stratification based on the nomogram scores of all samples, to compare the correlation between risk classification and triage level. The nomogram, calibration curve, and DCA were performed by the R4.0.2 Other statistical analyses were conducted using IBM SPSS 23.0. R4.0.2 for Online visualization tool development.

Result

Baseline characteristic and predictor selection

The development cohort included 827 patients with chest pain in the ED of the chest pain database. After the application of exclusion criteria, 405 patients were retained, of whom 135 (33.3%) were at high risk of chest pain. A total of 142 patients with chest pain were included in the validation cohort, of which 39.4% were high-risk patients. We extracted 28 potential predictors for each patient and compared the baseline characteristics of patients in the high-risk chest pain group with those without high-risk chest (Table 1). Results of the univariate analysis are shown in Table 1. Predictor variables associated with high-risk (P-value < 0.05) were selected for multivariate analysis: age, smoking, hypertension, diabetes, hyperlipidemia, coronary heart disease, peripheral vascular disease, heart failure, pain position, simultaneous phenomenon, temperature, oxygen saturation, numerical rating scale, Electrocardiogram findings. We made a multi-collinear diagnosis of the selected variables, the results show that the variance inflation factor of each variable is < 5.

Development of a triage assessment model for patients with chest pain

Multivariate logistic regression analysis identified independent predictors for high-risk populations (Table 2). Based on these predictors, we developed the nomogram, as illustrated in Fig. 1.

Performance of the model

ROC analysis of predictors of high-risk chest pain in the development and validation cohorts showed the area under the curve (AUC) (95% CI) results of 0.919 (0.891–0.947) and 0.904 (0.855–0.952), respectively, the difference was not significant. (DeLong test, $P = 0.586$). Moreover, the results of this model confirmed its good

Table 2 Multivariate logistic regression analysis

Risk factors	β	SE	Walsχ²	*P*	OR (95%CI)
Age	0.074	0.014	27.106	<0.001	1.077(1.047–1.107)
Smoking	1.550	0.339	20.925	<0.001	4.713(2.426–9.158)
Hypertension	0.850	0.362	5.507	0.019	2.339(1.150–4.755)
Diabetes	1.110	0.342	10.525	<0.001	3.035(1.552–5.935)
Hyperlipemia	1.210	0.345	12.302	<0.001	3.355(1.706–6.597)
Coronary heart disease	1.380	0.352	15.358	<0.001	3.973(1.993–7.921)
Pain position					
Front	0.320	0.916	0.122	0.727	1.377(0.229–8.292)
Left	2.557	1.010	2.53	0.011	12.903(1.782–93.425)
Praecordia	0.713	0.916	0.605	0.437	2.039(0.339–12.279)
Right	0.859	1.079	0.634	0.426	2.361(0.285–19.566)
Thoracnal	1.032	0.934	1.222	0.269	2.807(0.450-17.504)
Under the sword					
Simultaneous phenomenon					
No					
Only atypical symptoms	2.324	0.438	28.100	<0.001	10.213(4.325–24.114)
Radiating pain	2.680	0.513	27.241	<0.001	14.583(5.331–39.892)
Both have	3.742	0.507	54.367	<0.001	42.166(15.596-113.998)
Electrocardiogram findings					
Normal					
Nonspecific abnormalities	1.632	0.425	1.632	<0.001	5.116(2.224–11.767)
Ischemia	3.492	0.463	3.492	<0.001	32.837(13.263–81.299)

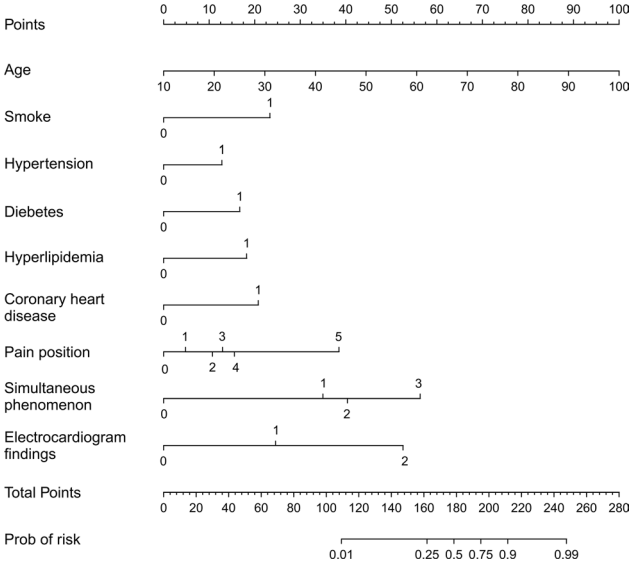

Fig. 1 Nomogram of the triage risk assessment of patients with chest pain

discriminatory ability in accuracy, sensitivity, specificity, PPV, NPV, and F1, as shown in Fig. 2A. To further evaluate the calibration performance of the nomogram model, we generated a calibration map of the prediction model in both the development and validation cohorts (Fig. 2B), and both curves showed preferable calibration performance of the model. The decision curve analysis showed that the use of this model in both cohorts has higher clinical utility than strategies in which all patients neither intervened nor all patients intervened (Fig. 2C).

Risk classification

By predicting individual patient risk scores based on the nomogram in the development cohort, we applied the decision tree analysis to produce a tree structure and developed a risk classification system for patients with chest pain. Based on the stratified results combined with triage data, we found that low and medium risk could be triage level 3 and high risk could triage level 2 (Fig. 3).

Constructure online tool

Based on the model performance, we developed an online visualization tool to assist triage nurses in evaluating high-risk patients with chest pain (https://leixiantu.shinyapps.io/DynNomapp_CP_triage/). The triage nurse can input the extracted data into the tool, and according to the evaluation results, triage them to a suitable area to wait for treatment. This alerts physicians and makes them respond at the appropriate time to reduce the risk of waiting adverse events, which can translate into an acceptable number needed to treat (NNT) to prevent a major cardiovascular event, especially in high-risk crowds.

Discussion

The prevalence of high-risk chest pain in patients with chest pain

Patients with chest pain are at risk of major complications, including acute coronary syndrome, acute aortic syndrome, acute pulmonary embolism, and even death. In our development and validation cohorts, the incidence of high-risk chest pain was 33.3% and 39.4%, respectively. Stepinska J et al. [14] pointed out that the incidence of high-risk chest pain in patients with acute non-traumatic chest pain was between 12.2% ~ 59.1%. Harskamp R E et al. [15] systematically analyzed the characteristics of patients with chest pain and pointed out that the incidence of high-risk conditions such as ACS was about 22.0% ~ 47.8%. According to the statistics of the China Chest Pain Center in 2021 [16], more than 2.42 million patients with acute chest pain were treated, including more than 520,000 patients with high-risk chest pain such as acute myocardial infarction. In addition, high-risk chest pain is characterized by acute onset, severe

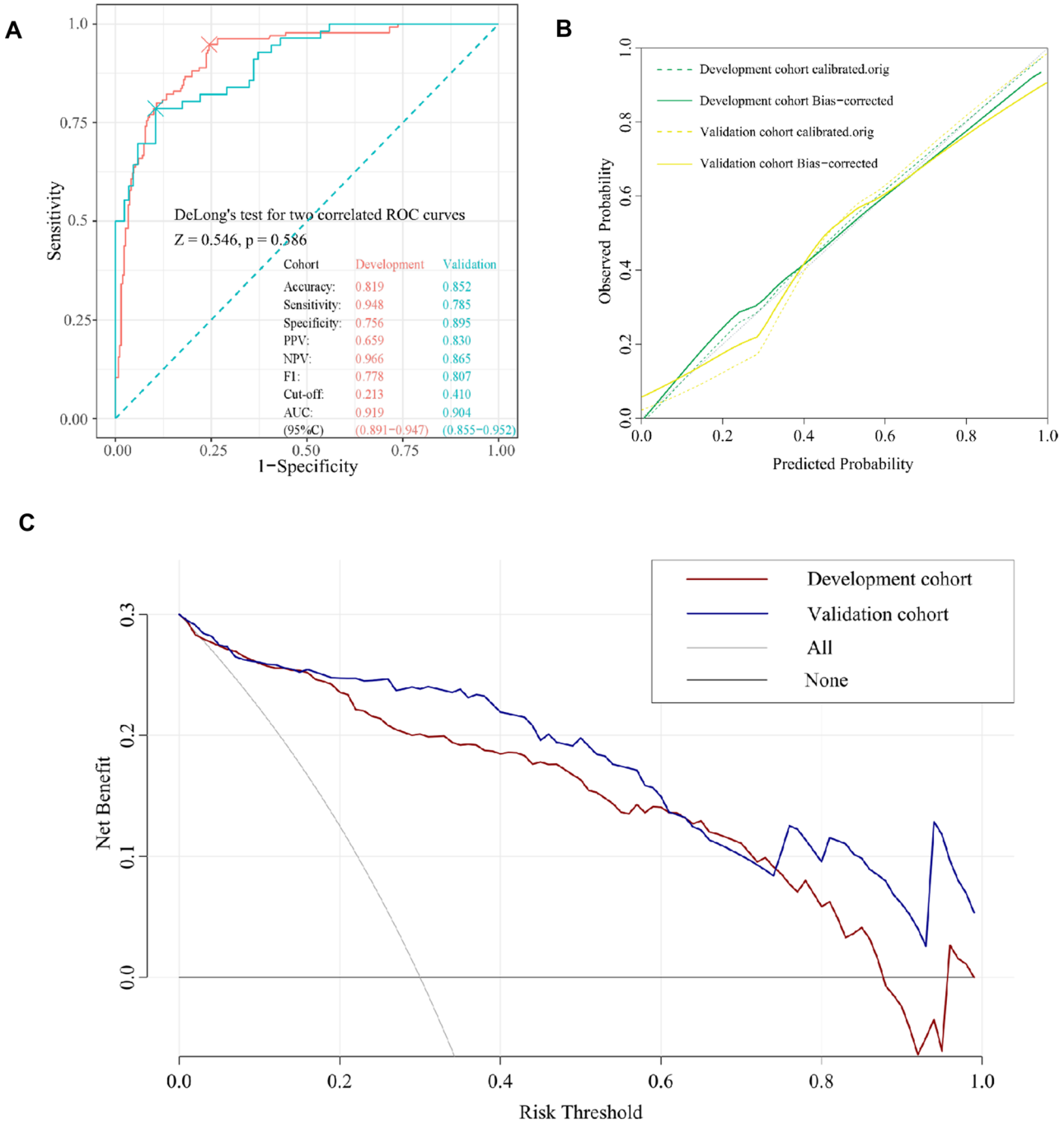

Fig. 2 ROC analysis (**A**), Calibration plot (**B**), and decision curve analysis (**C**) for the development cohort and validation cohort

disease, and a high mortality rate [4]. Early identification of patients with high-risk chest pain and targeted chest pain management appears to be the best way to manage patients with chest pain until further progress in therapeutic interventions will reduce adverse cardiac events or improve clinical outcomes in crowds.

Influencing factors of high-risk chest pain patients

Demographic data

Chest pain is one of the most common complaints in the ED, and the severity of the disease can be seen in different age groups but is more common in the elderly [17]. Age in this study was an independent risk factor for emergency untraumatic chest pain triage assessment ($P<0.05$), the higher the age, the greater risk. Age is an important evaluation factor for cardiovascular disease,

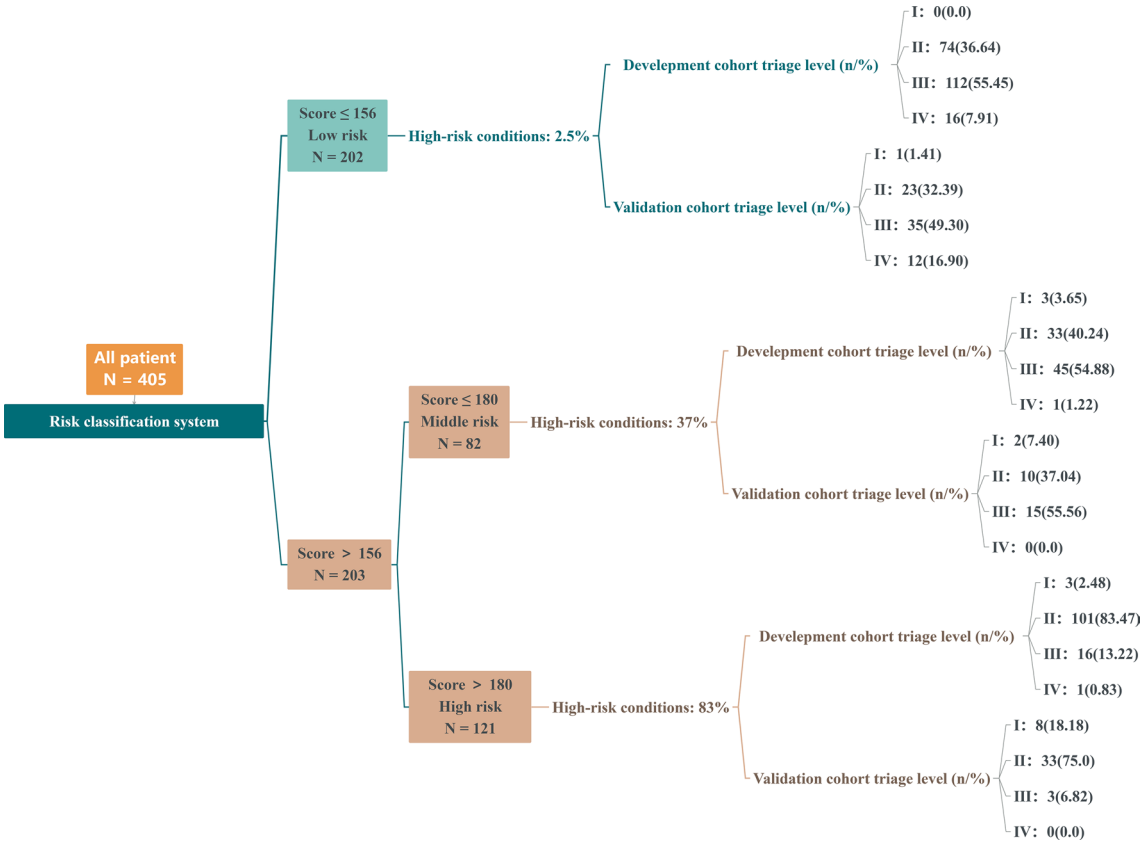

Fig. 3 Risk stratification in the model

while untraumatic chest pain is mostly caused by cardiovascular disease, and the incidence of chest pain also increases with age [18]. This is similar to tools such as the HEART score, GRACE score, etc., where age is one of the important evaluation indicators [13, 19].

Risk factors

Tobacco harm is one of the most serious public health problems in the world today. Tobacco kills more than 8 million people around the world every year, and in China, more than 1 million deaths result from smoking-related diseases every year [20]. Studies indicate that smoking is a strong and independent predisposing factor for chest pain [21]. Our findings showed that smokers with chest pain had a higher risk of disease ($P<0.05$). Patients with chest pain with a history of coronary heart disease (CHD) often have coronary artery lumen with stenosis or obstruction. They are prone to internal and external stimulation for vasospasm causing acute chest pain [22]. We found that 44.4% of patients in the high-risk group had a previous history of CHD, and multivariate logistic regression analysis showed they were positively associated with high-risk chest pain ($P<0.05$). Hypertension, diabetes, and hyperlipidemia are well-established synergistic risk factors for the risk assessment of chest pain. Chunli S et al. [23] pointed out that patients with hypertension, diabetes, and hyperlipidemia have a high lifetime risk of cardiovascular disease, which can cause a sharp decrease or even interruption of the blood supply to the large arteries when stimulated by external factors, resulting in acute necrosis of the local myocardium and ischemic chest pain. The results of Nonnenmacher C L et al. [24] and Junhua G et al. [25] showed that previous hypertension, diabetes, and hyperlipidemia were independent risk factors for risk assessment in patients with chest pain (OR = 2.34, 3.04, 3.36). Therefore, triage nurses should pay attention to the history of patients with chest pain and timely screen patients for high-risk factors.

ED manifestations

Chest pain site is one of the main contents of inquiry by clinical triage workers. The pain site can indicate the general location of the lesion site for the triage nurse, and provide some basis for the triage nurse to judge the risk of patients with chest pain. Multivariate logistic regression analysis showed that the site of pain was an independent risk factor for the triage assessment of acute non-traumatic chest pain ($P<0.05$), which was similar to the study of Kristoffer L M et al. [26]. We found that the pain site had a greater risk of chest pain in the left chest.

High-risk patients with chest pain are mainly caused by cardiac diseases, most of which are relatively fixed and limited. Concomitant symptoms are an important part of chest pain triage assessment, and our study showed that patients with chest pain (e.g. nausea, vomiting, radiation pain, etc.) had a higher risk of disease ($P<0.05$). One possible explanation is that after the occurrence of high-risk chest pain such as acute coronary syndrome, because the myocardium borders the gastrointestinal tract, it can stimulate the gastrointestinal tract reaction, resulting in nausea, vomiting, and other symptoms [27]. In addition, due to the large distribution of the thoracic nerve, the lesion site can stimulate local pain and can be extended to the affected sensory nerve area, while radiation pain occurs [14]. Previous studies have confirmed that the accompanying symptoms in patients with chest pain often indicate the potential high risk in patients with chest pain [28].

Initial evaluation

An electrocardiogram (ECG) is an advantageous auxiliary examination for the triage evaluation of patients with chest pain [29]. It has the characteristics of fast, simple, painless, and non-invasive, and is an important tool to realize the early and rapid identification of cardiac chest pain. In our study, the discrimination of ECG was interpreted by AI and professionally trained emergency specialist nurses or physicians, which can ensure the accuracy of ECG [30–32]. The 2021 AHA Guideline [13] recommends that all patients with chest pain should undergo an ECG to detect cardiac chest pain. A positive correlation with high-risk disease risk ($P<0.05$). This may be because high-risk patients with chest pain are mostly cardiac chest pain, and an ischemic ECG such as typical ST segment elevation is one of the important diagnostic indicators of acute coronary syndrome [33]. Although the ECG in this study was definite, not all of the high-risk chest pain patients had characteristic ECG findings. Zha K L et al. [34] and Gao Xiangyu [35] found that some patients with high-risk chest pain could present a normal ECG, which may be related to the failure of coronary occlusion recanalization ECG or the relatively insensitive surface ECG at the lesion site. Therefore, in addition to the attention of acute non-traumatic chest pain patients, the patient's history assessment and other accompanying symptoms cannot be ignored.

Establishment and application of the triage evaluation model

Since early and timely intervention will improve patient outcomes, various teams have sought to develop tools to identify patients with high-risk chest pain. Most score-based methods include biomarker assays, such as HEART, ADAPT, 2020 ESC/hs-cTn, etc [33, 36–38]., which are sensitive to 97%~100% for acute myocardial infarction. However, the need for troponin development, is elements that seem to deter the use of them in triage. Zaboli A, et al. indicated that EDACS is accurate and predictive for the risk of acute cardiovascular events in the context of a triage assessment that is rapid and stressful [10]. While, The EDACS assessment rules cover both addition and subtraction, which can interfere with correct calculations. And, it is unable to support triage operations on its own because it is limited in lack of specificity indicators, such as the ECG. To improve the specificity of EDACS, the investigators combined EDACS with accelerated diagnostic pathway to facilitate the discharge of low-risk patients, but did not propose a risk reference for Triage priority [39]. Moreover, these studies [33, 36–39] focused more on the potential to use different data algorithms to improve model performance, and none of these efforts resulted in a visual, simple, and rapid tool for clinical use. Additionally, most of these tools are based on cohorts from other countries and ethnicities, which may affect the suitability of these tools for Asian populations.

We developed a nomogram model with high discriminative, calibration, and clinical utility based on datasets collected by the Fujian Provincial Emergency Center, and performed independent external validation. In addition, a rapid and simple online tool has been developed to predict the probability of high-risk situations in patients with chest pain, reducing the time-consuming assessment and unnecessary emergency resource consumption. We tried to connect the constructed prediction model with the emergency triage classification, use the decision tree algorithm to divide the risk scores and assist the triage nurses in the triage decision of patients, with low and medium risk reference level III and high-risk reference level II. Providing hierarchical reference through the model is conducive to making timely triage decisions and providing preventive intervention measures, effectively reducing the incidence of waiting for adverse events, improving the risk perception and risk management ability of triage nurses, and protecting patient safety.

Clinical utility of the model

Accurate and reliable models and minimal prediction error will help Clinical worker to prioritize patients correctly [40]. In our study, the validation cohort showed reduced sensitivity of the model compared to the development cohort results. Since the development cohort is analyzed using self-modeling data, the predictive performance is generally superior to external validation originating from other centers [41]. This may be related to the fact that we are applying the model to a new dataset, but through the analysis of the independently validation cohort, we truly reflected that the model still has a good prediction effect in the new dataset. Besides, we still

necessary to further expand the diversity of the validation sample to improve the generalization ability of the model. Models with more variables and continuous predictor variables often have the potential to perform better and provide more accurate predictions [42]. Our results have important implications. Our model complexity and usage are low (constructure online tool), and its discriminative ability is marked with heart pathway, which shows better calibration. In general, it can be inferred that our model is more cost-effective and can easily be applied as a great alternative to the HEART pathway to detect patients at high risk of chest pain. However, to guarantee the interpretation of the model, triage professionals need to be trained. In the future, the promotion and application of the tool can strengthen the risk management ability of medical staff in chest pain, improve the prevention and control mechanism of chest pain risk, and continuously promote the construction and management of chest pain centers.

Limitation

There were several important limitations in our study. First, our study is a single-center study. Although external validation uses session validation, we suggest that further validation studies with large multicenter samples are needed before ensuring routine clinical use. Secondly, the research and developed online tools also need to conduct a user-centered evaluation, and further adjust and optimize the tools from the perspective of use proficiency and interface aesthetics. This is convenient for nurses can effectively navigate and use the tool in a high-pressure environment. In the future, online tools can be embedded into the triage information platform and chest pain management center to realize regional first-aid information sharing and promote the connection between pre-hospital and in-hospital treatment. Finally, the corresponding grading results after risk stratification using the decision tree algorithm are mainly concentrated in two levels. It is necessary to further explore the correspondence between risk stratification and grading results by expanding the sample size and refining the triage criteria for chest pain.

Conclusion

We developed a chest pain assessment model combining key clinical risk factors and chest pain characteristics, with the best performance by internal and external validation that can be used for screening high-risk chest pain patients. Based on this model, online tools were developed to assist triage nurses in chest pain triage, enrich the early screening methods of chest pain, provide timely and targeted individual intervention for patients, improve the utilization rate of emergency medical resources, and promote patients' health.

Supplementary Information

The online version contains supplementary material available at https://doi.org/10.1186/s12873-025-01176-1 .

Supplementary Material 1

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Author contributions
Conception and design: R.Z., G.J. Collection and assembly of data: Y.H., Y.H., J.Z. Data analysis and interpretation: X.Z., S.W., Y.W. Manuscript writing: X.Z. All authors reviewed the manuscript.

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Data availability
All raw data generated or analyzed during this study are available from the corresponding author upon reasonable request.

Declarations

Ethics approval and consent to participate
The study was approved by the ethics committees of the Fujian Provincial Hospital. All participants were enrolled in the investigation using the principles of informed consent and confidentiality. All data are treated in confidence. Clinical trial registration number: ChiCTR2200061918.

Consent for publication
Not applicable.

Competing interests
The authors declare no competing interests.

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