

Development and Validation of a Concise Prediction Scoring System for Asian Lung Cancer Patients with EGFR Mutation Before Treatment

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Abstract

Purpose We aimed to determine the epidermal growth factor receptor (EGFR) genetic profile of lung cancer in Asians, and develop and validate a non-invasive prediction scoring system for EGFR mutation before treatment. **Methods** This was a single-center retrospective cohort study using data of patients with lung cancer who underwent EGFR detection ($n=1450$) from December 2014 to October 2020. Independent predictors were filtered using univariate and multivariate logistic regression analyses. According to the weight of each factor, a prediction scoring system for EGFR mutation was constructed. The model was internally validated using bootstrapping techniques and temporally validated using prospectively collected data ($n=210$) between November 2020 and June 2021. **Results** In 1450 patients with lung cancer, 723 single mutations and 51 compound mutations were observed in EGFR. Thirty-nine cases had two or more synchronous gene mutations. We developed a scoring system according to the independent clinical predictors and stratified patients into risk groups according to their scores: low-risk (score <4), moderate-risk (score 4-8), and high-risk (score >8) groups. The C-statistics of the scoring system model was 0.754 (95% CI 0.729-0.778). The factors in the validation group were introduced into the prediction model to test the predictive power of the model. The results showed that the C-statistics was 0.710 (95% CI 0.638-0.782). The Hosmer-Lemeshow goodness-of-fit showed that $\chi^2=6.733$, $P=0.566$. **Conclusions** The scoring system constructed in our study may be a non-invasive tool to initially predict the EGFR mutation status for those who are not available for gene detection in clinical practice.

Keywords

epidermal growth factor receptor, lung cancer, predictive model, scoring system

Abbreviations:

AFP, alpha fetoprotein; AIS, adenocarcinoma in situ; ARMS-PCR, amplification refractory mutation system-polymerase chain reaction; BRAF, B-Raf proto-oncogene, serine/threonine kinase; CA, carbohydrate antigen; CEA, carcinoembryonic antigen; CI, confidence interval; CK, cytokeratin; CT, computerized tomography; CTNNB1, catenin beta 1; EGFR, epidermal growth factor receptor; EML4, echinoderm microtubule-associated protein-like 4; ERBB2, erb-b2 receptor tyrosine kinase 2; ERBB4, erb-b2 receptor tyrosine kinase 4; FBXW7, F-box and WD repeat domain containing 7; FERR, ferritin; FGFR3, fibroblast growth factor receptor 3; GGO, ground-glass opacity; HRAS, HRas proto-oncogene; HRCT, high resolution computed tomography;

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KRAS, KRAS proto-oncogene; MET, mesenchymal to epithelial transition factor; NGS, next-generation sequencing; NSCLC, non-small cell lung cancer; NRAS, NRAS proto-oncogene; NSE, neuron-specific enolase; OR, odds ratio; PIK3CA, phosphatidylinositol-4, 5-bisphosphate 3-kinase catalytic subunit alpha; PTEN, phosphatase and tensin homolog; ROC, receiver operating characteristic curve; ROS1, c-ros oncogene 1; SCCA, squamous cell carcinoma antigen; CYFRA21-1, soluble fragment of cytokeratin 19; STK11, serine/threonine kinase 11; TKI, tyrosine kinase inhibitor; TP53, tumor protein p53; TRIPOD, transparent reporting of a multivariable prediction model for individual prognosis or diagnosis; TSC1, TSC complex subunit 1; TTF-1, thyroid transcription factor-1; UICC/AJCC, International Union Against Cancer and the American Joint Committee on Cancer.

Introduction

Lung cancer is the leading cause of cancer-related deaths worldwide, accounting for 22%–23% of all cancer-related deaths.¹ During recent years, with the rapid development of precision medicine and tumor molecular biology, targeted therapy has become an important treatment for lung cancer following the traditional approaches of surgery, radiotherapy, and chemotherapy. Considerably high positive response rate and safety have made individualized and refined treatment possible. Epidermal growth factor receptor (EGFR)-tyrosine kinase inhibitors (TKIs) such as gefitinib, osimertinib, and erlotinib have increased the overall survival of patients expressing EGFR.² EGFR mutation is the most common genetic mutation related to lung cancer, with a mutational frequency of approximately 46%–58% in China.^{3–5}

Currently, the sources of tumor material for gene detection include tumor tissue specimens, cytology specimens, and serum specimens. Paraffin-embedded tumor tissue specimens have conventionally been the main source and still account for most diagnostic samples in clinical practice. Cytology specimens have been shown to be an adequate alternative source when tissue samples are not available or contain insufficient amounts of tumor DNA, and their use has increased over recent years.⁶ Serum specimens, known as liquid biopsies, are not popular in clinical practice owing to the lack of standardized techniques, limited coverage of hotspot mutations, lack of sensitivity, and insufficient clinical validation.⁷ For patients with advanced lung cancer, biopsy specimens are the only available histological evidence. However, tumor heterogeneity is a major challenge, as gene information from local tumor tissue might not accurately reflect the whole genetic profile. In addition, these specimens may be difficult to obtain from some patients with advanced age, poor pulmonary function, or poor coagulation. Furthermore, in some remote areas in Asia, some patients cannot afford the cost of hospitalization, and primary hospitals lack gene detection technology. Thus, it is necessary to establish a non-invasive and convenient method to initially predict the EGFR mutation status and evaluate the clinical treatment efficacy.

To date, there have been various small-scale studies revealing the relationship between some clinicopathological characteristics and EGFR mutation.^{8,9} A few studies have also established the prediction scoring system for EGFR mutation but have low credibility because of the use of too few cases or having a lack of validation.¹⁰

In this study, we summarized the mutational status of EGFR mutation, subtype mutations and co-mutations in several cases, systematically identified the risk factors of EGFR mutation, and developed a prediction scoring system that is concise and readily adoptable at most institutions, aiding those who were unavailable for gene detection. Furthermore, we validated our model using prospectively collected data to examine its generalizability and reliability.

Methods

Data Collection and Definitions

This was a single-center retrospective cohort study. We performed the study in accordance with the transparent reporting of a multivariable prediction model for individual prognosis or diagnosis (TRIPOD) reporting checklist.¹¹ The development cohort (n = 1450) was retrospectively compiled from patients with lung cancer admitted to our institution between December 2014 to October 2020. Temporal validation samples (n = 210) were prospectively collected from the same institution as the development cohort but at a later time point, between November 2020 and June 2021. The criteria for inclusion were patients with pathologically diagnosed lung cancer who underwent EGFR detection in our institution. The exclusion criteria were patients 1) whose medical records could not be obtained and 2) who were treated with any therapy before EGFR detection. We have de-identified all patient details.

We collected clinicopathological data from the electronic medical records of patients, including sex, age, smoking status, smoking index, family history of malignant tumors, history of other malignant tumors, tumor location, computerized tomography (CT) imaging manifestation, gross type, TNM and clinical stage, serum tumor markers, including carcinoembryonic antigen (CEA), alpha fetoprotein (AFP), ferritin (FERR), carbohydrate antigen (CA) 125, carbohydrate antigen (CA) 15–3, carbohydrate antigen (CA) 19–9, squamous cell carcinoma antigen (SCCA), soluble fragment of cytokeratin 19 (CYFRA21-1), carbohydrate antigen (CA) 72–4, and neuron-specific enolase (NSE), histologic subtype, differentiation grade, mucus component, and some immunohistochemical results, including thyroid transcription factor-1 (TTF-1), napsin A, P63, P40, CK-7, and Ki67. The smoking index (Brinkman index) was defined as the number of cigarettes smoked per day multiplied by the number of smoking years. Tumors were staged according to the eighth edition of the

TNM staging classification of the International Union against Cancer and the American Joint Committee on Cancer (UICC/AJCC) for lung cancer.¹² Ground-glass opacity (GGO) is defined as hazy opacity on high resolution computed tomography (HRCT), through which pulmonary vessels or bronchial structures can be visualized.¹² The upper limit of each tumor marker was as follows: CEA, 5 ng/mL; AFP, 8.78 ng/mL; FERR, 130 ng/mL (male); FERR, 55 ng/mL (female); CA125, 35 U/mL; CA15-3, 31.3 U/mL; CA19-9, 37 U/mL; SCCA, 1.5 ng/mL; CYFRA 21-1, 3.3 ng/mL; CA72-4, 6.9 U/mL; and NSE 15.2 ng/mL. The above tumor markers were considered positive if their values were higher than the upper limit. Histologic subtypes were determined according to the diagnostic criteria of the 2015 WHO histological classification of lung cancer.¹³

EGFR Detection Methods

All tumor tissue samples were fixed in 10% neutral formalin solution and embedded in paraffin. We used the QIAamp DNA formalin-fixed paraffin-embedded (FFPE) tissue kit (Qiagen NV, Venlo, Netherlands) to extract genomic DNA and RNA from FFPE tissues, according to the manufacturer's instructions. The *EGFR* analysis results were obtained and analyzed by amplification refractory mutation system-polymerase chain reaction (ARMS-PCR) or using next-generation sequencing (NGS) method.

Development and Validation of the Scoring System

A scoring system was developed with (a) a β -coefficient obtained for each significant factor from the multivariate logistical regression model (b) each of the coefficient variables rounded off to whole integers and (c) the score of each variable set as its corresponding coefficient.¹⁴ The discriminatory ability of the model was evaluated

using receiver operating characteristic curve (ROC) analysis and the area under the ROC curve. Goodness-of-fit was assessed using Hosmer-Lemeshow test. The scoring system was stratified into the following three groups: low, moderate, and high risks.

The scoring system was validated in the internal and temporal validation cohorts by assessing model discrimination and calibration. The C-statistic was adopted for the quantification of discrimination, which is equal to the area under the ROC. Calibration was studied from graphical representations of the relationship between the observed outcome frequencies and the predicted probabilities (calibration curves). The internal validation involved bootstrapping techniques. Thousand bootstrap samples were drawn from the original data set with replacement. The model was temporally validated using prospectively collected data.

Statistical Analysis

All data were analyzed using R.4.0.5, SPSS 22.0 software (IBM Corp., Armonk, NY, USA) and Microsoft Excel (2019). Count data are expressed as the number of cases or rate (%), and the difference between groups was evaluated using the chi-square test or Fisher's exact test. Statistical significance was set at $P < 0.05$. The relationships between clinicopathological characteristics and gene mutations were analyzed using univariate and multivariate logistic regression analyses. Parameters were included in the multivariate analysis only when the P value was <0.05 in the univariate analysis.

Results

Study Population

A total of 1450 participants with lung cancer who underwent *EGFR* detection from December 2014 to October 2020 were

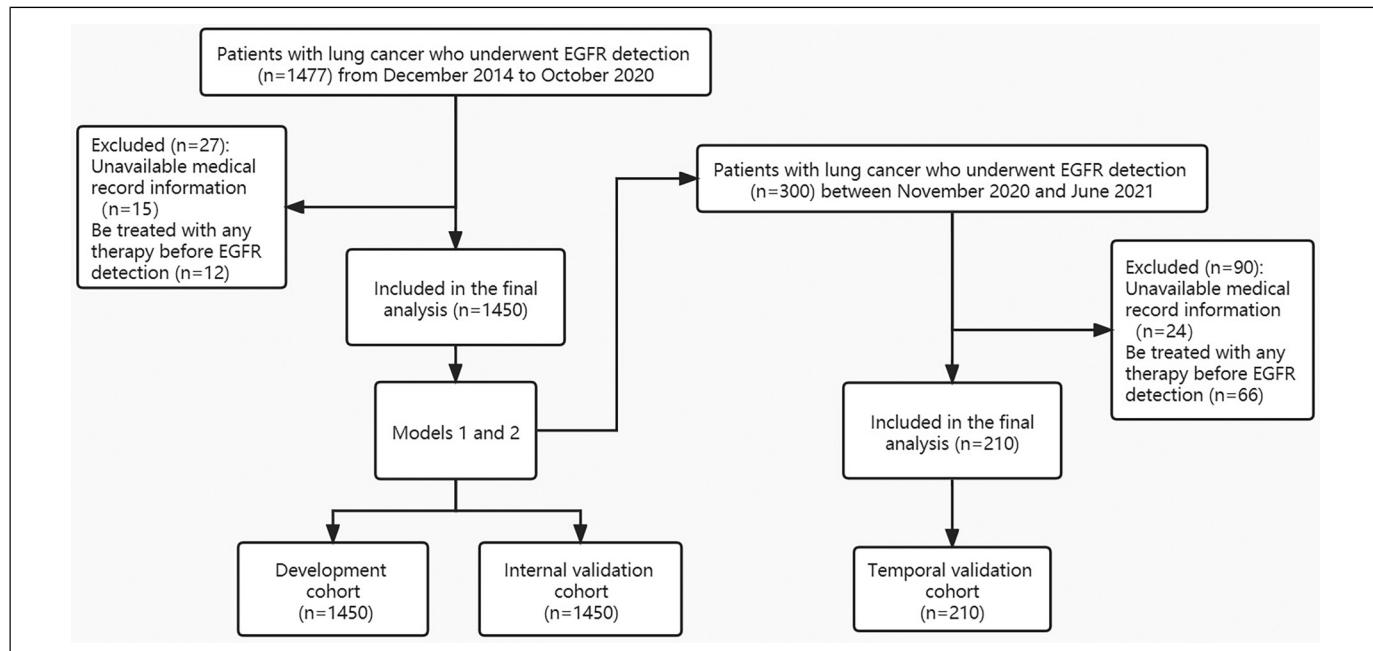


Figure 1. Flow diagram of patient selection for the development and temporal validation cohort.

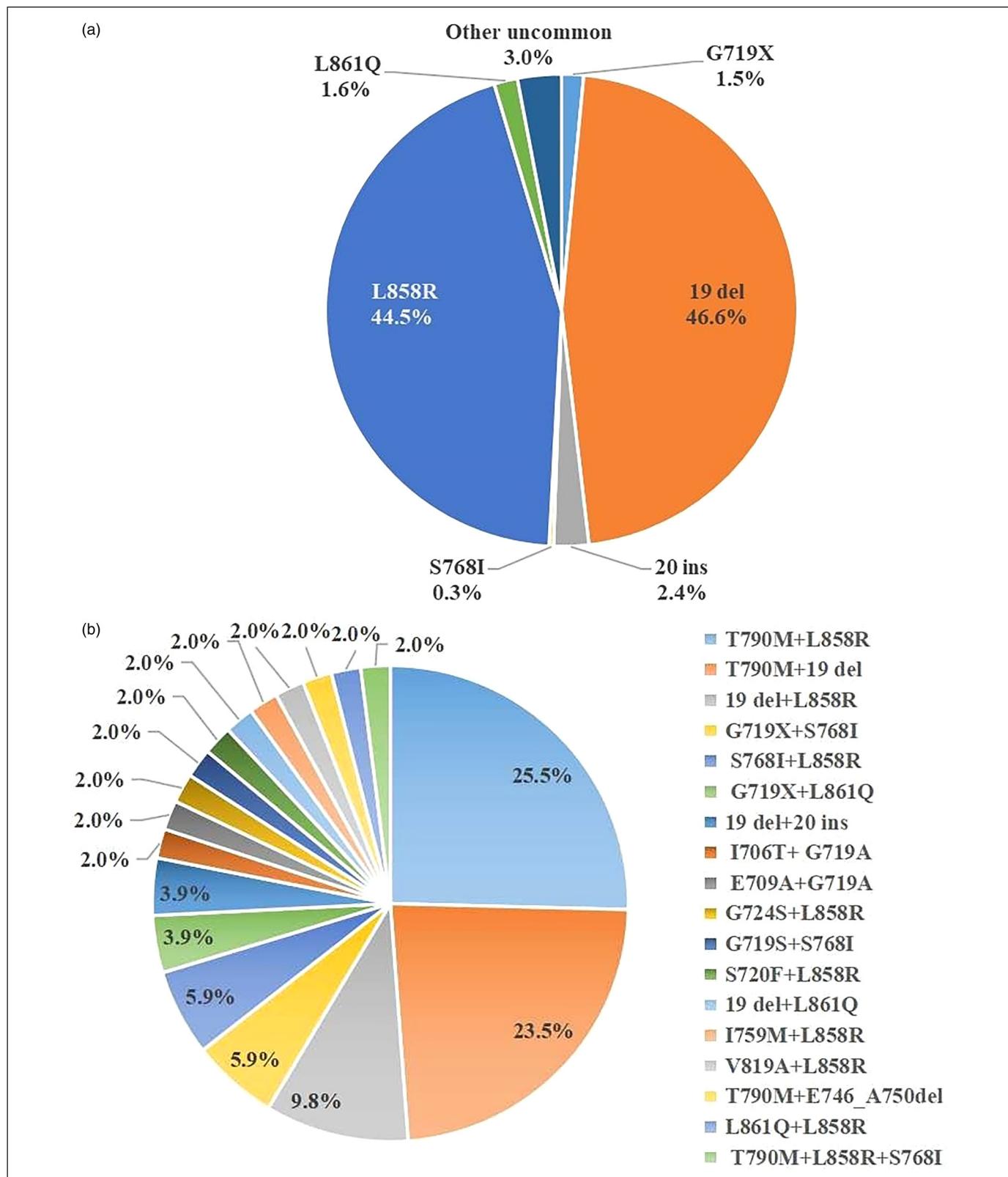


Figure 2. Pie charts showing the distribution of *EGFR* mutations in the study cohort. (A) Single mutation, (B) compound mutation.

included in our study. Furthermore, 210 samples whose data were prospectively collected between November 2020 and June 2021 were included in temporal validation cohort. A detailed flow diagram of patient selection is presented in Figure 1.

Status of EGFR Mutation

The identified mutations in *EGFR* in the 1450 patients were 723 single mutations and 51 compound mutations. The single mutations comprised 337 cases with 19 del, 322 cases with L858R, 17 cases with 20 ins, 12 cases with L861Q, 11 cases with G719X, 2 cases with S768I, and 22 cases with uncommon mutations (Figure 2A).

The compound mutations comprised 13 cases with T790M + L858R, 12 cases with T790M + 19 del, 5 cases with 19 del + L858R, 3 cases with S768I + L858R, 3 cases with G719X + S768I, 2 cases with 19 del + 20 ins, 2 cases with G719X + L861Q, 1 case with I706T + G719A, 1 case with E709A + G719A, 1 case with G724S + L858R, 1 case with G719S + S768I, 1 case with S720F + L858R, 1 case with 19 del + L861Q, 1 case with I759M + L858R, 1 case with V819A + L858R, 1 case with T790M + E746_A750del, 1 case with L861Q + L858R, and 1 case with T790M + L858R + S768I (Figure 2B).

Furthermore, among the 1450 patients, 39 cases had 2 or more synchronous gene mutations. Among these, *EGFR* + *TP53* was found to be the most frequent co-mutation, followed by *EGFR* + *EML4-ALK*, *EGFR* + *BRAF*, *EGFR* + *ROS1*, *EGFR* + *KRAS*, *TP53* + *EML4-ALK*, *EGFR* + *FGFR3* + *TP53*, *KRAS* + *TP53*, *EGFR* + *KRAS* + *NRAS*, *EGFR* + *PIK3CA* + *FBXW7*, *EGFR* + *TP53* + *PTEN*, *EGFR* + *PIK3CA*, *EGFR* + *TP53* + *CTNNB1*, *EGFR* + *KRAS* + *TP53*, *EGFR* + *PTEN*, *EGFR* + *NRAS*, *EGFR* + *HRAS*, *KRAS* + *PTEN* + *TSC1*, *KRAS* + *STK11* + *TP53*, *PIK3CA* + *TP53*, *MET* + *ERBB4*, *ERBB2* + *PTEN*, and *ERBB2* + *NRAS* (Figure 3).

Relationship Between the EGFR Mutation and Clinicopathological Characteristics

The multivariate logistic regression analysis showed that sex; smoking status; smoking index; family history of malignant tumors; history of other malignant tumors; CT imaging manifestation; gross type; levels of CEA, CA19-9, and SCCA; histologic type and subtype; differentiation grade; and levels of TTF-1 and napsin A were significantly correlated with the mutations in *EGFR* (Table 1).

Development and Validation of Prediction Models

Model 1 based on the clinical predictors demonstrated both good discrimination and calibration, as determined using the C-statistics and Hosmer–Lemeshow goodness-of-fit of 0.754 (95% CI 0.729-0.778) ($\chi^2=6.733$, degrees of freedom = 8, P = 0.566) for the development and 0.710 (95% CI 0.638-0.782) for the temporal validation cohort. The components of model 1 were sex; smoking status; smoking index; family history of malignant tumors; history of other malignant

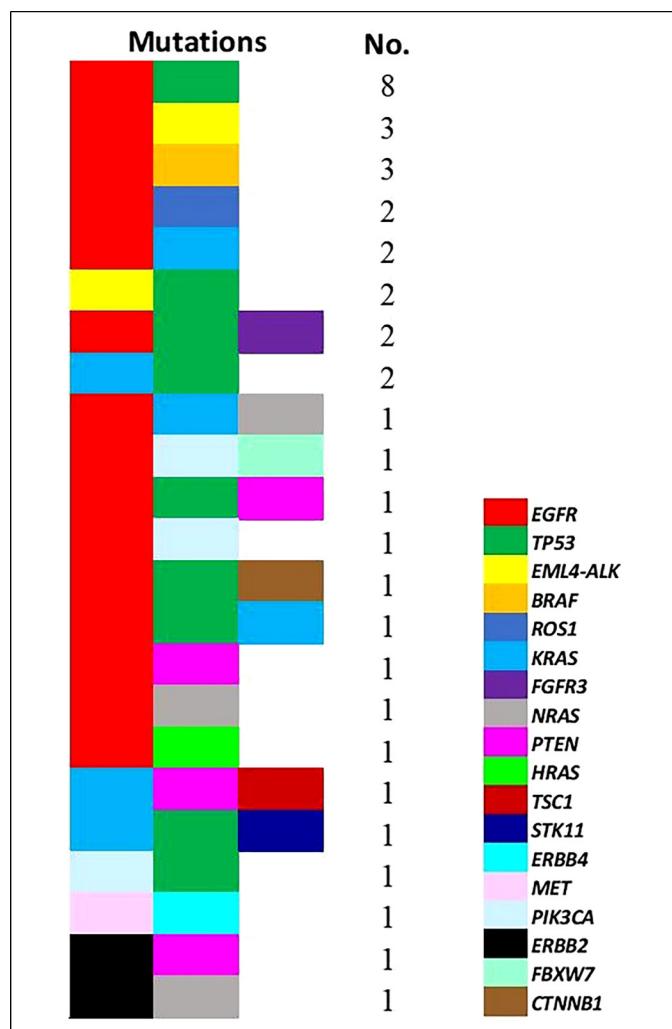


Figure 3. Co-mutated genes and their count observed in the study cohort.

tumors; CT imaging manifestation; gross type; and levels of CEA, CA19-9, and SCCA.

Model 2 based on the clinicopathological predictors demonstrated both good discrimination and calibration, as determined using the C-statistics and Hosmer–Lemeshow goodness-of-fit of 0.812 (95% CI 0.790-0.834) ($\chi^2=6.418$, degrees of freedom = 8, P = 0.989) for the development and 0.790 (95% CI 0.730-0.851) for the temporal validation cohort. The components of model 2 were sex; smoking status; smoking index; family history of malignant tumors; history of other malignant tumors; CT imaging manifestation; gross type; levels of CEA, CA19-9, and SCCA, histologic type and subtype; differentiation grade; and levels of TTF-1 and napsin A.

Figure 4 shows the ROC curves of prediction for models 1 and 2 in the development cohort (A,C) and temporal validation cohort (B,D). The calibration of the internal validation was good, as shown in Figure 5. The x-axis is the prediction calculated from the model and the y-axis is the actual *EGFR* mutation observed in the cohort. The reference line indicates the difference between

Table 1. Univariate and multivariate analysis of clinicopathological characteristics with EGFR mutational status from the development cohort.

Characteristics	n	Univariate analysis		Multivariate analysis*	
		EGFR (+)	EGFR (-)	P value	OR [95% CI]
Age (y)				0.015	0.378
Mean ± SD	61.9 ± 9.8	61.3 ± 9.8	62.6 ± 9.7		
<62	657	376	281		Reference
≥62	793	398	395		0.892 [0.693, 1.150]
Sex				<0.001	<0.001
Male	876	358	518		Reference
Female	574	416	158		1.853 [1.352, 2.541]
Smoking status				<0.001	<0.001
Current/Former	771	233	538		Reference
Never	645	529	116		1.932 [1.367, 2.729]
Unknown	34	12	22		
Smoking index				<0.001	
Mean ± SD	774.6 ± 522.3	664.8 ± 491.3	836.6 ± 529.7		0.009
≥770	300	215	85		Reference
<770	1116	677	439		1.646 [1.133, 2.390]
Unknown	34	12	22		
Family history of malignant tumors				0.001	0.030
Yes	117	74	43		1.701 [1.053, 2.748]
No	1299	488	811		Reference
Unknown	34	12	22		
History of other malignant tumors				0.002	0.007
Yes	70	25	45		Reference
No	1346	737	609		2.249 [1.254, 4.032]
Unknown	34	12	22		
Tumor location				0.239	
Left	603	329	274		
Right	798	402	396		
Bilateral	16	7	9		
Unknown	33	12	21		
CT imaging manifestation				<0.001	0.005
Solid	1355	711	644		Reference
GGO (Pure/Mix)	58	49	9		3.515 [1.463, 8.447]
Unknown	37	14	23		
Gross type				<0.001	0.025
Central type	208	87	121		Reference
Peripheral type	1205	673	532		1.535 [1.056, 2.232]
Unknown	37	14	23		
T stage				<0.001	0.740
T1	277	177	100		Reference
T2	280	138	142		
T3	143	65	78		1.057 [0.760, 1.471]
T4	237	114	123		
Unknown	513	280	233		
N stage				0.191	
N0	388	213	175		
N1	90	55	35		
N2	344	176	168		
N3	165	80	85		
Unknown	463	250	213		
M stage				0.328	
M0	537	276	261		
M1a	91	48	43		
M1b	288	160	128		
M1c	207	121	86		
Unknown	327	169	158		

(continued)

Table 1. (continued)

Characteristics	n	Univariate analysis		Multivariate analysis*	
		EGFR (+)	EGFR (-)	P value	OR [95% CI]
Clinical stage					
IA	155	100	55	0.019	
IB	52	24	28		
II A	25	8	17	0.142	
II B	80	39	41		
III A	124	65	59	0.094	
III B	81	33	48		
III C	22	7	15		
IV A	390	215	175	0.436	
IV B	207	121	86		
I-III	814	423	391	0.108	
IV	597	336	261		
Unknown	39	25	14		
CEA				0.011	0.002
Positive	578	332	246		1.627 [1.195, 2.217]
Negative	659	331	328		Reference
Unknown	213	111	102		
AFP				0.724	
Positive	23	11	12		
Negative	803	414	389		
Unknown	624	349	275		
FERR				0.387	
Positive	68	29	39		
Negative	147	72	75		
Unknown	1235	673	562		
CA125				0.031	0.624
Positive	455	226	229		1.085 [0.783, 1.503]
Negative	729	409	320		Reference
Unknown	266	139	127		
CA15-3				0.074	
Positive	86	57	29		
Negative	382	213	169		
Unknown	982	504	478		
CA19-9				0.030	0.029
Positive	152	66	86		Reference
Negative	687	365	322		1.646 [1.052, 2.577]
Unknown	611	343	268		
SCCA				<0.001	0.006
Positive	78	19	59		Reference
Negative	273	157	116		2.572 [1.311, 5.046]
Unknown	1099	598	501		
CYFRA 21-1				0.004	0.881
Positive	206	92	114		0.958 [0.547, 1.677]
Negative	130	79	51		Reference
Unknown	1114	603	511		
CA72-4				0.163	
Positive	45	17	28		
Negative	145	72	73		
Unknown	1260	685	575		
NSE				0.252	
Positive	237	121	116		
Negative	869	480	389		
Unknown	344	173	171		
Adenocarcinoma component				<0.001	0.001
With	1313	758	555		Reference
Without	117	15	102		3.025 [1.539, 5.945]

(continued)

Table 1. (continued)

Characteristics	n	Univariate analysis		P value	Multivariate analysis*	
		EGFR (+)	EGFR (-)		OR [95% CI]	P value
NOS#	9	0	9			
Unknown	11	1	10			
Predominant component in adenocarcinoma				<0.001		
Micropapillary/Solid	78	25	53		Reference	
Acinar/Papillary	211	141	70		2.962 [1.587, 5.528]	0.001
AIS/Lepidic	73	53	20		2.983 [1.316, 6.766]	0.009
Minimally invasive	2	0	2			
Unknown	909	521	388			
Adenocarcinoma	1273	740	533	0.098		
Adenosquamous carcinoma	40	18	22			
Differentiation grade				<0.001		
Poor	271	86	185		Reference	
Moderate	241	158	83		2.566 [1.657, 3.973]	<0.001
Well	70	50	20		3.131 [1.590, 6.165]	0.001
Unknown	868	480	388			
Mucus component				0.005		0.073
Yes	36	11	25		0.457 [0.194, 1.075]	
No	1414	763	651		Reference	
TTF-1				<0.001		0.002
Positive	866	483	383		2.853 [1.480, 5.500]	
Negative	138	17	121		Reference	
Unknown	446	274	172			
Napsin A				<0.001		<0.001
Positive	648	374	274		3.003 [1.775, 5.083]	
Negative	193	29	164		Reference	
Unknown	609	371	238			
P63				0.974		
Positive	210	61	149			
Negative	294	85	209			
Unknown	946	628	318			
P40				0.009		0.441
Positive	67	21	46		1.340 [0.637, 2.822]	
Negative	360	175	185		Reference	
Unknown	1023	578	445			
CK-7				<0.001		0.280
Positive	687	343	344		0.549 [0.185, 1.629]	
Negative	42	8	34		Reference	
Unknown	721	423	298			
Ki67 (%)				<0.001		0.052
Mean ± SD	36.4 ± 21.6	32.9 ± 20.9	40.0 ± 21.8			
<36	461	264	197		Reference	
≥36	453	205	248		1.396 [0.996, 1.956]	
Unknown	536	305	231			
Specimen type				0.140		
Biopsy	811	419	392			
Surgical resection	639	355	284			
Technology				0.430		
ARMS	1167	617	550			
NGS	283	157	126			

Abbreviations: AIS: adenocarcinoma in situ, AFP: alpha fetoprotein, ARMS: amplification refractory mutation system, CA: carbohydrate antigen, CEA: carcinoembryonic antigen, CI: confidence interval, CK: cytokeratin, CT: computerized tomography, EGFR: epidermal growth factor receptor, FERR: ferritin, GGO: ground-glass opacity, NGS: next-generation sequencing, NSE: neuron-specific enolase, OR: odds ratio, SCCA: squamous cell carcinoma antigen, SD: standard deviation, CYFRA21-1: soluble fragment of cytokeratin 19, TTF-1: thyroid transcription factor-1.

*Items were included in the multivariate analysis only when the P value is <0.05 in univariate analysis.

#NOS, not otherwise specified indicates pathologically confirmed NSCLC, but the pathologic type was not clearly identified.

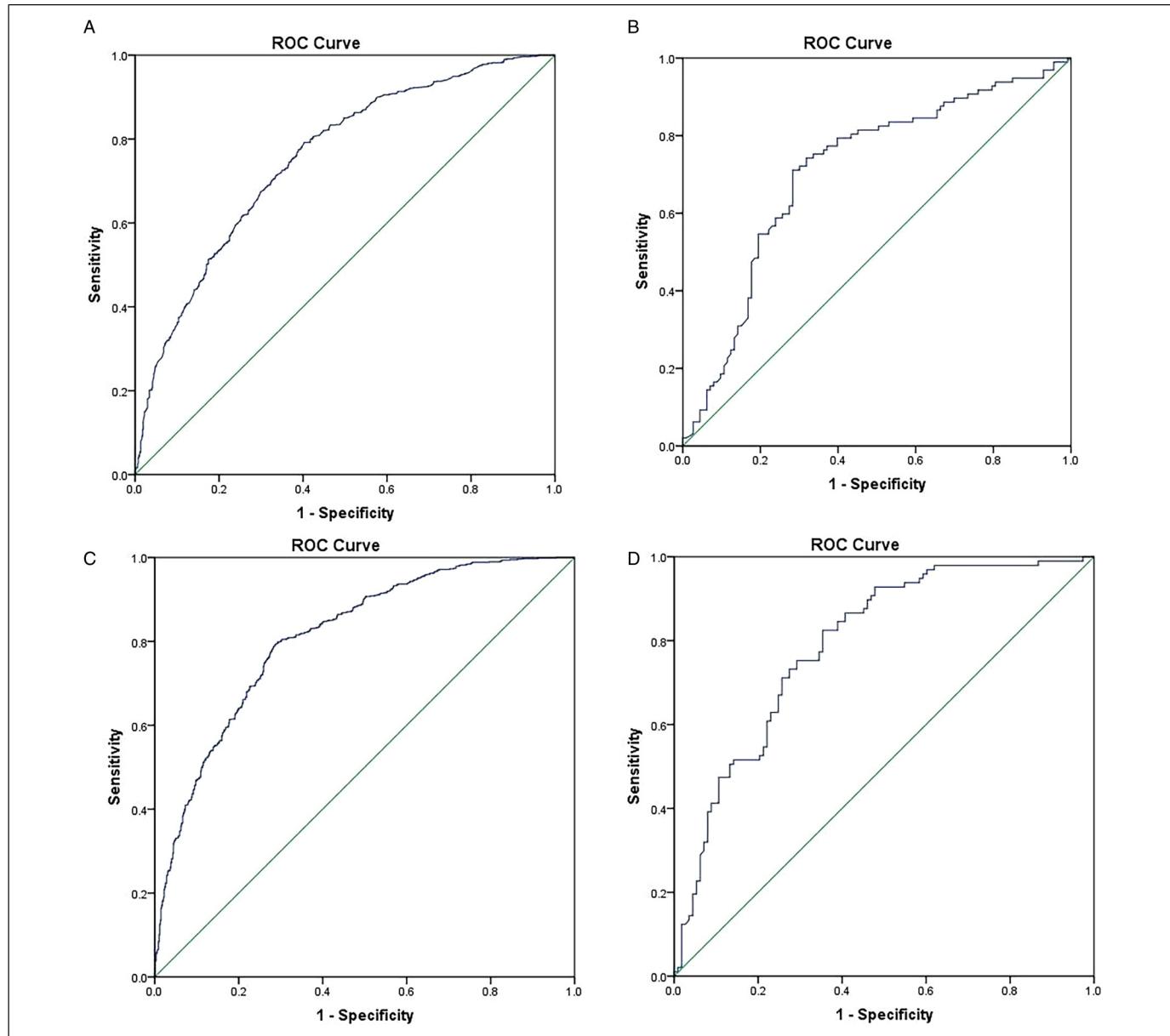


Figure 4. Receiver operating characteristic curve of models 1 and 2 in the development cohort (A,C) and temporal validation cohort (B,D).

the predicted probabilities. The calibration plots showed a small deviation from ideal predictions.

As shown in Table 2, there was no significant difference in the prediction accuracy between the models ($P = 0.455$).

Construction of a Clinical Scoring System

We developed a concise scoring system enabling the differentiation of *EGFR* mutations based on the β coefficients obtained for the independent clinical predictors from the multivariate logistical regression model (Table 3). The predictive equation was logistic ($p = -4.208 + (0.802 \times \text{"female"}) + (0.625 \times \text{"never smoking"}) + (0.591 \times \text{"smoking index} < 770\text{"}) + (0.592 \times \text{"with family history of malignant tumors"}) + (0.973 \times \text{"without history of other malignant tumors"}) + (1.314 \times \text{"ground-glass opacity"}) + (0.555 \times \text{"peripheral type"}) + (0.659 \times \text{"positive CEA"}) + (0.567 \times \text{"negative CA19-9"}) + (1.180 \times \text{"negative SCCA"})$. Model scores ranged from 0 to 13.

$\times \text{"with family history of malignant tumors"}) + (0.973 \times \text{"without history of other malignant tumors"}) + (1.314 \times \text{"ground-glass opacity"}) + (0.555 \times \text{"peripheral type"}) + (0.659 \times \text{"positive CEA"}) + (0.567 \times \text{"negative CA19-9"}) + (1.180 \times \text{"negative SCCA"})$. Model scores ranged from 0 to 13.

Risk Group Stratification and Probability of EGFR Mutation

Patients were stratified into risk groups according to their scores: low-risk (score < 4), moderate-risk (score 4–8), and high-risk (score > 8) groups. In the development cohort, compared

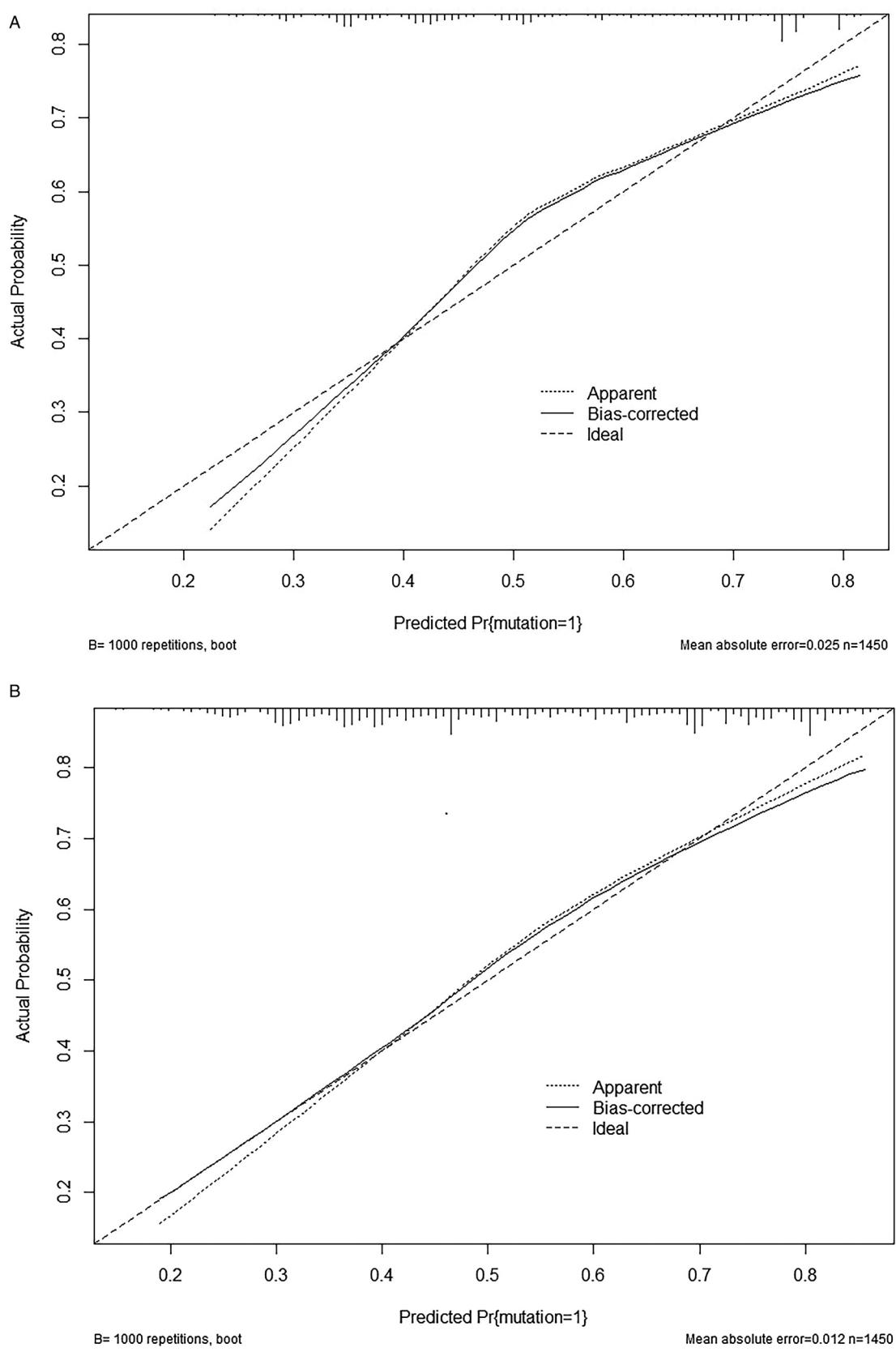


Figure 5. Calibration plot comparing the actual and predicted probabilities of the EGFR mutation. (A) Model 1; (B) model 2.

with that in the low-risk group, the occurrence of *EGFR* mutation was increased in the moderate-risk ($OR = 5.22$, 95% CI 3.36-8.11, $P < 0.001$) and high-risk ($OR = 19.67$, 95% CI 11.22-34.50, $P < 0.001$) groups. In the temporal validation cohort, compared with that in the low-risk group, the occurrence of *EGFR* mutation was increased in the moderate-risk ($OR = 1.91$, 95% CI 0.75-4.85, $P = 0.172$) and high-risk ($OR = 8.08$, 95% CI 2.80-23.33, $P < 0.001$) groups (Table 4).

Figure 6 presents the probability of *EGFR* mutation. In the development cohort, among patients with low, moderate, and high risks of *EGFR* mutation, the actual mutation frequency was 18.2%, 53.7%, and 81.4%, respectively. In the temporal validation cohort, among patients with low, moderate, and

high risks of *EGFR* mutation, the actual mutation frequency was 28.0%, 42.6%, and 68.2%, respectively.

Discussion

There were two main parts to our study. In the first part, we described the *EGFR* genetic profile of lung cancer. We observed that among 1450 lung cancer cases, the most common mutation was identified in *EGFR*. More specifically, mutations in *EGFR* were detected in more than half of the patients (774/1450, 53.4%). A high frequency of mutations in *EGFR* in Chinese patients with lung cancer highlights the significance of exploring the mutational status of *EGFR*.^{3,5} In our study, the most common mutational subtype in *EGFR* was 19 del (46.6%), followed by L858R (44.5%). However, several studies have reported that the frequency of L858R was higher than that of 19 del,¹⁵ which might have been due to the number of samples, geographical differences, various tumor stages, different specimen types, and detection technologies. In addition, T790M was confirmed as the most important

Table 2. Comparison of prediction accuracy between two models.

	Successful prediction	Failure prediction	P value
Model 1	144	66	0.455
Model 2	151	59	

Table 3. Multivariate analysis for the independent clinical predictors in *EGFR* mutation and corresponding points.

Categories	β	S.E.	Wald	P value	OR [95% CI]	Points
Intercept	-4.208	0.541	60.496	<0.001	-	
Sex						
Male	0.802	0.149	29.150	<0.001	Reference 2.230 [1.667, 2.984]	0
Female						1
Smoking status						
Current/Former	0.625	0.162	14.807	<0.001	Reference 1.869 [1.359, 2.570]	0
Never						1
Smoking index						
≥ 770	0.591	0.177	11.155	0.001	Reference 1.806 [1.277, 2.555]	0
<770						1
Family history of malignant tumors						
No	0.592	0.226	6.877	0.009	Reference 1.808 [1.161, 2.815]	0
Yes						1
History of other malignant tumors						
Yes	0.973	0.279	12.213	<0.001	Reference 2.647 [1.533, 4.570]	0
No						2
CT imaging manifestation						
Solid	1.314	0.392	11.687	0.001	Reference 3.822 [1.772, 8.243]	0
GGO (Pure/Mix)						2
Gross type						
Central type	0.555	0.173	10.282	0.001	Reference 1.743 [1.241, 2.447]	0
Peripheral type						1
CEA						
Negative	0.659	0.144	21.048	<0.001	Reference 1.932 [1.458, 2.561]	0
Positive						1
CA19-9						
Positive	0.567	0.212	7.149	0.008	Reference 1.763 [1.163, 2.671]	0
Negative						1
SCCA						
Positive	1.180	0.316	13.903	<0.001	Reference 3.253 [1.750, 6.049]	0
Negative						2
Total						13

Abbreviations: CA: carbohydrate antigen, CEA: carcinoembryonic antigen, CI: confidence interval, CT: computerized tomography, EGFR: epidermal growth factor receptor, GGO: ground-glass opacity, OR: odds ratio, SCCA: squamous cell carcinoma antigen.

Table 4. Scoring system table.

Risk score quantities	n	EGFR (+), n (%)	OR [95% CI]	P value
Development Cohort				
Range (0, 12)				
Score<4	143	26 (18.2)	Reference	-
4≤Score ≤8	1108	595 (53.7)	5.22 [3.36, 8.11]	<0.001
Score >8	188	153 (81.4)	19.67 [11.22, 34.50]	<0.001
Temporal Validation Cohort				
Range (1, 13)				
Score<4	25	7 (28.0)	Reference	-
4≤Score ≤8	141	60 (42.6)	1.91 [0.75, 4.85]	0.172
Score >8	44	30 (68.2)	8.08 [2.80, 23.33]	<0.001

Abbreviations: CI: confidence interval, EGFR: epidermal growth factor receptor, OR: odds ratio.

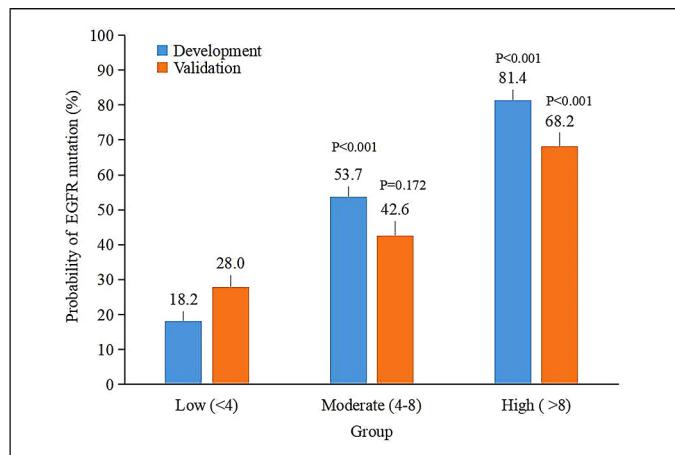


Figure 6. Histogram for the risk of EGFR mutation. According to the scoring system, a histogram of the proportions of the low-, medium-, and high-risk populations were drawn.

TKI-resistant mutation, accounting for more than half of the observed secondary resistance. We identified one instance with single T790M mutation, whereas all other instances were cases of coexistence with sensitive mutation sites. Furthermore, T790M was found to incline to co-mutate with L858R (25.5%) compared with 19 del (23.5%), suggesting that point mutations are more likely to have compound mutations.¹⁶ In our cohort, all patients with a T790M secondary mutation were treated with osimertinib, an irreversible third generation TKI drug.¹⁷

EGFR/TP53 co-mutation was found to be the most frequent in two or more synchronous gene mutations. TP53, as a tumor suppressor gene, is frequently identified in lung adenocarcinoma and is associated with a poor prognosis of patients with non-small cell lung cancer (NSCLC).¹⁸ Mutations in TP53

have been reported to result in DNA repair and excessive apoptosis, leading to cancer.¹⁹ A retrospective study of 1017 samples found that two of the most common mutations in the EGFR-mutant lung cancer were PIK3CA and MET,¹⁴ but this study did not analyze the tumor suppressor genes. Zhao *et al.* reported that patients with co-mutations in EGFR and TP53 accounted for 22.4% of all patients with lung adenocarcinoma and had higher tumor mutational burden and worse recurrence-free survival. In addition, the authors provided insights into the prognostic value of co-mutation of EGFR/TP53 for patients with lung adenocarcinoma.²⁰ Thus, patients with lung cancer harboring EGFR and co-mutational tumor suppressor genes should be regarded as a unique subgroup, and more informed and genetically empowered molecular diagnosis and monitoring, and dynamically applied rational polytherapy strategies should be employed to address the clonal and subclonal co-alterations driving disease progression and drug resistance in order to better control lung cancer.

In the second part, we established two prediction models based on the clinical and clinicopathological features and found there was no significant difference between them ($P = 0.455$). Thus, for patients who are not available for gene detection pathologically, we developed a practical predictive scoring system that could initially identify EGFR mutation, based on the independent clinical predictors, including sex, smoking status, smoking index, family history of malignant tumors, history of other malignant tumors, CT imaging manifestation, gross type, CEA, CA19-9, and SCCA. The discrimination of our scoring system in distinguishing patients with wild-type or EGFR-mutated tumors was good. The system uses coefficients to convert the features into quantitative data, demonstrating good discrimination with C-statistics of 0.754 (95% CI 0.729-0.778) for the development and 0.710 (95% CI 0.638-0.782) for the temporal validation cohorts.

The system demonstrated that mutations in EGFR were significantly associated with female sex and non-smokers or smokers with lower smoking index (<770), but not stage. A study of 884 patients reported that mutations in EGFR are common in Chinese patients with early-stage non-small cell lung cancer (NSCLC; I-II);⁵ whereas another study reported a contradictory conclusion.² Most surgical specimens reflect cases of early lung cancer, whereas most biopsy specimens reflect cases of advanced lung cancer. Therefore, inclusion of only a single specimen type is likely to be the underlying cause of the discordance in the results between these studies. Moreover, our study showed that biopsy specimens can replace surgical specimens for the detection of the mutational status of EGFR ($P > 0.05$), consistent with the findings of a previous study.¹⁶ In our study, we included the smoking index (Brinkman index), which can reflect the degree of influence of smoking.⁹ Approximately 83% of women with lung cancer do not have a smoking habit in China. Sex may influence the correlation between smoking status and EGFR mutation. Tomita *et al.*²⁰ compared the correlation between the Brinkman index and EGFR mutation status of 90 Japanese men and found that the Brinkman index of the EGFR mutation

group was lower than that of the wild-type group, but with no significant differences ($P=0.8357$). A recent Chinese study⁹ analyzed the Brinkman index in male subjects and found that the degree of smoking between the *EGFR* group and the control group was still significantly different ($P=0.020$). After excluding the influence of sex, our result was in agreement with the latter. A meta-analysis also showed that TKI therapy should be expanded to former smokers with less than 15 pack-years or those who did not smoke for more than 25 years.²¹ In addition, a family history of malignant tumors and history of other malignant tumors were found to be significantly related to mutations in *EGFR*. To the best of our knowledge, there have been no reports on these factors.

Our system showed that a higher proportion of GGO was linked with mutations in *EGFR*, consistent with most previous study findings.^{8,9,22} However, some previous studies have reported that either no significant correlation was observed between mutations in *EGFR* and GGO²³ or mutations in *EGFR* were more common in lesions with >50% solid component.^{24,25} The difference could be a result of insufficient recruitment of early-stage patients, or because different definitions were used for the quantification and classification of GGO.⁸

After excluding the influence of other malignant tumors, positive CEA, negative SCCA, and negative CA19-9 in serum were demonstrated to be predictors of mutations in *EGFR*. Niu *et al.* indicated that compared with the wild type, patients with *EGFR* mutations were more likely to have a high CEA level.²⁶ Moreover, high CEA levels may represent higher tumor burden; therefore, it has been recommended to successfully evaluate the efficacy and prognosis of treatment with EGFR-TKIs.²⁷ TKIs are known to disrupt abnormal downstream signaling pathways induced by mutations in *EGFR* to inhibit tumor proliferation, whereas overexpression of CEA has been reported to accelerate tumor development, suggesting that CEA might be a "cofactor" of mutations in *EGFR*. However, the opposite conclusion, that is, increased serum tumor markers are independent of driver genes, has also been drawn.²⁸ Therefore, further research needs to be performed in this regard. Besides, SCCA is known to be the preferred marker of squamous cell carcinoma, whereas mutations in *EGFR* are common in adenocarcinoma. Thus, detecting mutations in *EGFR* in patients with expressing of SCCA would be rare, consistent with the univariate analysis results of Wen *et al.*²⁹ However, the inconsistency with their multivariate analysis results may be related to sample size, inclusion criteria, and population differences. We also demonstrated the value of CA 19-9 for the prediction of *EGFR* mutations in patients with lung cancer. To date, no relevant research has been conducted. In addition, a study showed that cytological CYFRA21-1 correlated with the mutational status in *EGFR*, but not after its release into the serum.³⁰ Therefore, serum tumor markers, such as CEA, SCCA, and CA19-9, the detection of which is both convenient and easy in China, could be widely used in hospitals lacking gene detection technology.

The proposed scoring system is based on clinical characteristics with external validation to show its generalizability and

reliability. According to our scoring system, low-, moderate-, and high-risk grades may distinguish the *EGFR* mutation type and wild type. Although a few studies have evaluated the risk factors of *EGFR* mutation or propose a scoring system, the parameters were incomprehensive and the efficiency of these scoring systems was not externally validated.^{2,10,15} To the best of our knowledge, the current study proposes the first scoring system using various clinical parameters to predict the *EGFR* mutation status in a relatively large development cohort and validate its clinical value.

Regarding pathological features, we found that patients with well-differentiated adenocarcinoma and peripheral tumors were more likely to have *EGFR* mutations. The *EGFR* mutations were more common in patients with AIS or lepidic predominant adenocarcinoma. It has been reported that the CT findings of GGO tend to correspond to lepidic pattern observed pathologically, although this correlation is not absolute.³¹ The prognosis was best for AIS and lepidic predominant adenocarcinoma. The OS rate of patients with micropapillary or solid predominant adenocarcinoma was significantly lower than that of patients with minimally invasive, lepidic, acinar, or papillary adenocarcinoma. Patients with acinar and papillary adenocarcinoma exhibit a similar cumulative 1-year overall survival (OS) rate.³² Thus, we classified different subtypes of adenocarcinoma based on the corresponding prognosis when constructing the model. The results revealed that the *EGFR* mutation rate was the highest in patients with AIS/lepidic predominant adenocarcinoma, followed by patients with papillary/acinar predominant adenocarcinoma and micropapillary/solid predominant adenocarcinoma. Previous study findings indicated that *EGFR*-mutated tumors are significantly associated with lepidic or acinar predominant subtype.³²⁻³⁴ Thus, when performing subsolid lung nodule biopsy for *EGFR* mutation detection, it is recommended that interventional radiologists should target the GGO components as much as possible to increase the detection rate of *EGFR* mutations.

Additionally, TTF-1 and napsin A have been demonstrated to be significant predictive factors for *EGFR* mutation. TTF-1 is a tissue-specific transcription factor that helps to maintain the functions of terminal respiratory unit cells.³⁵ Among immunohistochemical markers, TTF-1 is considered the gold standard for primary lung adenocarcinoma.³⁶ Napsin A is an aspartic protease expressed in the lung and kidney³⁷ that is capable of cleaving the preform of surfactant protein B expressed in type II pneumocytes.³⁸ It has been reported that napsin A is a more sensitive marker than TTF-1 for pulmonary ADCs, which may complement immunohistochemical analyses using TTF-1.^{39,40} Hence, the immunohistochemical results might assist in guiding targeted therapy.^{35,41}

This study had some limitations. First, a retrospective single-center study could only reflect the mutational rate in patients in local areas in Asia. Second, we did not analyze the clinical value of radiomics signature or establish *EGFR* subtype prediction model. Third, owing to a small amount of *EGFR* compound mutations and co-mutations, we only described statistical association. Finally, NGS technology is expensive,

and most patients in our study could not afford it. Our research data on rare gene mutations was limited.

Conclusions

In conclusion, we determined the *EGFR* genetic profile of lung cancer in Asians and systematically analyzed the relevant clinicopathological factors. We developed and validated a concise and non-invasive scoring system based on the clinical predictors to initially predict the *EGFR* mutation status in those who are not available for gene detection.

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Declaration of Conflicting Interests

The Authors declare that there is no conflict of interest.

Ethics Approval and Consent to Participate

The study protocol was approved by the the Medical Ethics Committee of Zhongnan Hospital of Wuhan University, China (Ethical number: 2021057). There's no need for informed consent in our study since the unidentified data were free from medical ethics review.

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Authors' Contributions

WT A, SF T, and MY L conceived and designed the study. WT A, W F, FY Z, BC W, S W, and T G collected the data. WT A and FY Z analyzed the data and provided recommendations regarding statistical analyses. WT A and W F conducted literature search. WT A, FY Z, and BC W generated the tables and figures. WT A wrote the manuscript. MY L and SF T helped to critically review and comprehensively revise the manuscript. MY L supervised the research. All authors contributed to the research and approved the final version of this article.

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