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RESEARCH ARTICLE

Development and validation of a simple risk scoring system for a COVID-19 diagnostic prediction model

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ABSTRACT

Development and validation of a simple risk scoring system for a COVID-19 diagnostic prediction model

Introduction: *In a resource-constrained situation, a clinical risk stratification system can assist in identifying individuals who are at higher risk and should be tested for COVID-19. This study aims to find a predictive scoring model to estimate the COVID-19 diagnosis.*

Materials and Methods: *Patients who applied to the emergency pandemic clinic between April 2020 and March 2021 were enrolled in this retrospective study. At admission, demographic characteristics, symptoms, comorbid diseases, chest computed tomography (CT), and laboratory findings were all recorded. Development and validation datasets were created. The scoring system was performed using the coefficients of the odds ratios obtained from the multivariable logistic regression analysis.*

Results: *Among 1187 patients admitted to the hospital, the median age was 58 years old (22-96), and 52.7% were male. In a multivariable analysis, typical radiological findings (OR= 8.47, CI= 5.48-13.10, p< 0.001) and dyspnea (OR= 2.85, CI= 1.71-4.74, p< 0.001) were found to be the two important risk factors for COVID-19 diagnosis, followed by myalgia (OR= 1.80, CI= 1.08-2.99, p= 0.023), cough (OR= 1.65, CI= 1.16-2.26, p= 0.006) and fatigue symptoms (OR= 1.57, CI= 1.06-2.30, p= 0.023). In our scoring system, dyspnea was scored as 2 points, cough as 1 point, fatigue as 1 point, myalgia as 1 point, and typical radiological findings were scored as 5 points. This scoring system had a sensitivity of 71% and a specificity of 76.3% for a cut-off value of >2, with a total score of 10 (p< 0.001).*

Conclusion: *The predictive scoring system could accurately predict the diagnosis of COVID-19 infection, which gave clinicians a theoretical basis for devising immediate treatment options. An evaluation of the predictive efficacy of the scoring system necessitates a multi-center investigation.*

Key words: *COVID-19; scoring system; prediction model; diagnosis*

ÖZ

COVID-19 tanısal tahmin modeli için basitleştirilmiş risk skorlama sisteminin geliştirilmesi ve doğrulanması

Giriş: *Kaynakların kısıtlı olduğu bir durumda klinik risk skorlama sistemi, daha yüksek risk altında olan ve COVID-19 için test edilmesi gereken bireylerin belirlenmesine yardımcı olabilir. Bu çalışmanın amacı, COVID-19 tanısını tahmin edebilecek öngörücü bir skorlama modeli bulmaktır.*

Materyal ve Metod: *Çalışmaya Nisan 2020 ile Mart 2021 tarihleri arasında acil pandemi polikliniğine başvuran hastalar dahil edilmiştir. Başvuru sırasında olguların demografik özellikleri, semptomları, komorbid hastalıkları, toraks bilgisayarlı tomografi (BT) ve laboratuvar bulguları retrospektif olarak değerlendirilmiştir. Geliştirme ve doğrulama veri setleri oluşturulmuştur. Çok değişkenli lojistik regresyon analizi sonucunda elde edilen katsayılar kullanılarak skorlama sistemi gerçekleştirilmiştir.*

Bulgular: *Hastaneye başvuran 1187 hastanın ortanca yaşı 58'di (22-96) ve %52,7'si erkekti. Çok değişkenli analizde, tipik radyolojik bulgular (OR= 8,47, CI= 5,48-13,10, p< 0.001) ve dispne (OR= 2,85, CI= 1,71-4,74, p< 0,001) COVID-19 tanısı için iki önemli risk faktörü olarak bulunmuş, bunları miyalji (OR= 1,80, CI= 1,08-2,99, p= 0,023), öksürük (OR= 1,65, CI= 1,16-2,26, p= 0,006) ve yorgunluk semptomları (OR= 1,57, CI= 1,06-2,30, p= 0,023) izlemiştir. Skorlama sistemimizde dispne 2 puan, öksürük 1 puan, yorgunluk 1 puan, miyalji 1 puan ve tipik radyolojik bulgular 5 puan olarak değerlendirilmiştir. Toplam skor 10 ve >2 cut off değeri için bu skorlama sisteminin duyarlılığı %71, özgüllüğü ise %76,3 olarak bulunmuştur (p< 0,001).*

Sonuç: *Tanısal öngörücü skorlama sistemi COVID-19 enfeksiyonu tanısını doğru bir şekilde tahmin edebilmiş ve bu da klinisyenlere acil tedavi seçenekleri sunmaları için teorik bir temel sağlamıştır. Skorlama sisteminin öngörücü etkinliğinin değerlendirilmesi için çok merkezli bir araştırmaya ihtiyaç vardır.*

Anahtar kelimeler: *COVID-19; skorlama sistemi; tahmin modeli; tanı*

INTRODUCTION

A new Coronavirus (CoV) with clinical features comparable to SARS CoV-1 (SARS-CoV-1) and Middle East Respiratory Syndrome (MERS) CoV (MERS-CoV) emerged at the end of 2019 (1). This new CoV type, SARS-CoV-2, rapidly spread worldwide, with the first case identified on March 11, 2020, in Türkiye. As of September 21, 2022, there were 161.852.382 verified COVID-19 cases and 101.068 deaths.

Polymerase chain reaction (PCR) testing is, therefore, the gold standard for identifying and establishing a patient's COVID-19 viral infection (2). However, this type of diagnostic examination has several drawbacks and limits. It has been demonstrated, for instance, that upper respiratory tract samples contain the maximum viral loads three days following the onset of symptoms and that the results of PCR testing take at least one day to be obtained after sampling (3). As the SARS-CoV-2 pandemic spreads worldwide, we require improved diagnostic screening technologies that are rapid, accurate, validated, and broadly accessible.

The pandemic of COVID-19 has had a severe negative impact on Türkiye and the rest of the world. The capacity of hospitals in Türkiye to triage, identify, and treat COVID-19 patients has decreased since the onset of the COVID-19 pandemic. Improving hospital screening and classifying individuals at high risk of infection is critical for rapid and appropriate isolation, treatment, and use of limited health resources. There is no validated, widely available risk stratification system to assist clinicians in deciding when COVID-19 diagnostic testing is required. A clinical risk stratification approach can assist in identifying high-risk individuals who should be tested for COVID-19 when resources are limited. This study aims to identify clinical, radiographic, and laboratory parameters capable of predicting the presence or absence of COVID-19 infection. The goal is to develop and validate a diagnostic model that effectively selects individuals at risk for COVID-19 in a suitable and safe manner.

MATERIALS and METHODS

Patients who applied to the emergency pandemic clinic between April 2020 and March 2021 were enrolled in this retrospective study. At admission, demographic characteristics, symptoms, comorbid diseases, chest computed tomography (CT), and laboratory findings were all recorded. Before the COVID-19 patient's admission, comorbidities were those that had been diagnosed. Baseline ferritin, C-reactive protein (CRP), D-dimer, lymphocyte, and eosinophil values were obtained.

Symptomatic cases aged 18 years and older who applied to the emergency pandemic clinic were included in the study. Patients who were transported immediately to the critical care unit and those who did not undergo thorax computed tomography were excluded from the study. Figure 1 provides a summary of the study protocol.

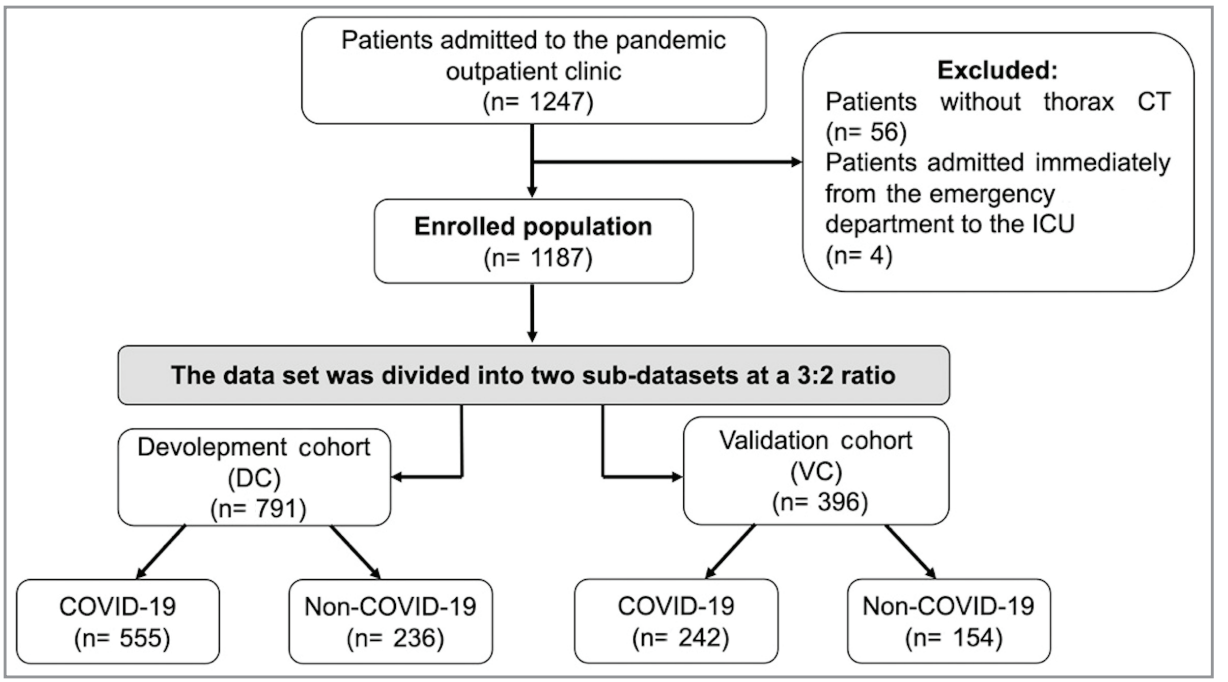

Figure 1. Study flow chart.

The study was authorized by the Uludağ University Faculty of Medicine Clinical Research Ethics Committee (Approval No: 2020-19/7), the Ministry of Health's Ethical Committee, and adhered to the principles of the Helsinki Declaration.

Definitions

Possible COVID-19 cases have been identified by national guidelines issued by the Republic of Türkiye Ministry of Health. When patients were admitted, nasopharyngeal swabs were taken for real-time reverse transcriptase-polymerase chain reaction testing (RT-PCR).

According to the expert consensus statement of the Radiological Society of North America (RSNA), chest CT patterns are classified as "negative for pneumonia," "indeterminate appearance," "atypical appearance," and "typical appearance." (4). In our study, an expert pulmonologist and a chest radiologist examined the chest CT of each suspected COVID-19 patient. The Roche Elecsys® Anti-SARS-CoV-2 immunological test was utilized to detect IgG antibodies against SARS-CoV-2 in serum samples from cases with negative SARS-COV-2-PCR and clinical and radiological suspicion of COVID-19 disease. The test, reported to calculate 95% sensitivity, 100% specificity, and positive and negative predictive values approaching 100% in diagnosing SARS-COV-2, was studied from serum samples taken at least two weeks after the disease of unvaccinated patients (5). Cases were categorized as "definite COVID-19 positive" if they tested positive for SARS-COV-2-PCR or if their PCR test was negative but the antibody test yielded a positive result.

Statistical Analysis

The development group (n= 791) and the validation group (n= 396) were separated into two sub-datasets at a 3:2 ratio from the entire data set (n= 1187). Clinical features were compared between COVID-19 and non-COVID-19 patient groups within each development and validation group. The Shapiro-Wilk test was used to determine if continuous variables conformed to the normal distribution. Since continuous variables did not follow a normal distribution, they were presented with the median (minimum: maximum), whereas categorical variables were provided with frequency and the accompanying percentage values. The Mann-Whitney U test was used to compare continuous data between groups, while the Chi-square and Fisher's exact tests were used to compare categorical variables. A univariate logistic regression analysis (LRA) was done on a development cohort to find factors that could affect the state of COVID-19. The multivariable logistic

regression analysis was performed using variables that met the p< 0.25 threshold as determined by the univariate logistic regression analysis. The coefficients derived from the logistic regression model were utilized to formulate risk score models. In the validation group, three risk score models were developed and validated.

Three risk scores were developed based on the coefficients of the final model. The scoring system used the coefficients of the odds ratios obtained from the multivariable logistic regression analysis (Model 1). The relevant coefficients have been rounded to the nearest integer (Model 2 and Model 3). The area under the receiver operating characteristic curve (AUC) was calculated for each of the risk score models. SPPS (IBM Corp. 2012 release). IBM SPSS Statistics for Windows, Version 21.0, Armonk, New York: IBM Corp. was utilized to conduct the statistical analysis. The type I error rate for statistical analysis was set at 5%.

RESULTS

During the research period, a total of 1.247 individuals were admitted to the pandemic emergency clinic. The study excluded 56 patients who did not have a chest CT scan and four patients who were directly referred to the critical care unit. Of the 1187 hospitalized patients, 797 (67.1%) tested positive for SARS-COV-2-PCR, while 390 (32.9%) did not. Twenty-one patients with negative PCR results had positive antibody tests. Table 1 describes the patients' characteristics. In the overall population, the median age was 58 (22-96), and 52.7% were male. There was at least one comorbid disease in 563 (47.4%) cases. Hypertension (28.9%), diabetes mellitus (17.7%), and coronary artery disease (11.1%) were the most prevalent comorbid diseases. The dataset was divided into separate development and validation datasets. Out of the 791 patients assigned to the development cohort, 555 individuals (70.5%) were identified as COVID-19-positive. Three hundred ninety-six patients were appointed to the validation cohort, of which 242 (61.1%) tested positive.

The most common symptoms in the patients were cough (49.8%), fatigue (33.4%) and dyspnea (24.1%), respectively. Cough, fatigue, and dyspnea were more common symptoms in COVID-19 patients as compared to non-COVID-19 cases in both the development cohort (p< 0.001, p= 0.03, p= 0.006, respectively) and the validation cohort (p< 0.001, p= 0.001, p= 0.011, respectively). Radiological findings were "typical" in 49% of the cases and "negative for pneumonia" in 30.7%. Table 1 shows each group's clinical and demographic information at baseline.

In both the development and validation cohorts, it was shown that typical COVID-19 radiological findings were statistically significant in COVID-19 patients compared to non-COVID-19 cases (both, p< 0.001). When compared to non-COVID-19 cases in both the development (p= 0.003, p< 0.001, p< 0.001, p< 0.001, respectively) and validation cohorts (p= 0.025, p= 0.001, p< 0.001, p< 0.001, respectively), higher CRP and ferritin levels, as well as lower lymphocyte and eosinophil levels, were found to be statistically significant in COVID-19 patients (Table 1).

The association between dyspnea and potential confounding comorbid diseases that may affect dyspnea symptoms was examined in univariate analyses. It has been shown that there is no statistically significant association between dyspnea symptoms with congestive heart failure [6 (3.4%) vs 169 (96.6%)], asthma [15 (8.6%) vs 160 (91.4%)], COPD [10 (5.4%) vs 165 (94.3%)], or chronic kidney failure [6 (3.4%) vs 169 (96.6%)]) (p= 0.114, p= 0.620, p= 0.267, p= 0.248, respectively). In a multivariable analysis, typical radiological findings (OR= 8.47, CI= 5.48-13.10, p< 0.001) and dyspnea (OR= 2.85, CI= 1.71-4.74, p< 0.001) were found to be the two important risk factors for COVID-19 diagnosis, followed by myalgia (OR= 1.80, CI= 1.08-2.99, p= 0.023), cough (OR= 1.65, CI= 1.16-2.26, p= 0.006) and fatigue symptoms (OR= 1.57, CI= 1.06-2.30, p= 0.023) (Table 2).

In the initial model, dyspnea was allocated 3 points, cough 2 points, fatigue 2 points, myalgia 2 points, and typical radiological findings in Thorax CT were assigned 8 points. The risk score resulting from the relevant scoring achieved 0.79 AUC in the development cohort, 0.81 AUC in the validation cohort, and 0.80 AUC in the overall patients. Conversely, the proposed second and third scoring systems involve adjusting the coefficients of the variables in the model based on total scores, setting them to 10 and 19, respectively (Models 2 and 3).

Table 1. The baseline characteristics of hospitalized patients in the development and validation cohorts

		Development cohort (n= 791)			Validation cohort (n= 396)		
	Overall population (n= 1187)	**Non-COVID (n= 236)**	**COVID (n= 555)**	**p**	**Non-COVID (n= 154)**	**COVID (n= 242)**	**p**
Age, years	58 (18-96)	56 (22-96)	58 (18-93)	0.680†	59 (18-88)	58.50 (21-93)	0.753†
Gender, male	625 (52.70%)	119 (50.40%)	261 (47%)	0.382‡	78 (50.60%)	104 (43%)	0.135‡
Comorbidity, n (%)	563 (47.40%)	111 (47%)	260 (46.80%)	0.962‡	74 (48.10%)	118 (48.80%)	0.891‡
Hypertension	343 (28.90%)	57 (24.20%)	169 (30.50%)	0.073‡	36 (23.40%)	81 (33.50%)	**0.032‡**
Diabetes mellitus	210 (17.70%)	47 (19.90%)	95 (17.10%)	0.348‡	28 (18.20%)	40 (16.50%)	0.671‡
Coronary artery disease	140 (11.80%)	22 (9.30%)	66 (11.90%)	0.293‡	18 (11.70%)	34 (14%)	0.498‡
COPD	51 (4.30%)	10 (4.20%)	21 (3.80%)	0.764‡	6 (3.90%)	14 (5.80%)	0.403‡
Asthma	82 (6.90%)	11 (4.70%)	44 (7.90%)	0.098‡	8 (5.20%)	19 (7.90%)	0.307‡
Malignancy	79 (6.70%)	21 (8.90%)	26 (4.70%)	**0.022‡**	22 (14.30%)	10 (4.10%)	**<0.001‡**
Chronic renal failure	27 (1.20%)	7 (3%)	8 (1.40%)	0.161§	4 (2.60%)	8 (3.30%)	0.772§
Chronic liver failure	24 (2%)	1 (0.40%)	3 (0.50%)	>0.99§	0	1 (0.40%)	>0.99§
Baseline vital signs, n (%)							
Fever	341 (28.70%)	62 (26.30%)	148 (26.70%)	0.908‡	45 (29.20%)	86 (35.50%)	0.193‡
Throat ache	120 (10.10%)	29 (12.30%)	54 (9.70%)	0.283‡	14 (9.10%)	23 (9.50%)	0.890‡
Dyspnea	286 (24.10%)	25 (10.60%)	156 (28.10%)	**<0.001‡**	15 (9.70%)	90 (37.20%)	**<0.001‡**
Cough	591 (49.80%)	109 (46.20%)	303 (54.60%)	**0.030‡**	53 (34.40%)	126 (52.10%)	**0.001‡**
Fatigue	397 (33.40%)	63 (26.70%)	204 (36.80%)	**0.006‡**	39 (25.30%)	91 (37.60%)	**0.011‡**
Diarrhea	65 (5.50%)	15 (6.40%)	30 (5.40%)	0.597‡	10 (6.50%)	10 (4.10%)	0.296‡
Myalgia	195 (16.40%)	28 (11.90%)	96 (17.30%)	0.054‡	29 (18.80%)	42 (17.40%)	0.709‡
Smell and taste dysfunction	61 (5.10%)	23 (9.70%)	21 (3.80%)	**0.001‡**	11 (7.10%)	6 (2.50%)	**0.026‡**
Chest CT images, n (%)							
Typical	582 (49%)	43 (18.20%)	361 (65%)	**<0.001‡**	25 (16.20%)	153 (63.20%)	**<0.001‡**
Indeterminate	154 (13%)	39 (16.50%)	51 (9.20%)		28 (18.20%)	36 (14.90%)	
Atypical	87 (7.30%)	29 (12.30%)	29 (5.20%)		22 (14.30%)	7 (2.90%)	
Negative	364 (30.70%)	125 (53%)	114 (20.50%)		79 (51.30%)	46 (19%)	
Initial laboratory findings							
C-reactive protein, mg/L	22.10 (0.20-15035)	11 (0.20-414)	27.15 (0.20-2916)	**0.003†**	15.55 (0.20-15035)	27 (0.20-35.20)	**0.025†**
D-dimer, mg/L	0.57 (0-967)	0.63 (0-28)	0.56 (0.17-967)	0.218†	0.59 (0.10-44.85)	0.54 (0.10-49)	0.511†
Ferritin, ng/mL	147.60 (2-11080)	95 (2-2843)	187.70 (4.90-11080)	**<0.001†**	107.15 (2-2431)	170.70 (2.67-4351)	**0.001†**
Lymphocyte, per mm^3	1510 (80-16402.50)	1750 (95.30-5295)	1390 (80-16402.50)	**<0.001†**	1775.50 (113-10470)	1387 (120-12250)	**<0.001†**
Eosinophil, per mm^3	10 (0-4025)	41 (0-4025)	5 (0-1200)	**<0.001†**	39.50 (0-910)	4 (0-1010)	**<0.001†**

Data were presented as median (minimum-maximum) and n (%).
†: Mann-Whitney U test, ‡: Chi-square test, §: Fisher's exact test.

Table 2. The outcomes of univariable and multivariate logistic regression analyses

	Univariable analysis			Multivariable analysis		
	Crude OR	**95% CI**	**p**	**Adjusted OR**	**95% CI**	**p**
Age, years	0.99	0.98-1.01	0.474	-	-	-
Gender, male	0.87	0.64-1.18	0.382	-	-	-
Symptoms						
Fever	1.02	0.72-1.44	0.908	-	-	-
Throat ache	0.77	0.48-1.24	0.284	-	-	-
Dyspnea	3.30	2.10-5.20	**<0.001**	2.85	1.71-4.74	**<0.001**
Cough	1.04	1.03-1.90	**0.031**	1.65	1.16-2.36	**0.006**
Fatigue	1.60	1.14-2.23	**0.006**	1.57	1.06-2.30	**0.023**
Myalgia	1.55	0.99-2.44	**0.056**	1.80	1.08-2.99	**0.023**
Chest CT images, n (%)			**<0.001**			**<0.001**
Typical	9.21	6.14-13.81	<0.001	8.47	5.48-13.10	**<0.001**
Indeterminate	1.43	0.88-2.34	0.148	1.53	0.91-2.59	0.111
Atypical	1.10	0.62-1.95	0.753	1.10	0.60-2.01	0.768
Initial laboratory findings						
Lymphocyte, per mm^3	1	0.99-1.01	0.722			
C-reactive protein, mg/L	1.01	1-1.01	**0.083**	0.99	0.98-1.01	0.148
D-dimer, mg/L	1.01	0.99-1.02	**0.200**	1.01	0.99-1.02	0.844
Ferritin, ng/mL	1	1-1.01	**0.009**	-	-	-

Significance for the multivariable model is p< 0.001, and significance for Hosmer and Lemeshow test is p= 0.494.

The second model had an AUC of 0.79 in the development cohort, 0.81 in the validation cohort, and 0.80 in the overall population, whereas the third scoring system had an AUC of 0.79 in the development cohort, 0.81 in the validation cohort, and 0.80 in the overall population (Table 3). Model 2 was identified as the final model because it had similar sensitivity and specificity as the other models and was applicable, practical, and easy to remember. Table 4 shows the sensitivity, specificity, and positive and negative predictive values for various cut-off values for Model 2.

DISCUSSION

This study aimed to evaluate clinical, radiographic, and laboratory factors that can predict the presence or absence of COVID-19 infection to develop and validate a diagnostic model for identifying people at risk for COVID-19.

In the initial scoring model we developed, dyspnea was allocated 3 points, cough 2 points, fatigue 2 points, myalgia 2 points, and typical radiological findings in Thorax CT were assigned 8 points. When the corresponding scoring was evaluated out of 17, it yielded a risk score of 0.79 AUC for the development cohort, 0.81 AUC for the validation cohort, and 0.80 AUC for the overall population. The coefficients of the model variables were adjusted to set them as 10 and 19, respectively, over the total scores in the second and third scoring systems. Model 2 was identified as the final model because it had similar sensitivity and specificity as the other models and was applicable, practical, and easy to remember.

In both the development and validation cohorts, cough, fatigue, and dyspnea were more prevalent in COVID-19 patients than in non-COVID-19 cases. The main symptoms of COVID-19, according to the Centers for Disease Control and Prevention, are high temperature, coughing, dyspnea, fatigue, musculoskeletal pain, headaches, loss of smell or taste, throat pain, vomiting or nausea, and diarrhea (6).

Compared to non-COVID-19 cases, it was determined that typical COVID-19 radiological findings in COVID-19 patients were statistically significant in both the development and validation cohorts.

Table 3. Receiver operating characteristic analysis of COVID-19 risk scores

	Model 1	Model 2	Model 3
Dyspnea	3 points	2 points	4 points
Cough	2 points	1 point	2 points
Fatigue	2 points	1 point	2 points
Myalgia	2 points	1 point	2 points
Typical chest CT images	8 points	5 points	9 points
	17 points	10 points	19 points
Development cohort			
AUC (95% CI)	0.79 (0.76-0.82)	0.79 (0.76-0.82)	0.79 (0.76-0.82)
Cut-off point	>4	>2	>4
Sensitivity	71%	71%	71%
Specificity	76.30%	76.30%	76.30%
p	**<0.001**	**<0.001**	**<0.001**
Validation cohort			
AUC (95% CI)	0.81 (0.77-0.85)	0.81 (0.77-0.85)	0.81 (0.77-0.85)
Cut-off point	>3	>2	>4
Sensitivity	78.50%	69%	69%
Specificity	72.10%	81.20%	81.20%
p	**<0.001**	**<0.001**	**<0.001**
Total			
AUC (95% CI)	0.80 (0.77-0.82)	0.80 (0.77-0.82)	0.80 (0.77-0.82)
Cut-off point	>4	>2	>4
Sensitivity	70.40%	70.39%	70.39%
Specificity	78.20%	78.21%	78.21%
p	**<0.001**	**<0.001**	**<0.001**

Table 4. Sensitivity, specificity, and predictive values for Model 2 cut-off values

	Development cohort				Validation cohort			
Risk score	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**	**NPV (%)**	**Sensitivity (%)**	**Specificity (%)**	**PPV (%)**	**NPV (%)**
>0	95.14	27.54	75.50	70.70	95.45	25.97	67	78.40
>1	81.62	63.98	84.20	59.70	80.58	64.94	78.30	68
>2	70.99	76.27	87.60	52.80	69.01	81.17	85.20	62.50
>3	66.85	78.39	87.90	50.10	64.46	83.77	86.20	60
>4	65.59	81.36	89.20	50.10	63.64	83.77	86	59.40
>5	60.72	85.17	90.60	48	57.85	87.01	87.50	56.80
>6	32.79	93.64	92.40	37.20	38.84	94.81	92.20	49.70
>7	12.43	97.03	90.80	32	20.66	99.35	98	44.30
>8	3.60	99.58	95.20	30.50	6.20	100	100	40.40
>9	0.36	100	100	29.90	0.83	100	100	39.10

PPV: Positive predictive value, NPV: Negative predictive value.

COVID-19 imaging characteristics have been observed to have a high sensitivity, particularly in high-prevalence areas (7). Hu et al. found that 50% of asymptomatic SARS-CoV-2 cases had typical ground-glass opacities, and 20% had atypical CT appearance (8). When RT-PCR was used as the gold standard, thorax CT had 97% sensitivity, 25% specificity, and 68% accuracy in detecting COVID-19 infection (9).

In both the development and validation cohorts, greater CRP and ferritin levels and reduced lymphocyte and eosinophil levels were found to be statistically significant in COVID-19 patients compared to non-COVID-19 cases. Lymphopenia and an increase in CRP, ferritin, and D-dimer are typical laboratory abnormalities observed; some of which indicate disease severity (10,11). Lymphopenia and eosinopenia are associated with increased disease severity and a poor prognosis (12). Several factors contribute to lymphopenia, including the cytotoxic effects of the virus, the induction of apoptosis, IL1-mediated pyroptosis, and the inhibition of bone marrow by inflammatory cytokines (13). Several reports have suggested lymphopenia as a strong indicator of COVID-19 infection (14-16).

The multivariable analysis revealed that, in diagnosing COVID-19, the presence of typical radiological features increased the risk by eight times, dyspnea by three times, myalgia by two times, cough by two times, and fatigue by 1.5 times. Clinical examinations and radiological diagnostics proved to be valuable diagnostic approaches, especially during the initial phases of the pandemic when confirmed molecular and serological testing options were not available (17,18). Kovács et al. demonstrated the sensitivity, specificity, and accuracy of RT-PCR, using thorax CT as the gold standard, as 65%, 83%, and 67%, respectively, as per the inverse calculation approach (19).

Testing techniques widely used for diagnosing COVID-19 include viral nucleic acid testing, computed tomography scans, and antigen testing (20,21). In the initial week of a suspected infection, both serological and molecular tests become ineffective due to the virus being in its incubation phase and resulting in insufficient copies of viral RNA present in circulation (22,23). The time lapse between sample collection and result retrieval often exceeds 24 hours, and it is recognized that testing samples from the upper respiratory tract can yield a false-negative rate (24). Effective acute care, infection control, and avoidance of nosocomial transmission all depend on a rapid COVID-19 diagnosis upon admission. The burden that periodic increases in the incidence of COVID-19 have placed on health systems worldwide highlights the importance of accurate early risk classification in the general population. In the absence of laboratory testing for SARS-CoV-2, Our diagnostic prediction model was designed for use by healthcare professionals to facilitate the clinical diagnosis of patients with COVID-19 and to support infection treatment decisions within the initial 24 hours of admission.

Limitations

Our study exhibits certain limitations. It is an observational study relying on data obtained from health records due to the impracticality of conducting in-person visits and interviews amid the pandemic. This research was retrospective, wherein symptom reporting was voluntary. This may have concluded as the response bias. The patients were asked about symptoms in a way that allowed them to indicate whether or not they were present subjectively. No specific symptom scales were employed. In our study, the nonspecific and subjective fatigue symptom was questioned in the pandemic outpatient clinic without a scale, and possible contributing factors, including anemia, undiagnosed sleep apnea syndrome, comorbidities, and medication therapy, were not assessed. Finally, the predictive performance of the models can also be influenced by the phase of the disease. Although we aimed to mitigate this effect by exclusively analyzing patients in the emergency department, the time lapse between the onset of symptoms could also be a contributing factor.

CONCLUSION

The predictive scoring system accurately predicted the diagnosis of COVID-19 infection, which gave clinicians a theoretical basis for devising immediate treatment options. However, to fully evaluate the predictive effectiveness of the scoring system, it must be externally validated in a multi-center study.

Ethical Committee Approval: This study was approved by the Uludağ University Faculty of Medicine Clinical Research Ethics Committee (Decision no: 2020-19/7, Date: 04.11.2020).

CONFLICT of INTEREST

The authors declare that they have no conflict of interest.

AUTHORSHIP CONTRIBUTIONS

Concept/Design: ÖAG, AU, GO, ED

Analysis/Interpretation: GO, ÖAG

Data acqusition: NAAÖ, DÖT, OET, UÖ, AGD, İS, FC, DE, EU, MK

Writing: ÖAG, AU

Clinical Revision: ÖAG, AU, HA

Final Approval: DE, ÖAG, AU, GO, ED, AGD, FC

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