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ORIGINAL RESEARCH CORONA EXPERIENCE

A simple diagnostic scoring system for COVID-19 screening

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Abstract

Background: The COVID-19 pandemic has prompted the world to make various efforts to control its spread by finding ways to diagnose COVID-19 quickly and accurately. Early identification of COVID-19 infection is essential, especially in hospitals with limited resources. We aimed to generate two scores based upon clinical and laboratory findings in patients screen for COVID-19 infection.

Methodology: This study used a retrospective cohort design that involved 705 adults (≥ 18 y old) admitted in Dr. Sardjito Hospital and Dr. S. Hardjolukito Hospital. The patients' data collected included demographic characteristics, anamnesis on signs and symptoms, history of contact with COVID-19 patients, history of staying or visiting an endemic area, comorbidities, and laboratory and radiologic indicators. All variables with a $P < 0.25$ on the bivariate test were included in a univariable logistic regression. If the $P < 0.05$, the variable was included in the multivariable logistic regression with a $P < 0.05$ considered significant. Receiver Operating Characteristic (ROC) producing an area under the curve (AUC) with 95% confidence intervals (CIs) was used to assess discrimination power.

Results: Two scores were generated; score in Model 1 consisted of clinical signs, basic laboratory indicators, and chest X-ray, and in Model 2 consisted of clinical signs, chest X-ray, basic and advanced laboratory indicators, including C-reactive protein (CRP), lactate dehydrogenase (LDH), albumin, and D-dimer. The ROC score of Model 1 was 0.801 (0.764−0. 838), which is considered good discrimination, and of Model 2 had excellent discrimination with a ROC of 0.858 (0.826−0. 891); the differences in the ROC of the two models was statistically significant ($P = 0.03$). The score of Model 1 more than 5 had 85% sensitivity and 61% specificity of positive COVID-19. A score of Model 2 more than 4 had 83% sensitivity and 72% specificity for diagnosing positive COVID-19.

Conclusions: A simple score consisting of clinical symptoms and signs, and simple laboratory indicators can be used to screen for COVID-19 infection.

Abbreviations: ARDS: Acute respiratory distress syndrome; CRP: C-reactive protein; MLR: monocyte-to-lymphocyte ratio; NLR: Neutrophil-to-lymphocyte ratio; RT-PCR: Reverse Transcription-Polymerase Chain Reaction;

Key words: COVID-19; Screening System; Clinical Symptoms; Laboratory Indicators

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1. Introduction

The COVID-19 pandemic has prompted the world to take various measures to control its spread by finding ways to diagnose COVID-19 quickly and accurately. Early identification is essential, especially in hospitals with limited resources. Reverse transcription-polymerase chain reaction (RT-PCR) has been the gold standard for COVID-19 diagnosis.[1,2]

Although considered the gold standard, RT-PCR has some drawbacks due to pre-analytical and analytical factors. These factors include lack of standardization in specimen collection, delays or poor storage before arriving at the laboratory, inadequately validated assays, contamination during procedures, insufficient specimens, viral load, disease incubation period, and presence of mutations that escape RT-PCR detection. RT-PCR also does not provide immediate results since amplification of viral RNA requires a long turnaround time and has false-negative results as high as 15%–20% depending on how many days the samples were collected since the onset.[2] A systematic review by Arevalo et al. showed that 54% of the patients with a diagnosis of COVID-19 showed negative RT-PCR swab results on the first swab result.[3]

Furthermore, not all health facilities in developing countries are well equipped with certified laboratories, advanced equipment, and trained personnel to perform RT-PCR tests. On the other hand, the limited capacity of isolation wards for COVID-19 patients is still a significant problem for hospitals in developing countries. Thus, a less expensive and more affordable diagnostic tool as an alternative method for screening suspected patients with COVID-19 like symptoms is necessary.

The ideal characteristics of a COVID-19 diagnostic score are; it should be accurate, fast, easy, inexpensive, widely applicable, and applicable for emergency and elective cases. Thus, the need for a validated clinical score is critical. The development of a COVID-19 diagnostic score system is impeded by the nature of the disease, which has a thousand faces due to its common and non-specific signs and symptoms, often found in other diseases.[4]

The clinical manifestations of COVID-19 are widely varied, with most patients reporting mild or subclinical symptoms after 2−14 days of virus exposure. The prevalent symptoms of these levels of severity include fever, cough, shortness of breath, headache, sore throat, runny nose, nausea, vomiting, and diarrhoea. At the same time, 16−26% of patients develop acute respiratory distress syndrome (ARDS), requiring intensive care. Diarrhoea and fever are the most common symptoms, although their severity varies between individuals.[5] Anosmia was a prominent symptom in 73% of COVID-19 patients, with 26.6% reporting it as an initial symptom, while myalgia was the initial symptom in 36% of patients.[6,7]

Studies showed that simple anamnesis, clinical signs and symptoms, and basic laboratory examination could generate valuable tools to screen the patients. For instance, Song et al. in China also found the associations between chest CT-scan pneumonia, contact history, fever, age, gender, temperature 37.8^{0}C, cough/dyspnoea, and neutrophil-to-lymphocyte ratio (NLR) as variables of COVID-19 diagnosis.[1] Guan et al. in China, and Sun et al., in Singapore showed that older age, contact history, fever, diarrhea, ground glass appearance of lungs CT-scan, lymphocytopenia, leukocytopenia, and thrombocytopenia could be used as screening tools for patients with COVID-19.[8] The monocyte-to-lymphocyte ratio (MLR) showed an acceptable efficiency to separate COVID-19 patients from healthy subjects. At the same time, the NLR may be a reliable marker for evaluating the disease severity of COVID-19.[9] Furthermore; A radiologic study of the lungs reported signs of consolidation, reticular interstitial thickening, and ground-glass opacities (GGO) in 81.3%, 39.9%, and 32.5% of COVID-19 patients, respectively.[10]

Based on clinical symptoms and laboratory examinations of COVID-19 from a previous study, we hypothesized that a scoring system based upon the patients' clinical symptoms and signs, and basic laboratory data would serve as an accurate diagnostic tool for COVID-19 in our population.

2. Methodology

This study used a retrospective cohort design. The study received ethical clearance from the Medical and Health Research Ethics Committee of Universitas Gadjah Mada, Yogyakarta, Indonesia (Ethical Clearance No KE-0527-06-2020) before data collection from April

Table 1: Demographic Data

Variable	Swab RT-PCR Results		Total	p
	Positive (n = 285)	Negative (n = 420)		
Sex				
- Female	112 (39.3)	181 (43.1)	293 (41.6)	0.315
- Male	173 (60.7)	239 (56.9)	412 (58.4)	
Age (y)	52.9 ± 15.1	54.1 ± 16.3	53.7 ± 15.8	0.314
Age (categorical)				
- ≥ 40 y	222 (77.9)	332 (79.0)	554 (78.6)	0.714
- < 40 y	63 (22.1)	88 (21.0)	151 (21.4)	
Height (m)	1.62 ± 0.07	1.6 ± 0.08	1.6 ± 0.07	< 0.001
Weight (Kg)	69.7 ± 14.3	56.7 ± 13.6	62 ± 15.3	< 0.001
Body Mass Index (BMI)	26.5 ± 4.9	22.2 ± 4.7	23.9 ± 5.2	< 0.001
Hypertension				
- Yes	83 (29.1)	99 (23.6)	182 (25.8)	0.098
- No	202 (70.9)	321 (76.4)	523 (74.2)	
Diabetes Mellitus				
- Yes	79 (27.7)	108 (25.7)	187 (26.5)	0.554
- No	206 (72.3)	312 (74.3)	518 (73.5)	
Heart disease				
- Yes	42 (14.7)	91 (21.7)	133 (18.9)	0.021
- No	243 (85.3)	329 (78.3)	572 (81.1)	
COPD				
- Yes	2 (0.7)	15 (3.6)	17 (2.4)	0.015
- No	283 (99.3)	405 (96.4)	688 (97.6)	
CKD				
- Yes	19 (6.7)	76 (18.1)	95 (13.5)	< 0.001
- No	266 (93.3)	344 (81.9)	610 (86.5)	
Immunocompromised				
- Yes	14 (4.9)	123 (4.9)	137 (19.4)	< 0.001
- No	271 (95.1)	297 (70.7)	568 (80.6)	

CKD: Chronic Kidney Disease; COPD: Chronic Obstructive Pulmonary Disease
Data presented as n (%) or Mean ± SD

2020−April 2021. The requirement of the informed consent was waived off, since we collected anonymous data from the medical records. The inclusion criteria were adult patients (≥ 18 y old) admitted at COVID-19 Clinics and Emergency Department at two referral hospitals designated for COVID-19. The exclusion criteria were: trauma patients and patients whose medical record data could not be collected during the sampling period.

The gold standard of COVID-19 diagnosis was positive results of RT-PCR from the nasal and oropharyngeal swabs. Data collected were: demographic characteristics (age, sex, body weight, height, BMI), history of contact with COVID-19 patients, history of travel to an endemic area, signs and symptoms (including fever in the last seven days, cough, shortness of breath, headache/sputum production/sore throat/anorexia, and fatigue/myalgia, anosmia), comorbidities (diabetes mellitus, hypertension, heart disease, chronic obstructive pulmonary disease (COPD), immunocompromise state, chronic kidney disease (CKD)), lab results (complete blood count (CBC), differential blood count, and calculated neutrophil-to-lymphocyte ratio (NLR)). We also collected other laboratory markers, such as albumin, C-reactive protein (CRP), Lactate Dehydrogenase (LDH), D-Dimer, X-ray, and thoracic CT-scan.

In this study, we created two models for COVID-19 screening. Model 1 consisted of anamnesis, clinical signs, simple laboratory indicators (complete blood count), and chest X-ray examination. Model 2 consisted of clinical signs, simple laboratory indicators, chest X-ray, and advanced laboratory data (CRP, LDH, albumin, and D-dimer). Based on previous studies, the leukocyte values < $10x10^3$, neutrophil < 8.9 x 10^3, lymphocyte values < 15%, CRP values > 30 mg/L, LDH values > 400U/L, albumin values < 3 g/dL, and D-dimer values > 500 ng/mL was significantly present in COVID-19 patients, so we categorize those parameters accordingly.[11,12]

Statistical analysis

Numerical variables are presented as mean and standard deviation, while nominal or categorical data are presented as percentages and proportions. All variables were screened using a bivariate test of the Student's t-test if the data was numeric. Categorical/dichotomous data were analyzed using the Chi-square test. All variables

Table 2: Data from anamnesis and physical examination; (Data presented as n (%)

Variable	Swab RT-PCR Results		Total	p
	Positive (n=285)	Negative (n=420)		
History of stay or visit to an endemic area				
- Yes	222 (77.9)	337 (80.2)	559 (79.3)	0.451
- No	63 (22.1)	83 (19.8)	146 (20.7)	
History of close contact				
- Yes	1 (0.4)	5 (1.2)	6 (0.9)	0.254
- No	284 (99.6)	415 (98.8)	699 (99.1)	
Fever in the previous seven days				
- Yes	189 (66.3)	255 (60.7)	444 (63.0)	0.022
- No	82 (28.8)	163 (38.8)	245 (34.8)	
- Data missing	14 (4.9)	2 (0.5)	16 (2.3)	
Temperature > 38 ˚C (on examination)				
- Yes	43 (15.1)	74 (17.6)	117 (16.6)	0.545
- No	227 (79.6)	344 (81.9)	571 (81.0)	
- Data missing	15 (5.3)	2 (0.5)	17 (2.4)	
Cough				
- Yes	217(76.1)	265 (63.1)	482 (68.4)	0.001
- No	53 (18.6)	152 (36.2)	205 (29.1)	
- Data missing	15 (5.3)	3 (0.7)	18 (2.6)	
Dyspnea				
- Yes	204 (71.6)	263 (62.6)	467 (66.2)	0.003
- No	61 (21.4)	133 (31.7)	194 (27.5)	
- Data missing	20 (7.0)	24 (5.7)	44 (6.2)	
Headache/sputum production/ sore throat/ anorexia				
- Yes	191 (67.0)	172 (41.0)	363 (51.5)	< 0.001
- No	47 (16.5)	217 (51.7)	264 (37.4)	
- Data missing	47 (16.5)	31 (7.4)	78 (11.1)	
Fatigue /Myalgia				
- Yes	167 (58.6)	183 (43.6)	350 (49.6)	< 0.001
- No	71 (24.9)	223 (53.1)	294 (41.7)	
- Data missing	47 (16.5)	14 (3.3)	61 (8.7)	

with a $P < 0.25$ were included in the multivariable analysis, and a $P < 0.05$ is considered significant. The score was generated from the coefficient (standard error (SE) ratio) divided by the smallest B/SE ratio.

The Area Under the Curve of Receiver Operating Characteristic (AUC - ROC) with 95% confidence intervals (CIs) was calculated to assess the discriminatory power of the score. The optimal cut-off points were based on sensitivity and specificity calculations using Youden Index. The Statistical Package for the Social Sciences (SPSS) (version 27.0 SPSS Inc., Chicago, IL, USA) was used for most of the analyses, while STATA® was used to assess the differences between ROC models based on DeLong's method.

3. Results

From April 24, 2020 to December 31, 2020, 914 patients undergoing RT-PCR from two referral hospitals for COVID-19 were categorized as 'probable', 'suspect', 'close contacts', and 'confirmed' cases. A total of 705 patients (aged ≥ 18 y) were included as subjects.

Due to many missing data on anosmia and thoracic CT scans, we omitted these variables from the analysis. The

Table 3: Data from laboratory examination and chest X-ray; (Data presented as n (%)

Variables	Swab RT-PCR Results		Total	p-value
	Positive (n = 285)	Negative (n = 420)		
Leukocyte				
- < 10x103 µL	196 (68.8)	164 (39.0)	360 (51.1)	< 0.001
- > 10x103 µL	89 (31.2)	256 (61.0)	345 (48.9)	
Neutrophil				
- < 8.9x103 µL	3 (1.1)	13 (3.1)	16 (2.3)	0.074
- > 8.9x103 µL	282 (98.9)	407 (96.9)	689 (97.7)	
Lymphocytes				
- Normal	121 (42.5)	169 (40.2)	290 (41.1)	< 0.002
- < 10%	149 (52.3)	195 (46.4)	344 (48.8)	
- < 15%	15 (5.3)	56 (13.3)	71 (10.1)	
Neutrophil-lymphocytes ratio (NLR)				
- Normal	85 (29.8)	120 (28.6)	205 (29.1)	0.464
- 3,5−5	41 (14.4)	49 (11.7)	90 (12.8)	
- > 5	159 (55.8)	251 (59.8)	410 (58.2)	
Thrombocyte				
- < 200 x103 µL	115 (40.4)	158 (37.6)	273 (38.7)	0.465
- > 200 x103 µL	170 (59.6)	262 (62.4)	432 (61.3)	
CRP				
- ≥ 30 mg/mL	198 (69.5)	226 (53.8)	424 (60.1)	< 0.001
- < 30 mg/L	54 (18.9)	155 (36.9)	209 (29.6)	
- No data	33 (11.6)	39 (9.3)	72 (10.2)	
LDH				
- > 400 U/L	119 (41.8)	139 (33.1)	258 (36.6)	0.003
- ≤ 400 U/L	121 (42.5)	231 (55.0)	352 (49.9)	
- No data	45 (15.8)	50 (11.9)	95 (13.5)	
Albumin				
- < 3 g/dL	75 (26.3)	195 (46.4)	270 (38.3)	< 0,001
- > 3 g/dL	172 (60.4)	192 (45.7)	364 (51.6)	
- No data	38 (13.3)	33 (7.9)	71 (10.1)	
D-dimer				
- > 500 ng/mL	184 (64.6)	124 (29.5)	308 (43.7)	< 0.001
- < 500 ng/mL	70 (24.6)	252 (60.0)	322 (45.7)	
- No data	31 (10.9)	44 (10.5)	75 (10.6)	
Abnormal Chest X-ray				0.111
- Yes	246 (86.3)	389 (92.6)	635 (90.1)	
- No	30 (10.5)	31 (7.4)	61 (8.7)	
- No data	9 (3.2)	0 (0)	9 (1.3)	

CRP: C-reactive protein, LDH: Lactate Dehydrogenase; Data presented as n (%)

subject demographic and comorbidity data are presented in Table 1. The majority of participants in this study were male (58.4%) with a mean age of 53 ± 15.8 y. Demographic data such as mean height, weight, and BMI were significantly higher in the RT-PCR positive group. Patient data such as the history of heart disease, COPD, kidney disease, and immunocompromise were also statistically higher in the positive RT-PCR group.

Table 4: Model 1 of COVID-19 diagnostic screening

Variables	B	SE.	Adj. OR	95% CI	P value	Score Model 1
Fever in the last 7 days	0.271	0.23	1.312	0.836−2.059	0.238	
Cough	0.619	0.245	1.857	1.15−2.999	0.011	1
Dyspnea	0.7	0.242	2.014	1.253−3.238	0.004	1
Headache/sputum production/ sore throat/ anorexia	1.538	0.236	4.657	2.935−7.389	< 0.001	3
Fatigue /Myalgia	0.764	0.222	2.147	1.389−3.319	0.001	1
Low Leukocyte (< 10x10^3 μL)	1.497	0.216	4.468	2.923−6.829	< 0.001	3
Low Neutrophil	0.124	0.723	1.132	0.275−4.666	0.864	
Low Lymphocyte (< 10%)	−0.648	0.393	0.523	0.242−1.13	0.099	
Low lymphocyte (< 15%)	0.164	0.22	1.178	0.766−1.812	0.455	
Abnormal Chest X-ray	−0.167	0.375	0.846	0.406−1.763	0.655	
Constant	−3.893					

Table 5: Model 2 of COVID-19 diagnostic screening

Variables	B	SE.	Adj. OR	95% CI	P value	Score Model 2
Fever in the last 7 days	0.158	0.277	1.171	0.68−2.016	0.569	
Cough	0.435	0.286	1.544	0.882−2.705	0.128	
Dyspnea	0.689	0.292	1.992	1.125−3.529	0.018	1
Headache/sputum production/ sore throat/ anorexia	1.601	0.278	4.959	2.875−8.552	<0.001	2
Fatigue /Myalgia	0.695	0.263	2.004	1.197−3.354	0.008	1
Low leukocyte count (<10x10^3 μL)	1.412	0.256	4.104	2.483−6.782	<0.001	2
Low Neutrophil count	−0.404	0.818	0.667	0.134−0.842	0.621	
Low lymphocyte count (<10%)	−1.025	0.435	0.359	0.153−0.842	0.018	−1
Low lymphocyte count (<15%)	0.062	0.264	1.064	0.634−1.786	0.813	
CRP ≥ 30 mg/L	0.861	0.305	2.366	1.303−4.299	0.005	1
LDH > 400	0.119	0.257	1.126	0.681−1.862	0.643	
Albumin < 3 g/dL	−1.08	0.259	0.34	0.205−0.564	<0.001	−2
D−dimer > 500 ng/mL	1.776	0.261	5.905	3.544−9.84	<0.001	3
Abnormal chest X-ray	−0.123	0.447	0.884	0.368−2.122	0.783	
Constant	−4.765					

CRP: C-reactive protein, LDH: Lactate Dehydrogenase

Table 2 shows that the patient history and clinical symptoms, fever in the last seven days, cough, shortness of breath, headache/sputum production/ sore throat/ anorexia, and fatigue/myalgia were also significantly higher in positive RT-PCR (P < 0.25).

Laboratory data and chest X-ray results are presented in Table 3. The presence of low leukocyte count (< 10x10^3 mL), low neutrophil count (< 8.9x10^3 mL), low lymphocyte count (< 10−15%,), low albumin (< 3 g/dL), CRP > 30 mg/L, LDH > 400 U/L, D-dimer > 500 ng/mL and abnormal chest X-ray had P < 0.25, so they were included in the multivariable test.

Model 1 was built from the patients' clinical history, clinical signs derived from the history, physical examination and basic laboratory examination (complete blood count). The significant variables for screening for

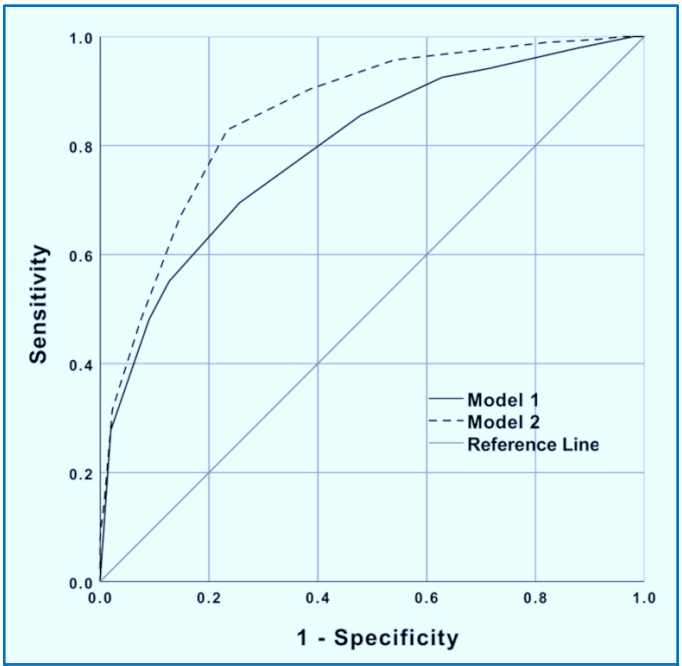

Figure 1: AUROC of the two models showing relative accuracy

COVID-19 infection were cough, dyspnea, headache/sputum production/sore throat/anorexia, fatigue/myalgia and low leukocyte count (Table 4).

Model 2 was derived from clinical symptoms, chest X-ray, and basic and advanced laboratory examinations (Table 5). Variables that independently predict the occurrence of COVID-19 are as follows: dyspnea, headache, sputum production. sore throat, anorexia, fatigue, myalgia, low leucocyte count, low lymphocyte count, CRP ≥ 30 mg/L, LDH > 400U/L, albumin > 3 g/dL, and D-dimer > 500 ng/mL.

The accuracy of the models is presented in Figure 1. Discrimination of Model 1 is good with area under the receiver operating characteristic (AUROC) ± CI: 0.801 (0.764−0. 838), and Model 2 has a higher AUROC ± CI: 0.858 (0.826−0.891). The difference in the AUROC of both models was significant (P = 0.034).

Score of Model 1 had a range from −1 to 10, with a cut-off score of more than 5 having 85% sensitivity and 61% specificity for positive COVID-19. Meanwhile, score of Model 2 ranged from −3 to 12, with a cut-off score of more than 4 having 83% sensitivity and 72% specificity for positive COVID-19.

4. Discussion

This study showed that including routine data from patient's characteristics, anamnesis, physical examination and laboratory examination could accurately predict the positive RT-PCR of COVID-19. The model with anamnesis, clinical findings and simple laboratory data only (Model I) has good accuracy but is significantly lower than the accuracy of the more complex model (Model 2).

The variables and the accuracy of Model 1 are similar to other studies based on simple variables from routine anamnesis, physical examinations, and basic laboratory findings.[13,14] Most of those studies produced models with good accuracy and were applicable to health facilities with limited resources. For instance, Sun et al. in Singapore showed that older age, contact history, fever, diarrhea, ground glass appearance on pulmonary CT-scan, lymphocytopenia, leukocytopenia, and thrombocytopenia could be used as a screening tool for COVID-19 patients.[5] Sung et al. developed a COVID-19 screening scoring system for nursing home patients using contact history with patients with confirmed COVID-19, symptoms of fever, chills, myalgia, cough, shortness of breath, hypoxia, obesity, and leukocytosis. Each variable was scored and added up, with a total score of 3 considered a high risk of COVID-19 infection, with the AUC value of ROC 0.83 (95% CI 0.76−0.90) that considered a strong discrimination ability.[13] Zavascki et al. examined age, fever, dyspnea, fatigue, and coryza. A total score of 5 was regarded as a high risk of COVID-19. The model had good discrimination with the AUC value of ROC 0.80 (95% CI 0.76−0.86).[14] Dyspnea and fatigue were consistently reported as predictors.[13,14] Low leucocyte count had the highest score in Model 1 or Model 2, as found in the previous studies.[11,15]

Model 2 also had similar variables to previous studies and has good accuracy.[11,12,15] The specific hematologic parameters were altered in COVID-19 patients, and the previous studies showed lower LDH, CRP, and higher albumin are a predictor of COVID-19 infection.[5,12] The history of contact with COVID-19 patient, fatigue, bilateral pneumonia, pulse < 100x/min, CRP < 5 mg/L, neutrophil count 6.3×109/L, eosinophil count ≤ 0.02 ×109/L, D-dimer 0.5 mg/L, and glucose 6 mmol/L were used to predict COVID-19 with the cut-off value of 20 points (specificity: 0.866; sensitivity: 0.813) and an AUC of ROC 0.921 (95%CI: 0.896−0.945; P < 0.01).[11]

A cross-sectional retrospective study by Vieceli et al., from 100 suspected COVID-19 patients aged >18 y, taken between the period of March 17 to April 10, 2020, found a strong relationship between the leukocyte count < 7.7 × 10^3 mm3, LDH > 273 U/L, and abnormal radiological features, and positive COVID-19 cases. However, this study was limited due to its small sample and severe comorbidities in most patients that did not

match the general population. Furthermore, there was a risk of missing diagnosis due to the absence of second RT-PCR testing.[15]

The AIFELL score was developed as a simple triage instrument for an ER setting using frequently available elements, like patient symptoms (fever ≥ 38°C, altered smell or taste), laboratory tests (lymphocytopenia < 1.45 G/L, CRP ≥ 30 mg/L, elevated LDH > 400 U/L), and thoracic imaging (pulmonary infiltrates). The AIFELL Score categorizes a score between 0 and 3 points associated with other respiratory conditions. Patients scoring higher than 5 points had a higher paraclinical component value than those with 2 points.[10] Still, these scoring systems include CRP and LDH, which may not be applicable for small hospitals without a complete laboratory examination facility.[12]

The lower CRP (< 44.5 mg/L) and LDH (< 256 U/L) also the higher albumin (> 35.8 g/L) predict the COVID-19 nucleic acid test will turn negative in 14 days. CRP is an acute-phase protein secreted by liver cells during the inflammatory response. CRP and LDH have a negative correlation with S-IgG. S-specific antibodies blocked the S protein's binding to hACE2, a cellular receptor that mediated SARS-COV-2 binding and entering target cells.[16] LDH is well-known as a marker of inflammation and a predictor of various types of pneumonia.[17] In contrast with this study, our study showed that albumin < 3 g/dL have a lower risk of positive COVID-19 infection; it may be because only 38% of patient in our population have albumin less than 3 g/dL, and the mean of albumin in our population. Lower albumin (< 3.5 g/dL) also did not increase the odds of hospitalization in one study.[18]

The data from this study may be useful for several reasons. First, the patients' characteristics were similar to other developing countries where the mean age of COVID-19 patients was lower than those in the developed countries.[19]

Furthermore, the model used is based on the facilities available. For example, Model 1 only used anamnesis, physical symptoms, and basic laboratory examination rather than more complex variables, which reflect the various healthcare facility levels in many developing countries.[20] The simple models in this study were accurate, cheap, uncomplicated, and widely applicable. Therefore, the research data from this study is valuable and can be used as a source for further research in COVID-19 diagnosis.

5. Limitations

This study was performed at two hospitals, the province's final referral centers for COVID-19 patients. Most of the patient data were obtained from the early phase COVID-19 pandemic, so most cases were probable, suspected, close contact confirmed, and had moderate to severe and critical conditions. Therefore, the patient inclusion increased the risk of overfitting with low generalizability.

6. Conclusion

A simple COVID-19 screening tool can be built from patients' history, clinical signs and symptoms and basic laboratory indicators; with better accuracy when the advanced laboratory tests are available.

7. Data availability

The numerical data generated during this research is available with the authors.

8. Acknowledgement

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9. Conflict of interest

The authors declare no conflicts of interest.

10. Authors' contribution

YW, DS, JK, AYJ: study design concept, conduction of study work, manuscript preparation

KS, PJ, CFRW, UW, DW: conduction of study work, manuscript preparation

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