Early triage of patients diagnosed with COVID-19 based on predicted prognosis: A Korean national cohort study

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Abstract

We developed a tool for early triage of a COVID-19 patient based on a predicted prognosis, using a Korean national cohort of 5,596 patients. Predictors chosen for our model were older age, male sex, subjective fever, dyspnea, altered consciousness, temperature ≥ 37.5°C, heart rate ≥ 100 bpm, systolic blood pressure ≥ 160 mmHg, diabetes mellitus, heart disease, chronic kidney disease, cancer, dementia, anemia, leukocytosis, lymphocytopenia, and thrombocytopenia. Our model was better in predicting prognosis than protocols that are not based on data. The AUC of our model utilizing all the selected predictors was 0.907 in predicting whether a patient will require at least oxygen therapy and 0.927 in predicting whether a patient will need critical care or die from COVID-19. Even with age, sex, and symptoms alone used as predictors, AUCs were ≥ 0.88. In contrast, the protocols currently recommended in Korea showed AUCs less than 0.75.

Introduction

Since the World Health Organization (WHO) declared the coronavirus disease 2019 (COVID-19) a pandemic in March 2020, it has been raging on, taking the lives of many people (over 1.32 million as of November 17, 2020)[1]. However, since no effective anti-viral drug or vaccine has been developed yet, the treatment mainly relies on symptomatic relief and supportive care, oxygen therapy, and critical care, depending on the disease severity. Thus, it is crucial to triage COVID-19 patients rapidly and efficiently so that limited medical resources, including quarantine facilities, hospital beds, and critical care equipment, can be allocated appropriately.

The current protocols recommended for triage and referral of COVID-19 patients in many countries or by WHO are based on known risk factors and expert opinion but have not been validated on the actual patient data[2–5]. Furthermore, since sudden disease progression in initially mild or asymptomatic COVID-19 patients is not rare with reported incidences of 6 to 12%[6–9], we should base the triage and referral of COVID-19 patients on the worst severity expected during the disease course, rather than the severity at the time of diagnosis.

The data accumulated for several months now have enabled development of such a data-driven prediction model. Several prediction models for disease severity in COVID-19 patients have been proposed[10–15]. There may be limitations, however, to applying these models for COVID-19 patient triage under some real-world circumstances. Most of these models require patients' information obtained from a blood test or imaging study. However, we often need to triage and refer COVID-19 patients immediately after the diagnosis with limited information depending on the situation.

Therefore, we aimed to develop an easy-to-use tool for COVID-19 patient triage based on a predicted prognosis, with the flexibility to adapt to variable availability. We categorized variables into four groups—demographics and symptoms, underlying diseases, vital signs, and laboratory findings—and develop separate algorithms for different combinations of the

variable groups. We also compared the performance of our models with the currently used triage protocols.

Materials and Methods

Ethical approval

The Institutional Review Board of *** blinded *** approved this retrospective Health Insurance Portability and Accountability Act-compliant cohort study and waived the informed consent from the participants. We performed all methods in accordance with relevant guidelines and regulations.

Data source and patients

This study used a dataset containing the epidemiologic and clinical information of patients diagnosed with COVID-19 in South Korea, which the Korea Disease Control and Prevention Agency (KDCA) collected, anonymized, and provided to researchers for the public interest. The data included 5,628 patients who either were cured or died from COVID-19 infection by April 30, 2020. After excluding 32 patients who lacked the information on disease severity or the presence or absence of symptoms, a total of 5,596 patients comprised our study cohort.

The outcome variable was the worst severity during the disease course, determined by the type of treatment required: (1) none or supportive treatment, (2) oxygen therapy, (3) critical care such as mechanical ventilation or extracorporeal membrane oxygenation (ECMO), or death from COVID-19 infection.

For the development of prediction models, the dataset was randomly divided into training and test cohorts with a ratio of 7:3 while preserving the disease severity distribution. We trained and optimized models using the training cohort and tested them on the test cohort (Fig. 1).

Variables in four different tiers based on accessibility

We intended to develop a model that can be used flexibly in real-world circumstances where some of the variables may not be available. Therefore, we categorized variables into four tiers based on their accessibility (Table 1 and Fig. 1).

Tier 1: Basic demographics and symptoms

Tier 1 variables can be obtained by simply asking a patient questions: age, sex, body mass index (BMI), pregnancy, and symptoms. The symptoms included were subjective fever, cough, sputum, dyspnea, altered consciousness, headache, rhinorrhea, myalgia, sore throat, fatigue, nausea or vomiting, and diarrhea. We separated this group of variables from others because there could be times when we need to triage a patient quickly without physical contact.

Tier 2: Underlying diseases

Tier 2 variables are underlying medical conditions: hypertension, diabetes mellitus (DM), heart disease, asthma, chronic obstructive pulmonary disease (COPD), chronic kidney disease (CKD), chronic liver disease, cancer, autoimmune disease, and dementia. We categorized these variables into a separate group because sometimes patients may not know exactly their underlying medical conditions. In this case, further actions may be required, including reviewing medical records or other examinations.

Tier 3: Vital signs

Tier 3 variables are blood pressure, body temperature, and heart rate. Our data lacked information on breathing rate. We separated these variables from the first two tiers because these can be obtained only when a patient visits a medical facility or can measure their vital

signs on their own. Blood pressure and heart rate were transformed into binary categorical variables by merging categories that were not significantly associated with disease severity based on the preliminary results in the training cohort: severe hypertension (systolic blood pressure ≥160 mmHg) and tachycardia (heart rate ≥100 bpm). We assumed that many patients had their body temperature measured while taking antipyretics, although our data did not contain the information on such patients' proportion.

Tier 4: Blood test results

Tier 4 variables are hemoglobin, hematocrit, white blood cell (WBC) count, lymphocyte count, and platelet count, which are available only after a blood test. As with Tier 3, these variables were also transformed into binary categorical variables: anemia (hematocrit <40%), leukocytosis (WBC $\geq 11\times10^3/\mu L$), lymphocytopenia (lymphocyte <1,000/μL), and thrombocytopenia (platelet <150,000/μL).

Predictor selection

To identify robust and stable predictors, we repeated 10-fold cross-validation (CV) 100 times with shuffling and choose variables that were selected more than 900 times out of 1,000 trials (>90%) based on two algorithms: Least Absolute Selection and Shrinkage Operator (LASSO) and Random Forest (RF). A variable was selected if its coefficient was non-zero on LASSO, and its variable importance on RF was positive[16,17].

Development of prediction models

We used four machine learning algorithms: ordinal logistic regression (OLR), multivariate RF, linear support vector machine (L-SVM), and SVM with the radial basis function kernel (R-SVM). For each algorithm, five models were created using one of the following five predictor

sets: predictors chosen from the Tier 1 variables (Model 1), Tiers 1/2 variables (Model 2A), Tiers 1/3 variables (Model 2B), Tiers 1/2/3 variables (Model 3), and Tiers 1/2/3/4 variables (Model 4). We optimized the hyperparameters for RF and SVM through a 10-fold CV with a grid search in the training cohort, using the area under the receiver operator characteristics curve (AUC) as an evaluation metric.

Validation of prediction models in comparison with current protocols

We validated the optimized models in the test cohort after fitting them onto the entire training dataset. Based on the probabilities for each outcome category, we assessed the diagnostic performance of each model for whether or not a patient will require treatment (Outcome 1 vs. 2/3), and whether or not a patient will require critical care or die (Outcome 1/2 vs. 3). Sensitivity, specificity, accuracy, precision, and negative predictive value (NPV) according to different probability cutoffs were calculated, in addition to AUC. We also drew calibration curves to compare the predicted and observed probabilities visually.

As a baseline for comparison, we also tested two protocols used to triage a newly diagnosed COVID-19 patient: a protocol proposed by the Korean Medical Association and Modified Early Warning Score (MEWS)[5,18]. These are two of the protocols that the Korean government currently recommends using with some modifications depending on the situation[5]. Since we did not have information on smoking status, oxygen saturation, and respiratory rate, these variables were considered normal when applying the protocols. These protocols are described in detail in Supplementary Tables 1 and 2.

Results

Patients

Of the total 5,596 COVID-19 patients in our study cohort, approximately half of the patients

(52.1%) were 50 years or older, while people aged younger than 20 years accounted for only 4.9% (Table 1). The two most common age groups were 20–29 years (19.8%) and 50-59 years (20.4%). The ratio of males to females was 5.9:4.1. Most (86.4%) recovered without particular therapy, 9.3% of the patients required oxygen therapy, and the remaining 4.4% fell into severe conditions such as respiratory or multi-organ failure and required critical care such as mechanical ventilation or ECMO. The overall mortality from COVID-19 infection was 1.1% (63/5,596). The mean time between diagnosis and recovery or death was 25.6 days, with a standard deviation of 11.0 days. Patients who were older, male, under-weight or obese, or with symptoms (except for diarrhea), underlying diseases (except for autoimmune disease), abnormal vital signs (except for diastolic blood pressure), or abnormal blood test results tended to fall into more severe conditions (Table 1). The training and test cohorts comprised 3,940 and 1,656 patients, respectively. There was no significant difference in variables between the two cohorts (Supplementary Table 3).

Selected predictors for each model

The full results of predictor selection are in Supplementary Table 4.

Model 1: from history taking

The predictors selected from Tier 1 variables for Model 1 were age, sex, and symptoms of subjective fever, rhinorrhea, dyspnea, and altered consciousness. As opposed to other selected predictors, rhinorrhea was associated with a better prognosis (Table 2).

Model 2A: from history taking with known underlying disease status

The predictors chosen for Model2A were age, sex, subjective fever, dyspnea, and altered consciousness from Tier 1 (rhinorrhea excluded), and underlying diseases of hypertension, DM,

heart disease, CKD, cancer, and dementia from Tier 2 variables.

Model 2B: from history taking and physical examination with uncertain underlying disease

The predictors were age, sex, subjective fever, rhinorrhea, dyspnea, and altered consciousness from Tier 1, and high body temperature and tachycardia from Tier 3 variables.

Model 3: from history taking and physical examination with known underlying disease status

The predictors were age, sex, subjective fever, dyspnea, and altered consciousness from Tier 1 (rhinorrhea not included), severe hypertension (systolic blood pressure ≥160 mmHg), DM, heart disease, CKD, cancer, and dementia from Tier 2, and high body temperature and tachycardia from Tier 3.

Model 4: on admission

The predictors were age, sex, subjective fever, dyspnea, and altered consciousness from Tier 1, severe hypertension, DM, heart disease, CKD, cancer, and dementia from Tier 2, and high body temperature from Tier 3 (tachycardia excluded), and anemia, leukocytosis, lymphocytopenia, and thrombocytopenia from Tier 4 variables.

Variable effect size

Older age, altered consciousness, dyspnea, lymphocytopenia, leukocytosis, CKD, temperature of ≥ 38.5°C, dementia, thrombocytopenia, cancer, subjective fever, male sex, anemia, DM were associated independently with prognosis, in decreasing order of odds ratio (OR) from the multivariable OLR in the entire cohort (Table 2). Figure 2 is a flow diagram that shows the prognosis of different patient groups classified according to the age and the presence or absence of the symptoms and underlying diseases.

Model performance

Conventional protocols

In predicting whether a patient will require more than supportive care, the KMA model showed an AUC of 0.723 (95% confidence interval [CI], 0.693–0.753) with a sensitivity of 54.9 (48.3–61.4)% and a specificity of 7.6 (6.3–9.1)%, and the AUC, sensitivity, and specificity of the MEWS were 0.598 (0.563–0.633), 56.8 (50.1–63.4)%, and 23.5 (21.2–25.9)%, respectively. The performances of these two conventional models were not significantly different in predicting whether or not a patient will need critical care or die (Table 3).

Machine learning models

Machine learning models showed better performances than the conventional protocols (Table 3 and Supplementary Table 4). With the OLS algorithm, the AUCs of Models 1, 2A, 2B3, and 4 were 0.880 (95% CI, 0.855–0.904), 0.889 (0.865–0.912), 0.866 (0.841–0.892), 0.894 (0.871–0.917), and 0.907 (0.884–0.929) in predicting whether a patient will require at least oxygen therapy, and 0.903 (0.869–0.937), 0.905 (0.869–0.940), 0.922 (0.892–0.953), and 0.927 (0.894–0.960) in predicting whether a patient will need critical care or die, respectively (Table 3). The other machine learning algorithms—RF, L-SVC, and R-SVC—did not show superior performances to the OLS model (Supplementary Table 5).

The sensitivity, specificity, accuracy, precision, and NPV at different cutoff probabilities for the OLS models are presented in Table 4. The models showed good calibration in the training and testing, especially in the probability range of < 50% (Fig. 3). Figure 4 shows the nomogram of OLS Model 4 to predict the probability of recovering without particular treatment and the probability of requiring critical care or death from COVID-19 (see Supplementary Figure 1 for the nomograms of all the five models). When using a computer

device, it can be coded to choose an appropriate model automatically depending on available predictors; a simplified Python code with coefficients trained onto the entire dataset can be found in *** blinded ***.

Discussion

Our results demonstrate that a data-driven model to predict prognosis can be a good tool for early triage of COVID-19 patients. A significant shortcoming of the triage protocols that are not based on data is that risk factors are not weighted appropriately based on their effects on the outcome. For example, the WHO algorithm for COVID-19 triage and referral regards age > 60 years and the presence of relevant symptoms or co-morbidities as risk factors, but it does not put different weights on them[2]. However, if not treated as a continuous variable, age should be divided into multiple categories with appropriate weights because the risk continues to increase with age even after 60 years. Different symptoms or co-morbidities must also be weighted according to their importance when assessing the patients' status for triage. For example, in the current study, subjective fever, dyspnea, and altered consciousness were independent risk factors for severe illness, while other symptoms such as cough, sputum production, sore throat, myalgia, and diarrhea were not.

Our final prediction model used the OLR algorithm. We chose the OLR over the other machine learning algorithms (i.e., RF, L-SVM, and R-SVM) because it showed comparable or superior performances to the other algorithms in the final evaluation. Furthermore, a linear model like the OLR is more interpretable and easier to use even without a computer device, as nomograms can be used instead. We also observed the linear model's superiority in predicting COVID-19 prognosis in our previous study in which we developed a model to predict the risk of COVID-19 mortality based on demographics and medical claim data[15].

A difference of the current model from other earlier models is that we divided disease

severity into three categories. This is more helpful than the binary categorization (i.e., recovery vs. mortality), because not all medical facilities capable of oxygen therapy can also provide critical care, such as mechanical ventilation or ECMO. Furthermore, our model uses different algorithms depending on the available variable subsets. Health workers sometimes need to triage newly diagnosed COVID-19 patients even by a phone call alone in the real-world field, and patients commonly do not know their underlying disease exactly. Therefore, we expect that our model's flexibility may lead to a more widespread use.

The predictors chosen in this study are not much different from the known risk factors of developing into critical conditions from COVID-19[19]. However, it was unexpected that COPD, a known strong risk factor, was not selected as a predictor. We assume that this is because there were only 40 patients with COPD in the entire cohort, of whom 65% had dyspnea, and the disease severity of COPD might have varied widely. Thus, it is likely that the number of COPD cases was too small (even smaller in the training cohort after the training-test set split) to play a significant role independently from the other strong predictors. We hope to have more confirmatory results through further investigation as the KDCA plans to release the enhanced data with more patients soon.

There are limitations to our current model. First, we need to develop a more robust model by enrolling more patients and conduct prospective validation. We plan to use the current model in actual practice and keep improving the model using the newly accumulated data. Second, since we trained our model on Koreans' data, it is unsure whether it can be generalizable to patient cohorts in other countries or races. We hope to be able to develop a triage model that can be used globally through collaboration. Lastly, our data lacked some important variables, such as smoking, respiratory rate, and oxygen saturation, and had missing values in some of the Tiers-2/3/4 variables, which may have affected the training and performance of the algorithms using those variables. We did not perform imputation for

missing values because we did not want the uncertainty and potential bias from imputation, and imputation for missing values did not make significant differences in our preliminary analysis.

In conclusion, we developed a set of models that can be used for disease severity prediction and triage or referral of COVID-19 patients. Our prediction model has a good performance even with age, sex, and symptoms alone. The model performance can be enhanced if further information on underlying disease, vital signs, or blood test results is available.

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Author contributions

*** blinded ***

Competing interests

The authors declare no competing interests.

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Tables

Table 1. Patient characteristics by the worst severity during the disease course

Variable		Supportive care	O_2 therapy	Critical care	Mortality	*p*-value	Total
Number of patients		4780 (85.6%)	512 (9.1%)	241 (4.3%)	63 (1.1%)	<0.001	5596 (100%)
Days to recovery or death, mean (SD)		25.5 (10.3)	30.0 (12.1)	36.3 (16.1)	15.2 (13.4)	<0.001	25.6 (11.0)
Age	0-9 years	66 (100%)	0 (0%)	0 (0%)	0 (0%)	<0.001	66 (100%)
	10-19 years	203 (99%)	1 (0.5%)	0 (0%)	1 (0.5%)		205 (100%)
	20-29 years	1087 (98%)	20 (1.8%)	0 (0%)	2 (0.2%)		1109 (100%)
	30-39 years	546 (97.2%)	11 (2%)	2 (0.4%)	3 (0.5%)		562 (100%)
	40-49 years	703 (95.1%)	34 (4.6%)	2 (0.3%)	0 (0%)		739 (100%)
	50-59 years	999 (87.6%)	114 (10%)	15 (1.3%)	12 (1.1%)		1140 (100%)
	60-69 years	713 (78.7%)	135 (14.9%)	34 (3.8%)	24 (2.6%)		906 (100%)
	70-79 years	331 (60.7%)	125 (22.9%)	73 (13.4%)	16 (2.9%)		545 (100%)
	≥80 years	132 (40.7%)	72 (22.2%)	115 (35.5%)	5 (1.5%)		324 (100%)
Sex	Female	2858 (86.9%)	288 (8.8%)	114 (3.5%)	29 (0.9%)	<0.001	3289 (100%)
	Male	1922 (83.3%)	224 (9.7%)	127 (5.5%)	34 (1.5%)		2307 (100%)
Pregnancy	No	4752 (85.3%)	512 (9.2%)	241 (4.3%)	63 (1.1%)	0.353	5568 (100%)
	Yes	19 (100%)	0 (0%)	0 (0%)	0 (0%)		19 (100%)
	Missing	9 (100%)	0 (0%)	0 (0%)	0 (0%)		9 (100%)
Body mass index (kg/cm^2)	<18.5	225 (86.9%)	16 (6.2%)	16 (6.2%)	2 (0.8%)	<0.001	259 (100%)
	18.5-23	1660 (89.5%)	127 (6.9%)	46 (2.5%)	21 (1.1%)		1854 (100%)
	23-25	893 (86.4%)	108 (10.5%)	20 (1.9%)	12 (1.2%)		1033 (100%)
	25-30	865 (82.8%)	125 (12%)	39 (3.7%)	16 (1.5%)		1045 (100%)
	>30	178 (86%)	20 (9.7%)	5 (2.4%)	4 (1.9%)		207 (100%)
	Missing	959 (80.1%)	116 (9.7%)	115 (9.6%)	8 (0.7%)		1198 (100%)
Subjective fever	Absent	3818 (88.9%)	296 (6.9%)	148 (3.4%)	32 (0.7%)	<0.001	4294 (100%)
	Present	962 (73.9%)	216 (16.6%)	93 (7.1%)	31 (2.4%)		1302 (100%)
Cough	Absent	2836 (86.9%)	239 (7.3%)	160 (4.9%)	30 (0.9%)	<0.001	3265 (100%)
	Present	1944 (83.4%)	273 (11.7%)	81 (3.5%)	33 (1.4%)		2331 (100%)
Sputum	Absent	3456 (86.7%)	319 (8%)	169 (4.2%)	41 (1%)	<0.001	3985 (100%)
	Present	1324 (82.2%)	193 (12%)	72 (4.5%)	22 (1.4%)		1611 (100%)
Dyspnea	Absent	4445 (90.1%)	332 (6.7%)	128 (2.6%)	26 (0.5%)	<0.001	4931 (100%)
	Present	335 (50.4%)	180 (27.1%)	113 (17%)	37 (5.6%)		665 (100%)
Sore throat	Absent	3989 (84.4%)	446 (9.4%)	228 (4.8%)	61 (1.3%)	<0.001	4724 (100%)
	Present	791 (90.7%)	66 (7.6%)	13 (1.5%)	2 (0.2%)		872 (100%)
Rhinorrhea	Absent	4216 (84.7%)	468 (9.4%)	235 (4.7%)	60 (1.2%)	<0.001	4979 (100%)

	Present	564 (91.4%)	44 (7.1%)	6 (1%)	3 (0.5%)		617 (100%)
Myalgia	Absent	4005 (85.6%)	400 (8.6%)	220 (4.7%)	52 (1.1%)	<0.001	4677 (100%)
	Present	775 (84.3%)	112 (12.2%)	21 (2.3%)	11 (1.2%)		919 (100%)
Fatigue	Absent	4606 (85.9%)	475 (8.9%)	224 (4.2%)	58 (1.1%)	<0.001	5363 (100%)
	Present	174 (74.7%)	37 (15.9%)	17 (7.3%)	5 (2.1%)		233 (100%)
Headache	Absent	3931 (84.8%)	421 (9.1%)	228 (4.9%)	53 (1.1%)	<0.001	4633 (100%)
	Present	849 (88.2%)	91 (9.4%)	13 (1.3%)	10 (1%)		963 (100%)
Nausea or vomiting	Absent	4598 (85.9%)	470 (8.8%)	225 (4.2%)	59 (1.1%)	<0.001	5352 (100%)
	Present	182 (74.6%)	42 (17.2%)	16 (6.6%)	4 (1.6%)		244 (100%)
Diarrhea	Absent	4354 (85.7%)	446 (8.8%)	223 (4.4%)	57 (1.1%)	0.022	5080 (100%)
	Present	426 (82.6%)	66 (12.8%)	18 (3.5%)	6 (1.2%)		516 (100%)
Altered consciousnes s	Absent	4772 (85.8%)	512 (9.2%)	218 (3.9%)	59 (1.1%)	<0.001	5561 (100%)
	Present	8 (22.9%)	0 (0%)	23 (65.7%)	4 (11.4%)		35 (100%)
Diabetes mellitus	Absent	4322 (88%)	397 (8.1%)	143 (2.9%)	47 (1%)	<0.001	4909 (100%)
	Present	458 (66.7%)	115 (16.7%)	98 (14.3%)	16 (2.3%)		687 (100%)
Hypertension	Absent	3966 (90.2%)	304 (6.9%)	97 (2.2%)	31 (0.7%)	<0.001	4398 (100%)
	Present	814 (67.9%)	208 (17.4%)	144 (12%)	32 (2.7%)		1198 (100%)
Heart disease	Absent	4756 (85.9%)	497 (9%)	223 (4%)	61 (1.1%)	<0.001	5537 (100%)
	Present	24 (40.7%)	15 (25.4%)	18 (30.5%)	2 (3.4%)		59 (100%)
Asthma	Absent	4682 (85.6%)	495 (9.1%)	228 (4.2%)	63 (1.2%)	0.001	5468 (100%)
	Present	98 (76.6%)	17 (13.3%)	13 (10.2%)	0 (0%)		128 (100%)
Chronic obstructive pulmonary disease	Absent	4760 (85.7%)	502 (9%)	233 (4.2%)	61 (1.1%)	<0.001	5556 (100%)
	Present	20 (50%)	10 (25%)	8 (20%)	2 (5%)		40 (100%)
Chronic kidney disease	Absent	4757 (85.9%)	498 (9%)	225 (4.1%)	61 (1.1%)	<0.001	5541 (100%)
	Present	23 (41.8%)	14 (25.5%)	16 (29.1%)	2 (3.6%)		55 (100%)
Cancer	Absent	4679 (85.8%)	490 (9%)	219 (4%)	63 (1.2%)	<0.001	5451 (100%)
	Present	101 (69.7%)	22 (15.2%)	22 (15.2%)	0 (0%)		145 (100%)
Chronic liver disease	Absent	4404 (84.9%)	490 (9.4%)	234 (4.5%)	62 (1.2%)	0.033	5190 (100%)
	Present	61 (73.5%)	14 (16.9%)	7 (8.4%)	1 (1.2%)		83 (100%)
	missing	315 (97.5%)	8 (2.5%)	0 (0%)	0 (0%)		323 (100%)
Autoimmune disease	Absent	4430 (84.7%)	498 (9.5%)	238 (4.6%)	63 (1.2%)	0.356	5229 (100%)
	Present	29 (76.3%)	6 (15.8%)	3 (7.9%)	0 (0%)		38 (100%)
	missing	321 (97.6%)	8 (2.4%)	0 (0%)	0 (0%)		329 (100%)
Dementia	Absent	4355 (86.3%)	463 (9.2%)	166 (3.3%)	62 (1.2%)	<0.001	5046 (100%)
	Present	107 (47.8%)	41 (18.3%)	75 (33.5%)	1 (0.4%)		224 (100%)
	missing	318 (97.5%)	8 (2.5%)	0 (0%)	0 (0%)		326 (100%)
Heart rate	Bradycardia (<60)	87 (80.6%)	15 (13.9%)	6 (5.6%)	0 (0%)	0.001	108 (100%)

(beat/min)	Normal (60-100)	3799 (86.3%)	394 (8.9%)	160 (3.6%)	50 (1.1%)		4403 (100%)
	Tachycardia (>100)	784 (81.8%)	102 (10.6%)	61 (6.4%)	12 (1.3%)		959 (100%)
	Missing	110 (87.3%)	1 (0.8%)	14 (11.1%)	1 (0.8%)		126 (100%)
Body temperature (°C)	<37.5	4300 (88.0%)	380 (7.8%)	166 (3.4%)	39 (0.8%)	<0.001	4885 (100%)
	37.5-38	349 (75.4%)	70 (15.1%)	36 (7.8%)	8 (1.7%)		463 (100%)
	38-38.5	74 (54.4%)	31 (22.8%)	21 (15.4%)	10 (7.4%)		136 (100%)
	38.5≥38.5	32 (43.8%)	29 (39.7%)	6 (8.2%)	6 (8.2%)		73 (100%)
	Missing	25 (64.1%)	2 (5.1%)	12 (30.8%)	0 (0%)		39 (100%)
Systolic blood pressure (mmHg)	<120	1140 (87.3%)	95 (7.3%)	58 (4.4%)	13 (1%)	<0.001	1306 (100%)
	120-129	988 (86.8%)	110 (9.7%)	28 (2.5%)	12 (1.1%)		1138 (100%)
	130-139	939 (86.7%)	101 (9.3%)	32 (3%)	11 (1%)		1083 (100%)
	140-159	1190 (84%)	141 (10%)	68 (4.8%)	18 (1.3%)		1417 (100%)
	≥160	402 (78.4%)	65 (12.7%)	37 (7.2%)	9 (1.8%)		513 (100%)
	Missing	121 (87.1%)	0 (0%)	18 (12.9%)	0 (0%)		139 (100%)
Diastolic blood pressure (mmHg)	<80	1763 (83.9%)	208 (9.9%)	104 (4.9%)	27 (1.3%)	0.266	2102 (100%)
	80-89	1557 (86.7%)	156 (8.7%)	61 (3.4%)	22 (1.2%)		1796 (100%)
	90-99	907 (86%)	102 (9.7%)	36 (3.4%)	10 (0.9%)		1055 (100%)
	≥100	432 (85.7%)	46 (9.1%)	22 (4.4%)	4 (0.8%)		504 (100%)
	Missing	121 (87.1%)	0 (0%)	18 (12.9%)	0 (0%)		139 (100%)
Hemoglobin (g/dL)	Anemia	715 (69.8%)	162 (15.8%)	128 (12.5%)	20 (2%)	<0.001	1025 (100%)
	Normal*	2137 (84.7%)	267 (10.6%)	87 (3.4%)	32 (1.3%)		2523 (100%)
	Elevated	471 (88.5%)	40 (7.5%)	14 (2.6%)	7 (1.3%)		532 (100%)
	Missing	1457 (96.1%)	43 (2.8%)	12 (0.8%)	4 (0.3%)		1516 (100%)
Hematocrit (%)	Anemia	576 (66.1%)	151 (17.3%)	124 (14.2%)	21 (2.4%)	<0.001	872 (100%)
	Normal**	2235 (85%)	274 (10.4%)	90 (3.4%)	31 (1.2%)		2630 (100%)
	Elevated	505 (88.1%)	45 (7.9%)	16 (2.8%)	7 (1.2%)		573 (100%)
	Missing	1464 (96.3%)	42 (2.8%)	11 (0.7%)	4 (0.3%)		1521 (100%)
White blood cell count ($\times 10^3/\mu L$)	Leukocytopenia (<4)	555 (80.6%)	99 (14.4%)	27 (3.9%)	8 (1.2%)	<0.001	689 (100%)
	Normal (4-11)	2628 (83.3%)	336 (10.7%)	149 (4.7%)	41 (1.3%)		3154 (100%)
	Leukocytosis (≥ 11)	141 (59.2%)	35 (14.7%)	53 (22.3%)	9 (3.8%)		238 (100%)
	Missing	1456 (96.1%)	42 (2.8%)	12 (0.8%)	5 (0.3%)		1515 (100%)
Lymphocyte count ($\times 10^3/\mu L$)	Lymphocytopenia (<1)	407 (51.8%)	196 (25%)	147 (18.7%)	35 (4.5%)	<0.001	785 (100%)
	Normal (1-4.8)	2871 (88.7%)	267 (8.2%)	77 (2.4%)	23 (0.7%)		3238 (100%)
	Lymphocytosis (>4.8)	33 (100%)	0 (0%)	0 (0%)	0 (0%)		33 (100%)
	Missing	1469 (95.4%)	49 (3.2%)	17 (1.1%)	5 (0.3%)		1540 (100%)
Platelet count ($\times 10^3/\mu L$)	Thrombocytopenia (<150)	294 (58.8%)	106 (21.2%)	85 (17%)	15 (3%)	<0.001	500 (100%)
	Normal (150-450)	2971 (84.7%)	352 (10%)	142 (4%)	44 (1.3%)		3509 (100%)

	Thrombocytosis (>450)	59 (81.9%)	11 (15.3%)	2 (2.8%)	0 (0%)		72 (100%)
	Missing	1456 (96.1%)	43 (2.8%)	12 (0.8%)	4 (0.3%)		1515 (100%)

Values in cells and parentheses are the number and percentage of patients, respectively, except for the days to recovery or death.

*Male, 13.8–17.2 g/dL; Female, 12.1–15.1 g/dL

**Male, 41–50%; Female, 36–48%

Table 2. Odds ratio of predictors for COVID-19 severity by multivariable ordinal logistic regression in the entire dataset

		Univariable		**Multivariable with significant variables in univariable analysis**		**Multivariable with final predictors**	
Variable		OR	p-value	OR	p-value	OR	p-value
Age (years)	<50	reference		reference		reference	
	50-59	4.787 (3.589-6.385)	<0.001	2.802 (1.985-3.954)	<0.001	2.820 (2.007-3.962)	<0.001
	60-69	9.264 (7.019-12.227)	<0.001	3.954 (2.815-5.555)	<0.001	4.057 (2.903-5.67)	<0.001
	70-79	22.777 (17.15-30.251)	<0.001	6.867 (4.775-9.875)	<0.001	7.173 (5.024-10.243)	<0.001
	≥80	60.557 (44.304-82.773)	<0.001	15.463 (10.099-23.675)	<0.001	16.528 (10.896-25.071)	<0.001
Sex	Female	reference					
	Male	1.345 (1.159-1.561)	<0.001	1.520 (1.234-1.873)	<0.001	1.524 (1.244-1.866)	<0.001
BMI (kg/cm^2)	<23	reference					
	23-25	1.326 (0.910-1.933)	0.142				
	25-30	1.324 (0.892-1.963)	0.163				
	≥30	1.042 (0.612-1.773)	0.880				
Subjective fever		2.795 (2.394-3.264)	<0.001	1.781 (1.321-2.402)	<0.001	1.796 (1.338-2.41)	<0.001
Dyspnea		9.017 (7.579-10.727)	<0.001	5.241 (4.167-6.591)	<0.001	5.712 (4.578-7.127)	<0.001
Altered consciousness		51.916 (23.166-116.346)	<0.001	11.91 (4.282-33.13)	<0.001	13.519 (5.007-36.501)	<0.001
Cough		1.281 (1.104-1.486)	0.001	1.062 (0.843-1.338)	0.611		
Sputum		1.394 (1.193-1.630)	<0.001	1.229 (0.964-1.567)	0.096		
Sore throat		0.544 (0.428-0.693)	<0.001	0.792 (0.577-1.086)	0.147		
Rhinorrhea		0.509 (0.381-0.682)	<0.001	0.707 (0.475-1.052)	0.087		
Fatigue		2.042 (1.510-2.762)	<0.001	0.985 (0.634-1.53)	0.945		
Headache		0.733 (0.593-0.904)	0.004	0.763 (0.575-1.013)	0.062		
Nausea or vomiting		2.021 (1.505-2.714)	<0.001	1.122 (0.761-1.656)	0.561		
Myalgia		1.07 (0.880-1.300)	0.498				
Diarrhea		1.235 (0.972-1.569)	0.084				
Diabetes mellitus		3.834 (3.206-4.585)	<0.001	1.364 (1.071-1.738)	0.012	1.480 (1.163-1.885)	0.001
Hypertension		4.459 (3.815-5.210)	<0.001	1.193 (0.956-1.488)	0.119	1.280 (1.027-1.596)	0.028
Heart disease		9.145 (5.651-14.797)	<0.001	1.714 (0.902-3.260)	0.100	1.753 (0.931-3.301)	0.082
Chronic kidney disease		8.653 (5.258-14.239)	<0.001	2.351 (1.222-4.523)	0.010	2.443 (1.268-4.706)	0.008
Cancer		2.736 (1.912-3.914)	<0.001	1.654 (1.045-2.618)	0.032	1.835 (1.165-2.892)	0.009
Dementia		8.091 (6.198-10.562)	<0.001	2.214 (1.541-3.183)	<0.001	2.257 (1.577-3.230)	<0.001
Asthma		1.844 (1.220-2.787)	0.004	0.911 (0.520-1.596)	0.744		
COPD		5.978 (3.315-10.78)	<0.001	1.431 (0.702-2.916)	0.324		
Chronic liver disease		1.989 (1.222-3.237)	0.006	0.835 (0.437-1.594)	0.584		

Autoimmune disease		1.687 (0.802-3.548)	0.168				
Body temperature (°C)	<37.5	reference		reference		reference	
	37.5-38.0	2.405 (1.918-3.017)	<0.001	1.366 (0.928-2.012)	0.114	1.388 (0.951-2.027)	0.089
	38.0-38.5	6.361 (4.544-8.905)	<0.001	1.596 (0.937-2.720)	0.085	1.661 (0.989-2.79)	0.055
	≥38.5	7.572 (4.974-11.526)	<0.001	2.301 (1.281-4.135)	0.005	2.377 (1.329-4.251)	0.004
Systolic blood pressure (mmHg)	<120	reference		reference			
	120-129	0.898 (0.794-1.014)	0.083				
	130-139	0.935 (0.826-1.058)	0.289				
	140-159	1.084 (0.966-1.217)	0.172				
	≥160	1.731 (1.384-2.165)	<0.001	0.924 (0.688-1.241)	0.599		
Diastolic blood pressure (mmHg)	≥100	reference					
	90-99	0.945 (0.802-1.113)	0.496				
	80-89	0.934 (0.802-1.087)	0.377				
	<80	1.063 (0.915-1.235)	0.426				
Heart rate (beat/min)	60-100	reference		reference			
	<60	1.288 (0.959-1.730)	0.093				
	≥100	1.406 (1.170-1.689)	<0.001	1.163 (0.900-1.504)	0.248		
Anemia (based on hematocrit)		3.178 (2.682-3.766)	<0.001	1.379 (1.101-1.727)	0.005	1.424 (1.140-1.780)	0.002
Thrombocytopenia		3.973 (3.266-4.833)	<0.001	1.949 (1.516-2.507)	<0.001	1.992 (1.554-2.554)	<0.001
Leukocytosis		3.800 (2.903-4.973)	<0.001	2.924 (2.043-4.184)	<0.001	2.905 (2.049-4.119)	<0.001
Lymphocytopenia		7.664 (6.437-9.125)	<0.001	3.471 (2.806-4.294)	<0.001	3.563 (2.887-4.396)	<0.001

OR, odds ratio; BMI, body mass index; COPD, chronic obstructive pulmonary disease.

Table 3. Model performance in early prediction of prognosis in COVID19 patients

Model		No significant treatment Vs. O_2 therapy or more							No critical care required Vs. Critical care* or death						
		AUC	TP/TN/FP/FN	Sensitivity	Specificity	Accuracy	Precision	NPV	AUC	TP/TN/FP/FN	Sensitivity	Specificity	Accuracy	Precision	NPV
OLR	Model1	0.880 (0.855-0.904)	193/1199/236/48	80.1% (74.5-84.9)	83.6% (81.5-85.4)	83.1% (81.2-84.8)	45% (40.2-49.8)	96.2% (94.9-97.1)	0.903 (0.869-0.937)	75/1336/251/14	84.3% (75-91.1)	84.2% (82.3-85.9)	84.2% (82.4-85.9)	23% (18.5-28)	99% (98.3-99.4)
	Model2A	0.889 (0.865-0.912)	195/1119/209/43	81.9% (76.4-86.6)	84.3% (82.2-86.2)	83.9% (82-85.7)	48.3% (43.3-53.3)	96.3% (95-97.3)	0.905 (0.869-0.94)	81/1164/313/8	91% (83.1-96)	78.8% (76.6-80.9)	79.5% (77.4-81.5)	20.6% (16.7-24.9)	99.3% (98.7-99.7)
	Model2B	0.866 (0.841-0.892)	181/1147/261/53	77.4% (71.4-82.5)	81.5% (79.3-83.5)	80.9% (78.9-82.8)	41% (36.3-45.7)	95.6% (94.3-96.7)	0.914 (0.884-0.944)	72/1312/247/11	86.7% (77.5-93.2)	84.2% (82.2-85.9)	84.3% (82.4-86)	22.6% (18.1-27.6)	99.2% (98.5-99.6)
	Model3	0.894 (0.871-0.917)	192/1082/210/40	82.8% (77.3-87.4)	83.7% (81.6-85.7)	83.6% (81.6-85.4)	47.8% (42.8-52.8)	96.4% (95.2-97.4)	0.922 (0.892-0.953)	76/1199/242/7	91.6% (83.4-96.5)	83.2% (81.2-85.1)	83.7% (81.7-85.5)	23.9% (19.3-29)	99.4% (98.8-99.8)
	Model4	0.907 (0.884-0.929)	189/835/172/31	85.9% (80.6-90.2)	82.9% (80.5-85.2)	83.5% (81.3-85.5)	52.4% (47.1-57.6)	96.4% (95-97.6)	0.927 (0.894-0.96)	68/1046/100/13	84% (74.1-91.2)	91.3% (89.5-92.8)	90.8% (89-92.3)	40.5% (33-48.3)	98.8% (97.9-99.3)
KMA model		0.723 (0.693-0.753)	129/108/1308/106	54.9% (61.4)	7.6% (6.3-9.148.3-)	14.4% (12.7-16.1)	9% (7.5-10.6)	50.5% (43.6-57.4)	0.728 (0.678-0.778)	43/1395/171/42	50.6% (39.5-61.6)	89.1% (87.4-90.6)	87.1% (85.4-88.7)	20.1% (14.9-26.1)	97.1% (96.1-97.9)
MEWS		0.598 (0.563-0.633)	129/314/1023/98	56.8% (50.1-63.4)	23.5% (21.2-25.9)	28.3% (26.1-30.6)	11.2% (9.4-13.2)	76.2% (71.8-80.2)	0.631 (0.574-0.689)	41/1112/371/40	50.6% (39.3-61.9)	75% (72.7-77.2)	73.7% (71.5-75.9)	10% (7.2-13.3)	96.5% (95.3-97.5)

The results of other machine learning algorithms can be found in Supplementary Table 5. Values in parentheses are 95% confidence intervals. OLR, ordinal logistic regression; AUC, area under the receiver operator characteristics curve; TP, true positive; TN, true negative, FP, false positive, FN, false negative; NPV, negative predictive value; KMA, Korean Medical Association; MEWS, Modified Early Warning Score.

* the use of a ventilator or extracorporeal membrane oxygenation machine.

Table 4. Model performances by cutoff probabilities

Model	Cutoff	No significant treatment Vs. O_2 therapy or more						No critical care required Vs. Critical care* or death					
		TP/TN/FP/FN	Sensitivity	Specificity	Accuracy	Precision	NPV	TP/TN/FP/FN	Sensitivity	Specificity	Accuracy	Precision	NPV
Model 1	5%	227/714/721/14	94.2% (90.4-96.8)	49.8% (47.1-52.4)	56.1% (53.7-58.5)	23.9% (21.3-26.8)	98.1% (96.8-98.9)	76/1295/292/13	85.4% (76.3-92)	81.6% (79.6-83.5)	81.8% (79.9-83.6)	20.7% (16.6-25.2)	99% (98.3-99.5)
	10%	208/1090/345/33	86.3% (81.3-90.4)	76% (73.7-78.1)	77.4% (75.4-79.4)	37.6% (33.6-41.8)	97.1% (95.9-98)	69/1408/179/20	77.5% (67.4-85.7)	88.7% (87.1-90.2)	88.1% (86.5-89.6)	27.8% (22.3-33.8)	98.6% (97.8-99.1)
	15%	207/1107/328/34	85.9% (80.8-90)	77.1% (74.9-79.3)	78.4% (76.4-80.3)	38.7% (34.5-43)	97% (95.9-97.9)	51/1492/95/38	57.3% (46.4-67.7)	94% (92.7-95.1)	92.1% (90.7-93.3)	34.9% (27.2-43.3)	97.5% (96.6-98.2)
	20%	178/1237/198/63	73.9% (67.8-79.3)	86.2% (84.3-87.9)	84.4% (82.6-86.1)	47.3% (42.2-52.5)	95.2% (93.8-96.3)	44/1511/76/45	49.4% (38.7-60.2)	95.2% (94-96.2)	92.8% (91.4-94)	36.7% (28.1-45.9)	97.1% (96.1-97.9)
	25%	168/1277/158/73	69.7% (63.5-75.4)	89% (87.3-90.6)	86.2% (84.5-87.8)	51.5% (46-57.1)	94.6% (93.2-95.7)	32/1544/43/57	36% (26.1-46.8)	97.3% (96.4-98)	94% (92.8-95.1)	42.7% (31.3-54.6)	96.4% (95.4-97.3)
Model 2A	5%	224/711/618/14	94.1% (90.3-96.7)	53.5% (50.8-56.2)	59.7% (57.2-62.1)	26.6% (23.6-29.7)	98.1% (96.8-98.9)	79/1184/294/10	88.8% (80.3-94.5)	80.1% (78-82.1)	80.6% (78.6-82.5)	21.2% (17.1-25.7)	99.2% (98.5-99.6)
	10%	212/944/385/26	89.1% (84.4-92.7)	71% (68.5-73.5)	73.8% (71.5-75.9)	35.5% (31.7-39.5)	97.3% (96.1-98.2)	69/1328/150/20	77.5% (67.4-85.7)	89.9% (88.2-91.3)	89.2% (87.5-90.6)	31.5% (25.4-38.1)	98.5% (97.7-99.1)
	15%	202/1067/262/36	84.9% (79.7-89.2)	80.3% (78-82.4)	81% (79-82.9)	43.5% (39-48.2)	96.7% (95.5-97.7)	58/1379/99/31	65.2% (54.3-75)	93.3% (91.9-94.5)	91.7% (90.2-93)	36.9% (29.4-45)	97.8% (96.9-98.5)
	20%	192/1130/199/46	80.7% (75.1-85.5)	85% (83-86.9)	84.4% (82.5-86.1)	49.1% (44-54.2)	96.1% (94.8-97.1)	45/1416/62/44	50.6% (39.8-61.3)	95.8% (94.7-96.8)	93.2% (91.9-94.4)	42.1% (32.6-52)	97% (96-97.8)
	25%	168/1198/131/70	70.6% (64.4-76.3)	90.1% (88.4-91.7)	87.2% (85.4-88.8)	56.2% (50.4-61.9)	94.5% (93.1-95.7)	40/1431/47/49	44.9% (34.4-55.9)	96.8% (95.8-97.7)	93.9% (92.6-95)	46% (35.2-57)	96.7% (95.6-97.5)
Model 2B	5%	254/4317/858/33	88.5% (84.2-92)	83.4% (82.4-84.4)	83.7% (82.7-84.7)	22.8% (20.4-25.4)	99.2% (98.9-99.5)	736/2680/1986/60	92.5% (90.4-94.2)	57.4% (56-58.9)	62.5% (61.2-63.8)	27% (25.4-28.7)	97.8% (97.2-98.3)
	10%	225/4676/499/62	78.4% (73.2-83)	90.4% (89.5-91.1)	89.7% (88.9-90.5)	31.1% (27.7-34.6)	98.7% (98.3-99)	670/3489/1177/126	84.2% (81.4-86.6)	74.8% (73.5-76)	76.1% (75-77.3)	36.3% (34.1-38.5)	96.5% (95.9-97.1)
	15%	181/4861/314/106	63.1% (57.2-68.7)	93.9% (93.2-94.6)	92.3% (91.6-93)	36.6% (32.3-41)	97.9% (97.4-98.2)	620/3817/849/176	77.9% (74.8-80.7)	81.8% (80.7-82.9)	81.2% (80.2-82.3)	42.2% (39.7-44.8)	95.6% (94.9-96.2)

	20%	159/4940/235/128	55.4% (49.4-61.2)	95.5% (94.9-96)	93.4% (92.7-94)	40.4% (35.5-45.4)	97.5% (97-97.9)	569/4059/607/227	71.5% (68.2-74.6)	87% (86-87.9)	84.7% (83.7-85.7)	48.4% (45.5-51.3)	94.7% (94-95.4)
	25%	126/5029/146/161	43.9% (38.1-49.9)	97.2% (96.7-97.6)	94.4% (93.7-95)	46.3% (40.3-52.4)	96.9% (96.4-97.4)	531/4192/474/265	66.7% (63.3-70)	89.8% (88.9-90.7)	86.5% (85.5-87.4)	52.8% (49.7-56)	94.1% (93.3-94.7)
Model 3	5%	219/694/598/13	94.4% (90.6-97)	53.7% (51-56.5)	59.9% (57.4-62.4)	26.8% (23.8-30)	98.2% (96.9-99)	76/1182/259/7	91.6% (83.4-96.5)	82% (79.9-84)	82.5% (80.5-84.4)	22.7% (18.3-27.6)	99.4% (98.8-99.8)
	10%	209/912/380/23	90.1% (85.5-93.6)	70.6% (68-73.1)	73.6% (71.3-75.8)	35.5% (31.6-39.5)	97.5% (96.3-98.4)	63/1296/145/20	75.9% (65.3-84.6)	89.9% (88.3-91.4)	89.2% (87.5-90.7)	30.3% (24.1-37)	98.5% (97.7-99.1)
	15%	196/1045/247/36	84.5% (79.2-88.9)	80.9% (78.6-83)	81.4% (79.4-83.4)	44.2% (39.6-49)	96.7% (95.4-97.7)	54/1349/92/29	65.1% (53.8-75.2)	93.6% (92.2-94.8)	92.1% (90.6-93.4)	37% (29.2-45.4)	97.9% (97-98.6)
	20%	184/1114/178/48	79.3% (73.5-84.3)	86.2% (84.2-88.1)	85.2% (83.3-86.9)	50.8% (45.6-56.1)	95.9% (94.6-96.9)	44/1385/56/39	53% (41.7-64.1)	96.1% (95-97.1)	93.8% (92.4-94.9)	44% (34.1-54.3)	97.3% (96.3-98)
	25%	168/1156/136/64	72.4% (66.2-78.1)	89.5% (87.7-91.1)	86.9% (85.1-88.5)	55.3% (49.5-60.9)	94.8% (93.4-95.9)	38/1398/43/45	45.8% (34.8-57.1)	97% (96-97.8)	94.2% (92.9-95.3)	46.9% (35.7-58.3)	96.9% (95.8-97.7)
Model 4	5%	212/468/539/8	96.4% (93-98.4)	46.5% (43.4-49.6)	55.4% (52.6-58.2)	28.2% (25-31.6)	98.3% (96.7-99.3)	71/936/210/10	87.7% (78.5-93.9)	81.7% (79.3-83.9)	82.1% (79.8-84.2)	25.3% (20.3-30.8)	98.9% (98.1-99.5)
	10%	202/693/314/18	91.8% (87.4-95.1)	68.8% (65.9-71.7)	72.9% (70.4-75.4)	39.1% (34.9-43.5)	97.5% (96-98.5)	68/1039/107/13	84% (74.1-91.2)	90.7% (88.8-92.3)	90.2% (88.4-91.8)	38.9% (31.6-46.5)	98.8% (97.9-99.3)
	15%	190/807/200/30	86.4% (81.1-90.6)	80.1% (77.5-82.6)	81.3% (79-83.4)	48.7% (43.7-53.8)	96.4% (94.9-97.6)	62/1068/78/19	76.5% (65.8-85.2)	93.2% (91.6-94.6)	92.1% (90.4-93.5)	44.3% (35.9-52.9)	98.3% (97.3-98.9)
	20%	178/862/145/42	80.9% (75.1-85.9)	85.6% (83.3-87.7)	84.8% (82.6-86.7)	55.1% (49.5-60.6)	95.4% (93.8-96.6)	55/1094/52/26	67.9% (56.6-77.8)	95.5% (94.1-96.6)	93.6% (92.1-94.9)	51.4% (41.5-61.2)	97.7% (96.6-98.5)
	25%	162/896/111/58	73.6% (67.3-79.3)	89% (86.9-90.8)	86.2% (84.2-88.1)	59.3% (53.3-65.2)	93.9% (92.2-95.4)	48/1110/36/33	59.3% (47.8-70.1)	96.9% (95.7-97.8)	94.4% (92.9-95.6)	57.1% (45.9-67.9)	97.1% (96-98)

*multi-organ failure, the use of a ventilator or extracorporeal membrane oxygenation machine

TP, true positive; TN, true negative, FP, false positive, FN, false negative; NPV, negative predictive value

Figure legends

Figure 1. Study flow.

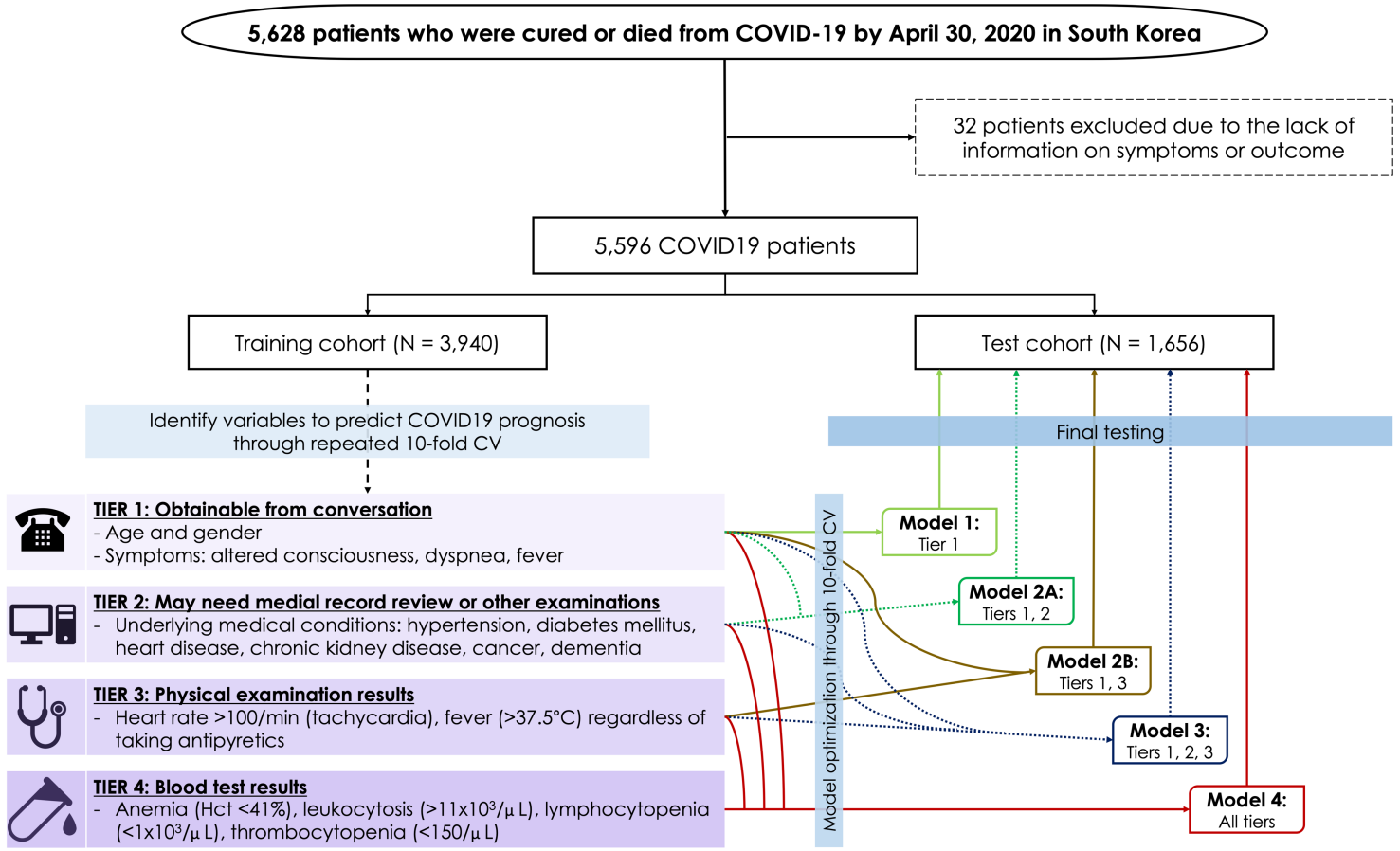
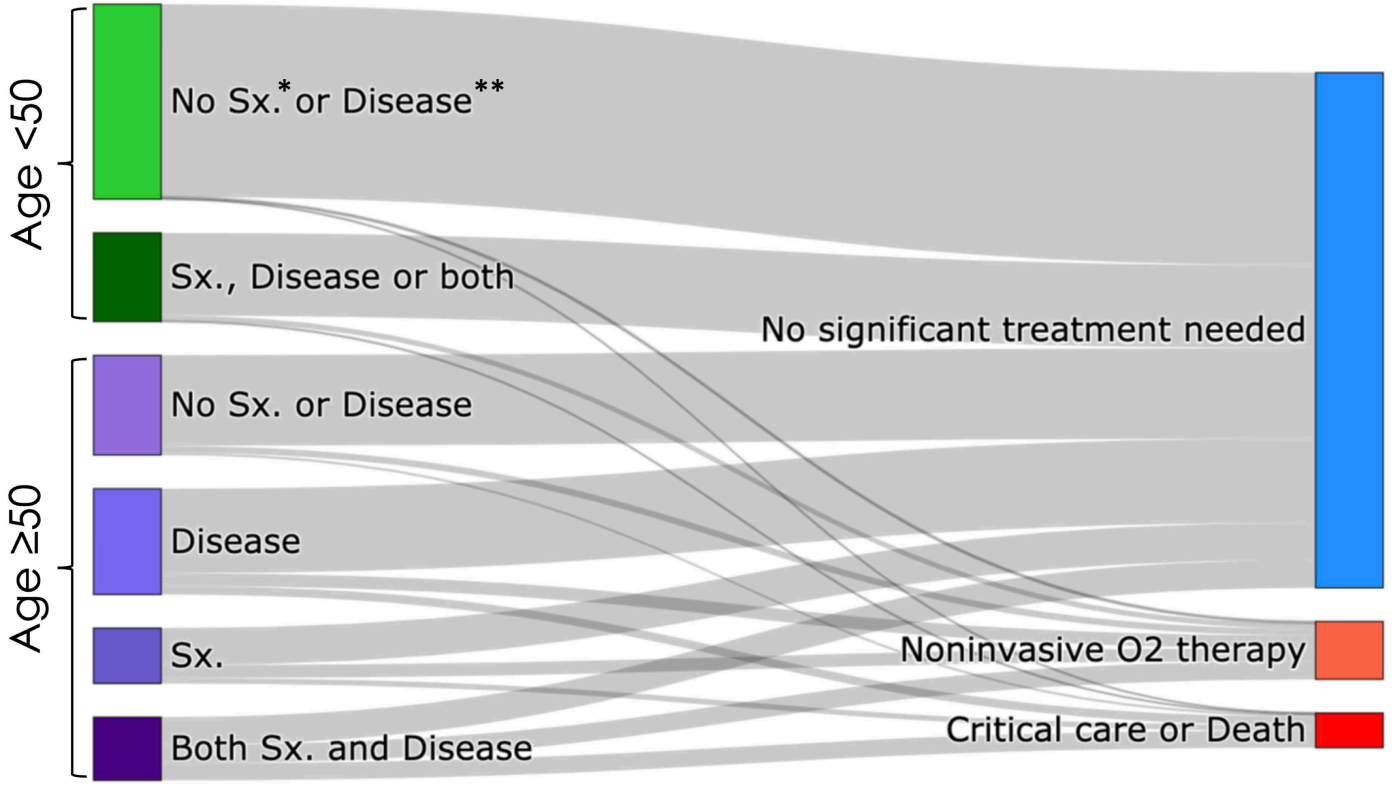


Figure 2. Sankey diagram. Sankey diagram is a type of flow diagram in which the arrows' width is proportional to the flow rate. This diagram shows that a patient who is older than 50 years and has relevant symptoms or underlying diseases is more likely to require oxygen therapy or critical care.



*Symptoms: altered consciousness, subjective fever, dyspnea
**Underlying diseases: diabetes mellitus, hypertension, heart disease, cancer, chronic renal disease, dementia

Figure 3. Calibration plot.

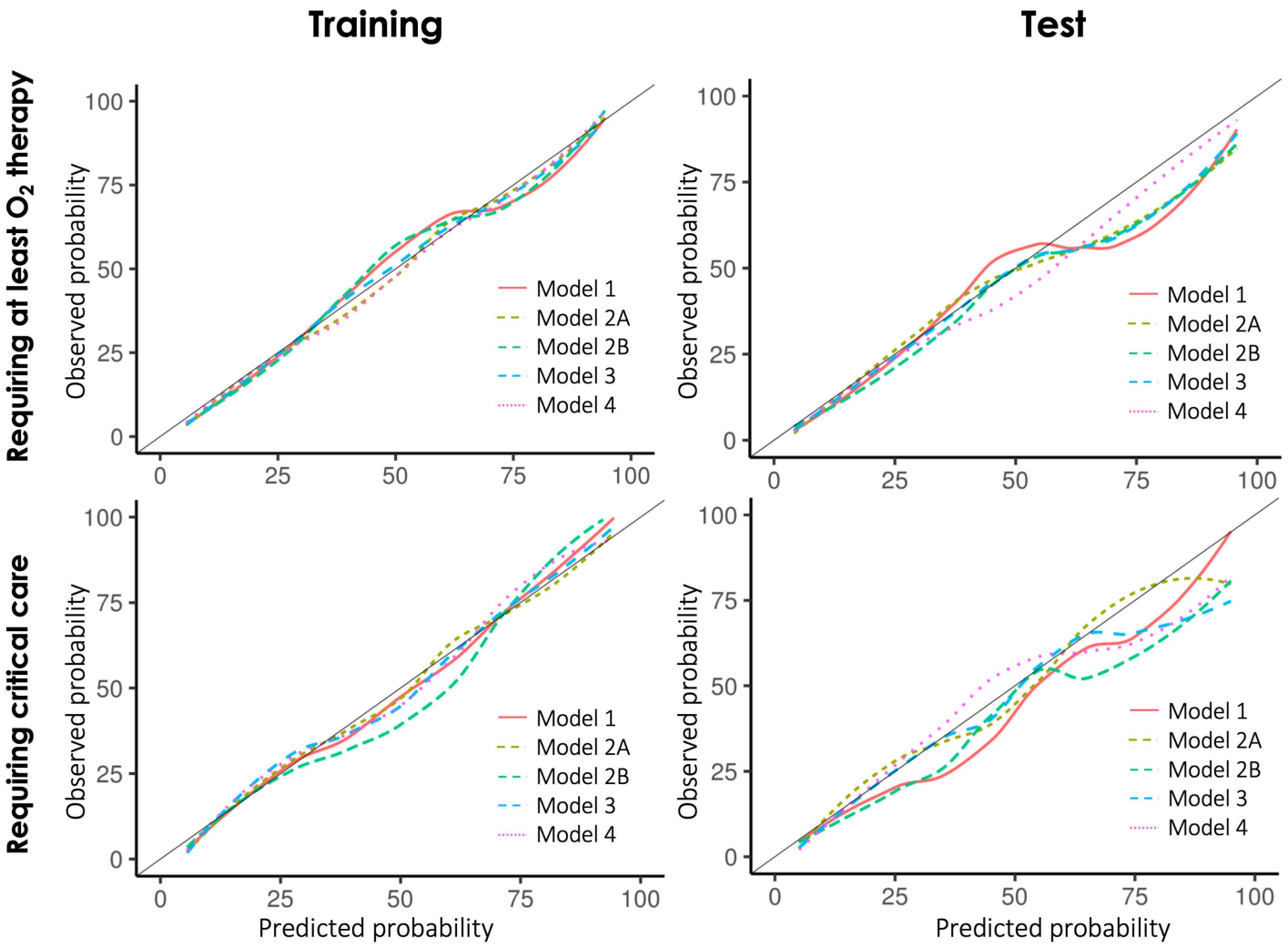
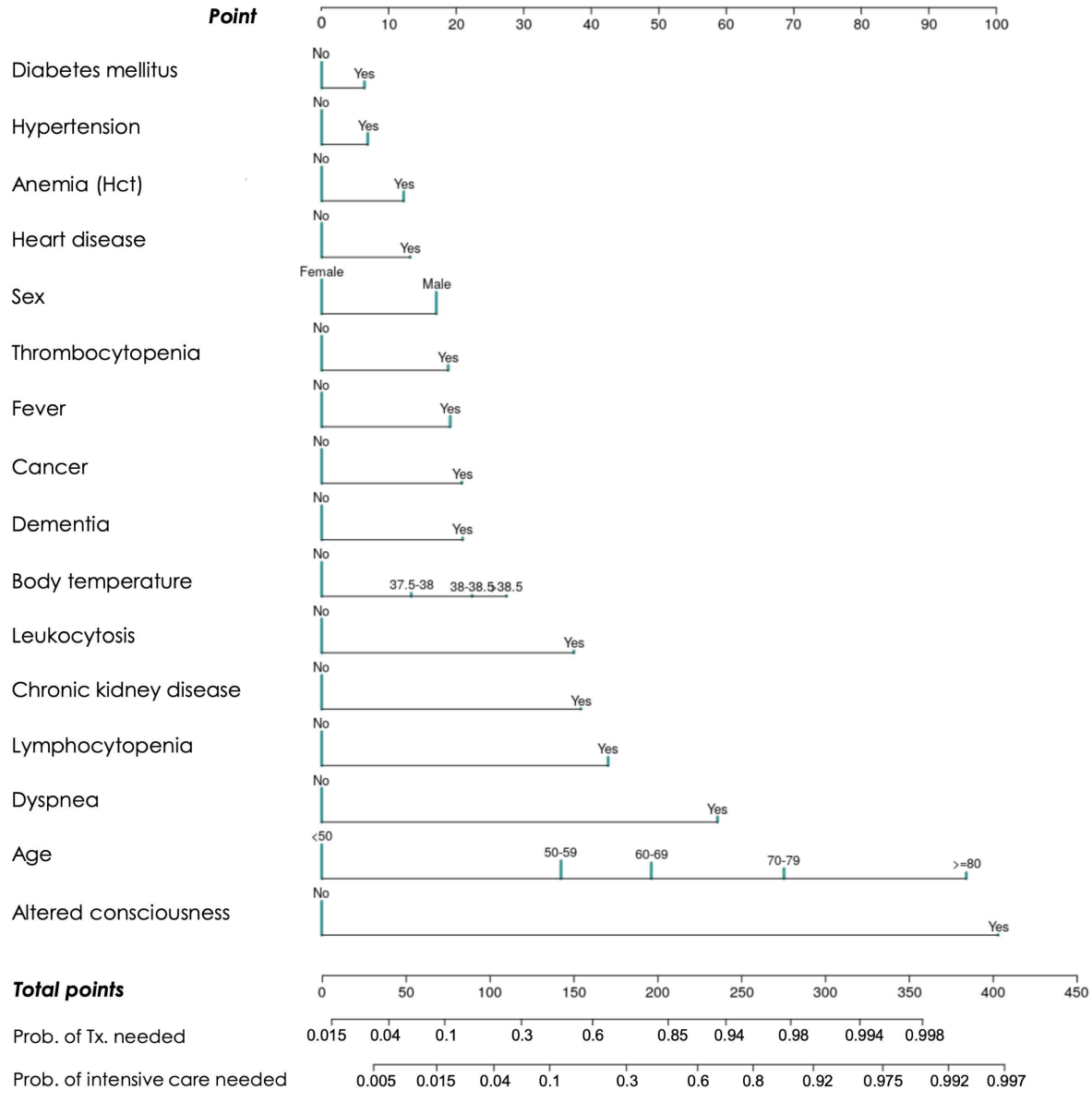


Figure 4. Nomogram of ordinal logistic regression model using all the predictors (Model 4). The nomogram is used by first giving each variable a score on the 'Point' scale. The points for all variables are then added to obtain the total points and a vertical line is drawn from the 'Total points' row to estimate the probability of requiring treatment and that of requiring critical care or death. The nomograms of the other models can be found in Supplementary Figure 1.



Figures

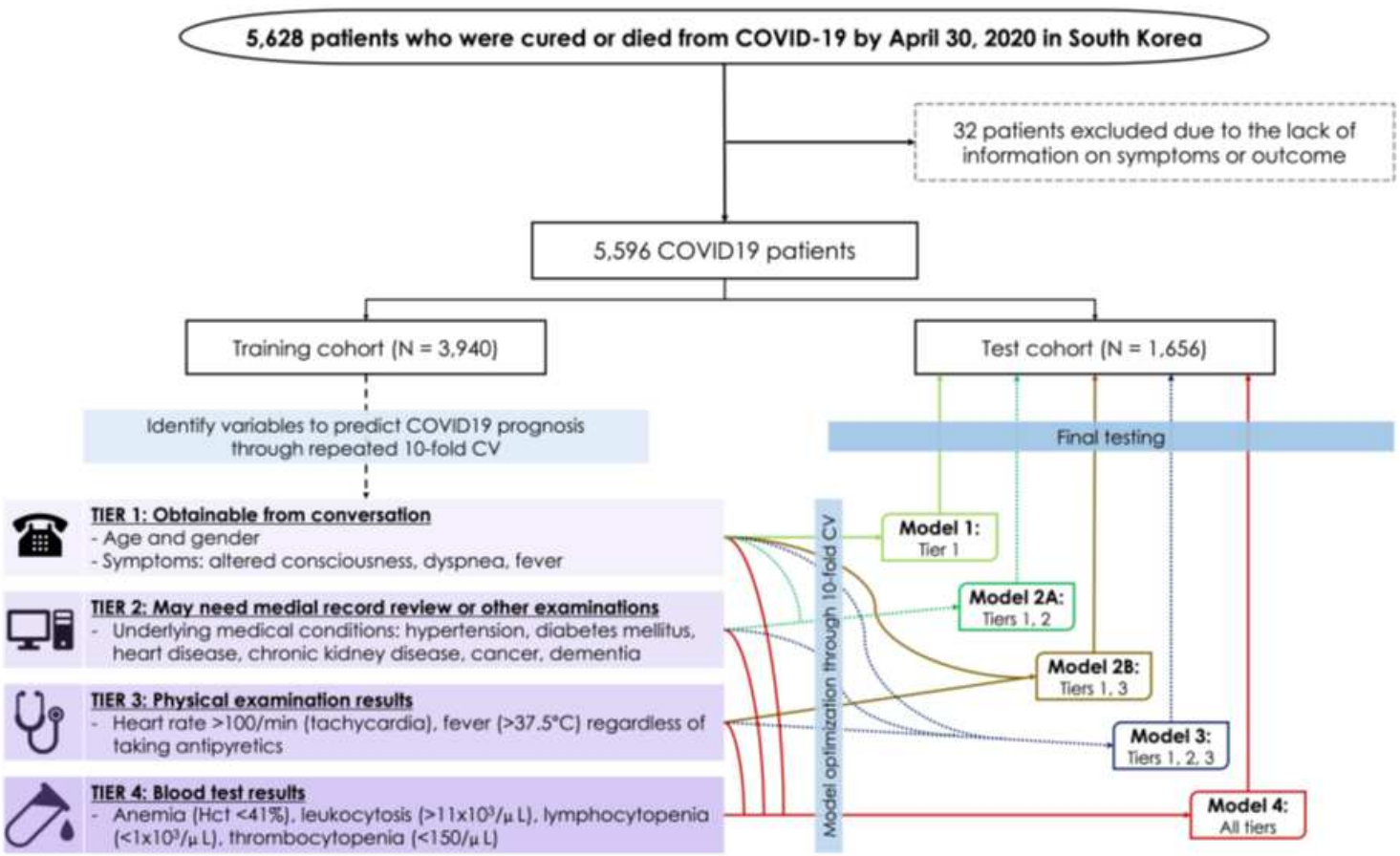


Figure 1

Study flow.

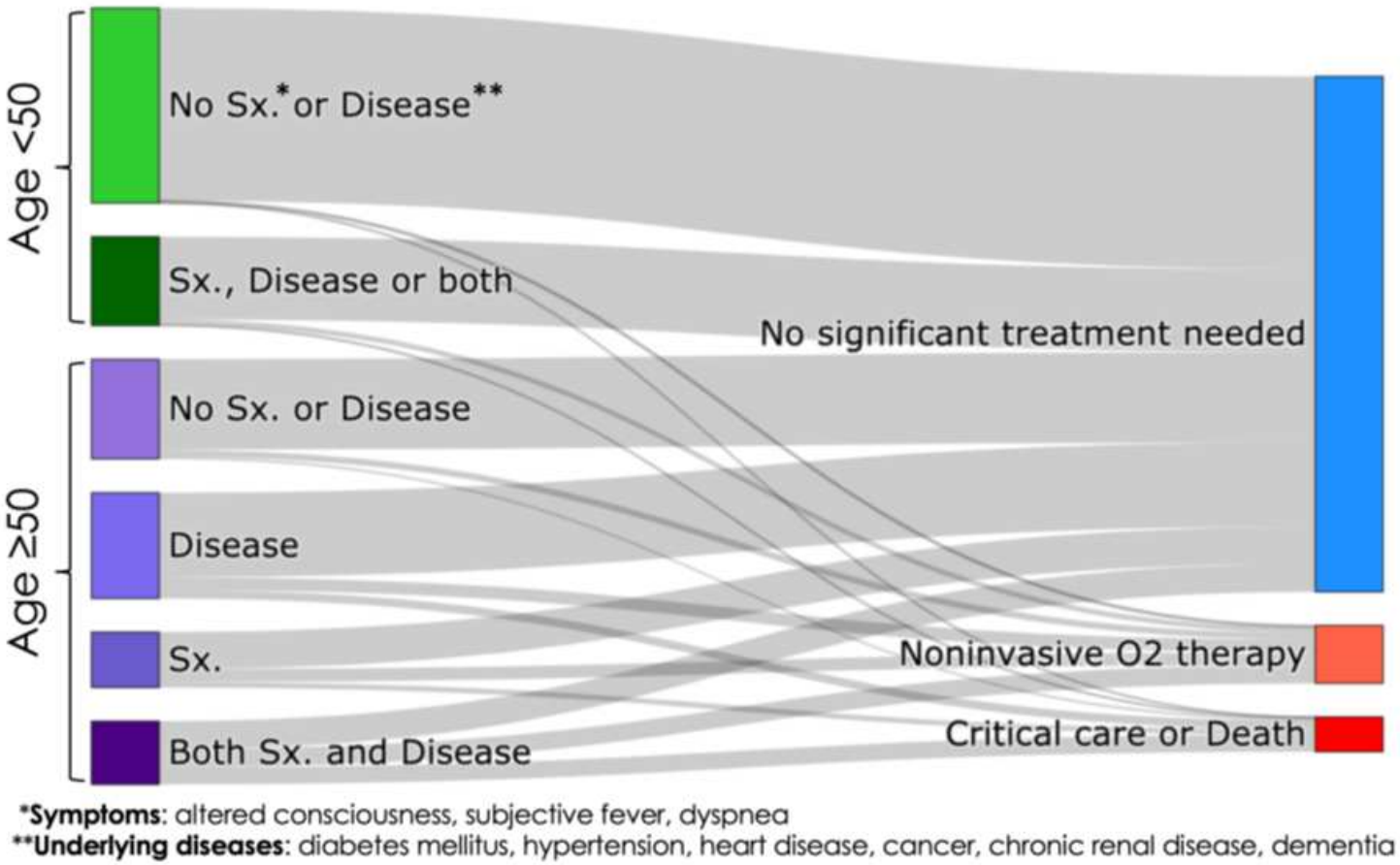


Figure 2

Sankey diagram. Sankey diagram is a type of flow diagram in which the arrows' width is proportional to the flow rate. This diagram shows that a patient who is older than 50 years and has relevant symptoms or underlying diseases is more likely to require oxygen therapy or critical care.

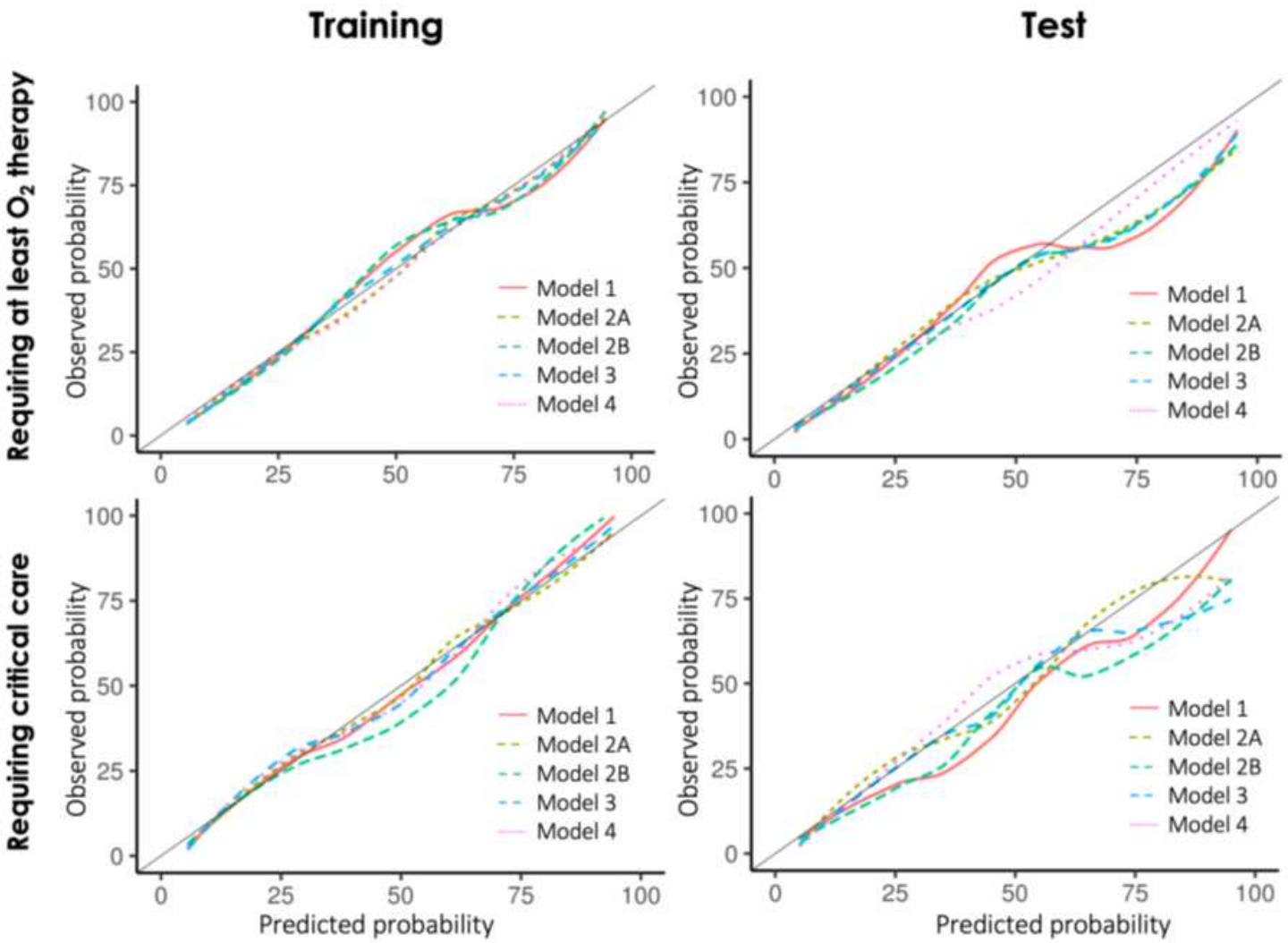


Figure 3

Calibration plot.

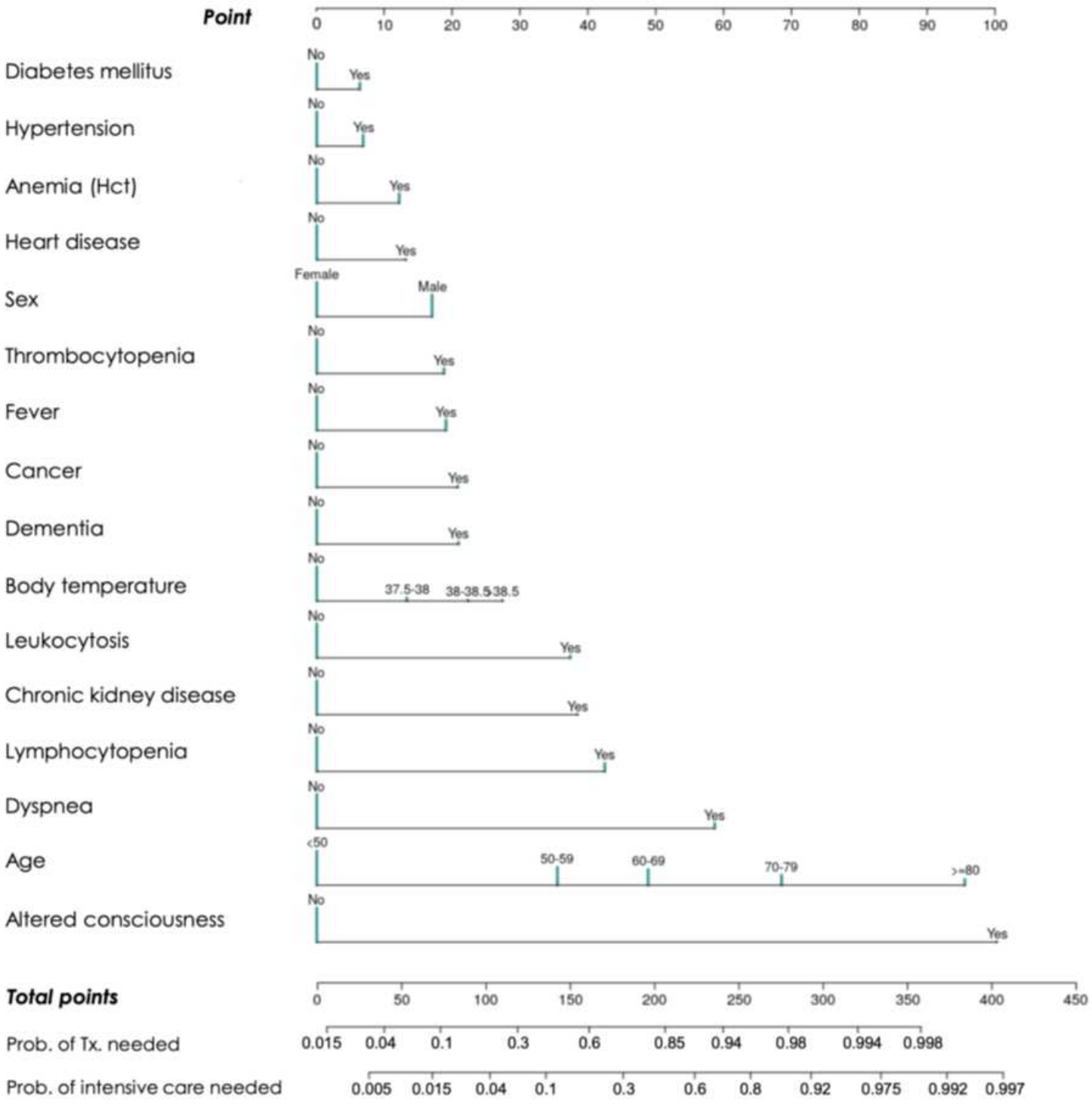


Figure 4

Nomogram of ordinal logistic regression model using all the predictors (Model 4). The nomogram is used by first giving each variable a score on the 'Point' scale. The points for all variables are then added to obtain the total points and a vertical line is drawn from the 'Total points' row to estimate the probability of requiring treatment and that of requiring critical care or death. The nomograms of the other models can be found in Supplementary Figure 1.

Supplementary Files

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- SupplementarymaterialsCOVID.docx