Table 1 – Predictive ability of Existing Scoring Systems for Covid-19 in-hospital mortality, sorted by AUROC (n=40)

Abbreviations: SBP = Systolic blood pressure, RR = respiratory rate, DM = diabetes mellitus, LoC = level of consciousness, GCS = Glasgow Coma Scale, HR = heart rate, HTN = hypertension, TIA = transient ischaemic attack, MABP = mean arterial blood pressure, IHD = ischaemic heart disease, COPD = chronic obstructive pulmonary disease, HCT = haematocrit, SpO2 = oxygen saturation, AF = atrial fibrillation, CVD = cardiovascular disease, CHF = congestive heart failure, CAP = community acquired pneumonia

Authors of paper evaluating system	Prognostic System	Intended application	Variables used	Number of variables included	AUROC
Wang, L et al[1]	**APACHE II** (acute physiology and chronic health evaluation II)	Scoring system for use in intensive care units to provide gross estimate of mortality risks	APS (Acute physiology score), Temp, MABP, HR, RR, PaO2 or aPO2, arterial pH or HCO3, serum Na, serum K, serum creatinine, HCt, WBCC, GCS, age, chronic health evaluation	12	0.9370
Zou, X et al[2]					0.9660
De Giorgi, A et al[3]	**mEI** (modified Elixhauser Index)	Specific development of a modified Elixhauser Index	Age, sex, presence of renal diseases, neurological dis-orders, lymphoma, solid tumour with metastasis, IHD, CHD, coagulopathy, fluid and electrolyte disorders, liver disease, weight loss, metastatic cancer	13	0.918
S. Liu et al[4]	**SOFA** (sequential organ function assessment)	Score for calculation of number and severity of organ dysfunction in six organ systems (respiratory, coagulatory, liver, cardiovascular, renal, and neurologic)	Oxygenation index, MABP, GCS, creatinine or urine volume, bilirubin, platelets	6	0.9150
Wang, L et al[1]					0.9260
Zou, X et al[2]					0.8760
D. Ji et al[5]	**RAS** (respiratory assessment scoring)	Assessment for progression and mortality in respiratory disease	RR, resting SpO2, Alveolar-arterial O2 gradient, Minimal exercise desaturation test	4	0.9000
Wang, L et al[1]	**PSI** (pneumonia severity index)	Index to identify CAP patients at a low risk of mortality who could safely be treated as outpatients	Age, sex, residence, comorbidity and acute pneumonia-associated morbidity	20	0.9270
X. Tang et al[6]					0.8500
C. Satici et al[7]					0.9100

Table 1 cont. part 2

F. Liu et al[8]	**NEWS** (National Early Warning Score)	Tool for early detection of in-hospital patient deterioration	RR, SpO2, Supplemental oxygen, SBP, temperature, HR, AVPU score	7	0.8815
X. Tang et al[6]	**A-DROP**	Modified CURB-65 system for prediction of mortality in hospitalized patients with CAP	Age, Dehydration, SpO2 or MABP, Confusion, SBP	5	0.8700
C. Satici et al[7]	**CCI** (Charlson Comorbidity Index)	Predicts survival in patients with multiple comorbidities, and is widely used as a measure of total comorbidity burden	Age and Comorbidities (MI, CHF, peripheral vascular disease, cerebrovascular disease, dementia, COPD, peptic ulcer disease, liver disease, DM, hemiplegia, moderate to severe CKD, solid tumor, leukaemia, lymphoma, AIDS)	2	0.8630
H. Hu et al[9]	**REMS** (Rapid emergency medicine score)	Predicts in-hospital mortality in non-surgical patients admitted to the ED	HR, BP, RR, GCS, SpO2, age	6	0.8330
H. Hu et al[9]	**MEWS**	Tool for assessment and early identification of pneumonia deterioration	HR, SBP, RR, body temperature, LoC	5	0.6770
P. Bradley et al[10]	**CURB-65**	Scoring system specific for CAP to predict all-cause mortality within 30 days	Confusion, Urea, RR, BP, Age ≥65	5	0.7500
D. Ortiz et al[11]					0.7200
X. Tang et al[6]					0.8500
Zou, X et al[2]					0.8440
R. Gupta et al[12]					0.7500
F. Liu et al[8]					0.7665
C. Satici et al[13]					0.8800
P. Bradley et al[10]	**NEWS2** (National Early Warning Score 2)	Disease agnostic early warning tool used to trigger escalation of care in the deteriorating patient, with high scores being associated with death or unanticipated intensive care unit (ICU) admission within 24 hours	RR, SpO2, air or oxygen, systolic BP, HR, LoC, temperature	9	0.6700
X. Tang et al[6]					0.8100
F. Liu et al[8]					0.8797

Table 1 cont. part 3

P. Bradley et al[10]	**qSOFA** (quick sequential organ function assessment)	Tool for predicting mortality and ICU admission among patients with suspected infection in prehospital, emergency department and ward settings	Mental status, RR <22, SBP <100	3	0.6200
S. Liu et al[4]					0.7420
Wang, L et al[1]					0.8860
Zou, X et al[2]					0.8760
F. Liu et al[8]					0.6936
A. Halalau et al[13]	**m-CHA_2D_2VASc (**Modified CHA_2D_2VASc)	Risk score created from CHA_2D_2VASc to improve predictive ability for COVID-19 mortality	Same as CHA_2D_2VASc but with gender criteria switched from female to male (male sex is reported by recent studies to be an important predictor of mortality in COVID-19 patients)	8	0.7000
G. Cetinkal et al[14]	**CHA_2D_2VASc**	Risk score principally used for estimating the risk of ischemic stroke in patients with AF and also predicts mortality in various CVD	CHF, HTN, Age (65 to 74), DM, Vascular disease, Female gender, 2 points for age ≥75 and history of TIA and/or stroke	7	0.6400
D. Ortiz et al[11]	**SMART-COP**	Assessing severity of CAP (community acquired pneumonia) confirmed by CXR	SBP, multilobar CXR involvement, Albumin, RR, HR, Confusion, SpO2, pH	8	0.5600

Table 2: New COVID-19 in-hospital mortality prediction models, displaying the number of patients and number of incorporated parameters, sorted by AUROC (n=37)

Author with scoring system	AUROC	Number of patients	Number of incorporated parameters
Liu et al.[15]	0.9940	336	3
Qin et al.[16]	0.9920	118	4
Wang et al.[17]	0.9905	126	7
Weng et al.[18]	0.9750	301	5
Soto-Mota et al.[19]	0.9600	400	7
Mei et al.[20]	0.9600	1088	4
Luo et al.[21]	0.9560	739	3
Luo et al.[22]	0.9550	1115	9
Zhou et al.[23]	0.9550	118	11
Cheng et al.[24]	0.9400	305	8
Laguna-Goya et al.[25]	0.9400	501	9
El-Solh et al.[26] (Shang score)	0.9200	1634	6
Shang et al.[327]	0.9190	1830	5
Mei et al.[28]	0.9120	492	6
El-Solh et al.[26] (Chen score)	0.9100	1634	6
Fumagalli et al.[29]	0.9000	516	5
Gude-Sampedro et al.[30]	0.8900	10545	6
Torres-Macho et al.[31]	0.8830	1968	5
El-Solh et al.[26] (Wang score)	0.8800	1634	6
Li et al.[32]	0.8700	1008	3
Hajifathalian et al.[33] (7-day score)	0.8600	265	8
Manocha et al.[34]	0.8340	1053	5
Hajifathalian et al.[33] (14-day score)	0.8300	265	7
Tusha et al.[35]	0.8130	163	8
Fernandez et al.[36]	0.8129	487	10
Cai et al.[37]	0.8070	126	5
Nunez-Gil et al.[38]	0.8070	1021	10
Varol et al.[39]	0.8020	383	6
Mancilla-Galindo et al.[40]	0.8000	83779	3
Altschul et al.[41]	0.7980	4711	3
Gue et al.[42]	0.7933	316	2

Table 2 cont part 2

Knight et al.[43]	0.7900	35463	3
Lorente-Ros et al.[44]	0.7900	707	7
Shi et al.[45] (COVID-GRAM score)	0.7750	257	5
El-Solh et al.[26] (Yu-score)	0.7700	1634	3
Rodriguez-Nava et al.[46]	0.7110	313	10
Shi et al.[45] (CALL-score)	0.6400	257	4

Table 3: Most common parameters incorporated into new prediction models of in-hospital mortality in patients with COVID-19 (n=37)

Abbreviations: CRP = C-reactive protein, SpO2 = Peripheral capillary oxygen saturation

Author with scoring system	AUROC	Lymphocyte count	D-dimer	CRP	SpO2	Platelet count	Age
Liu et al.[15]	0.9940	✓	✓				
Qin et al.[16]	0.9920	✓	✓				✓
Wang et al.[17]	0.9905	✓	✓				✓
Weng et al.[18]	0.9750		✓	✓			✓
Soto-Mota et al.[19]	0.9600	✓			✓		
Mei et al.[20]	0.9600	✓	✓			✓	✓
Luo et al.[21]	0.9560	✓					
Luo et al.[22]	0.9550	✓		✓			
Zhou et al.[23]	0.9550		✓				
Cheng et al.[24]	0.9400		✓				
Laguna-Goya et al.[25]	0.9400				✓		✓
El-Solh et al.[26] (Shang score)	0.9200	✓	✓				✓
Shang et al.[327]	0.9190	✓	✓	✓			✓
Mei et al.[28]	0.9120						✓
El-Solh et al.[26] (Chen score)	0.9100						✓
Fumagalli et al.[29]	0.9000				✓	✓	✓
Gude-Sampedro et al.[30]	0.8900						✓
Torres-Macho et al.[31]	0.8830	✓		✓	✓	✓	✓
El-Solh et al.[26] (Wang score)	0.8800						✓
Li et al.[32]	0.8700	✓				✓	✓
Hajifathalian et al.[33] (7-day score)	0.8600				✓		✓
Manocha et al.[34]	0.8340		✓	✓			
Hajifathalian et al.[33] (14-day score)	0.8300				✓		✓
Tusha et al.[35]	0.8130	✓					✓
Fernandez et al.[36]	0.8129			✓	✓	✓	✓
Cai et al.[37]	0.8070	✓	✓	✓			✓
Nunez-Gil et al.[38]	0.8070			✓			✓
Varol et al.[39]	0.8020	✓					✓
Mancilla-Galindo et al.[40]	0.8000						✓
Altschul et al.[41]	0.7980				✓		✓

Table 3 cont. part 2

Gue et al.[42]	0.7933					✓	✓
Knight et al.[43]	0.7900			✓	✓		✓
Lorente-Ros et al.[44]	0.7900		✓	✓			✓
Shi et al.[45] (COVID-GRAM score)	0.7750						✓
El-Solh et al.[26] (Yu-score)	0.7700	✓	✓				✓
Rodriguez-Nava et al.[46]	0.7110				✓		
Shi et al.[45] (CALL-score)	0.6400				✓		✓

Table 4: studies examining the association of novel blood parameters with mortality in patients admitted to hospital with COVID-19 (n=12)

Authors	Sample size	Category of parameters	Blood parameter(s) shown to be associated with mortality (p<0.05)	Proposed cut-offs for independently associated parameters	Sensitivity %
Fu et al. [47]	355	Hepatic function markers	Cholestasis markers (ALP, γ-GGT and TBA) Hypoproteinaemia markers (albumin and globulin)	Outside of normal range	Not reported
Garcia et al.[48]	639	arterial blood gas analyses, and laboratory values such as inflammatory, coagulation, renal, liver, cardiac	creatinine, D-dimer, lactate, potassium, P/F-ratio,alveolar-arterial gradient	Not reported	Not reported
Bellmann-Weiler et al.[49]	259	Presence of anaemia subgroups (mild/ moderate/severe)	Presence of moderate-serious anaemia	moderate-severe anaemia; defined as haemoglobin <109 g/L	Not reported
Liu et al.[50]	1525	Inflammatory biomarker	Procalcitonin	PCT≥0.05 ng/ml	Not reported
Wang et al.[51]	605	Admission fasting blood glucose	FBG	FBG ≥7.0 mmol/l	Not reported
Singh et al. [52]	276	Cardiac biomarker	Elevated initial high sensitivity cardiac troponin-T (hs-TnT)	- initial hs-TnT above the median (≥17 ng/L)	Not reported
Fois et al.[53]	119	complete blood cell count (CBC)-derived inflammation indexes	Systemic inflammation index (SSI)	>1835 $\times 10^9$ cells/L	SSI-55
Aloisio et al. [54]	427	Range of serum biomarkers	Lactate dehydrogenase Albumin	lactate dehydrogenase: >731 U/L ,albumin: 18 g/L or lower	Not reported
Foy et al.[55]	1641	Complete blood count (CBC) derived parameter	red blood cell distribution width (RDW)	elevated RDW was defined as greater than 14.5%	Not reported
Stefanini et al.[56]	397	Cardiac biomarkers	high-sensitivity cardiac troponin I (hs-TnI), B-type natriuretic peptide (BNP)	≥19.6 ng/L, BNP ≥100 pg/mL) hs-TnI serum levels	Not reported
Trabulus et al.[57]	336	Kidney function biomarker	eGFR	eGFR under 60 mL/min/1.73m^2	Not reported
Cao et al.[58]	244	Cardiac biomarkers	serum high-sensitivity cardiac Troponin I (hs-cTnI)	>20ng/L serum hs-cTnI levels	hs-cTnI -85.7

Table 5: studies examining the association of imaging modalities with mortality in patients admitted to hospital with COVID-19 (n=4)

Authors	**Sample size**	**Imaging modality and site**	**Imaging features(s) shown to be associated with mortality (p<0.05)**	**Proposed cutoffs for independently associated parameters**	**Sensitivity %**
Esposito et al.[59]	1394	Chest CT	Enlarged main pulmonary artery diameter (MPAD)	Enlargement (≥ 31 mm)	Not reported
Francone et al.[60]	130	Chest CT	CT-based semi-quantitative score of pulmonary lobar involvement (range 0-25)	CT score ≥ 18	Not reported
Lichter et al.[61]	120	Lung ultrasound (LUS)	LUS severity score (range 0-36)	Baseline LUS score > 18	LUS- 62
Xu et al.[62]	703	Chest CT	CT severity score	CT severity score > 14	Not reported

Table 6: Machine learning models that are used to predict mortality in patients admitted to hospital from COVID-19, with the training set being the number of people used to create the model and the test set being the number of people used when validating the model, sorted by highest AUROC. (n=12)

Author	Number of incorporated parameters	AUROC	Training set	Test set	Parameters looked at
An et al.[63]	5	0.9630	7166	3071	age > 80, taking of acarbose, age > 70, taking of metformin, and underlying cancer
Yuan et al. [64]	3	0.9551	1479	573	qSOFA, CURB 65, CRB65
Booth et al. [65]	5	0.9300	318	80	CRP, blood urea nitrogen (BUN), serum calcium, serum albumin, and lactic acid.
Yu et al. [66]	32	0.9220	172	74	lactate dehydrogenase, a.hydroxybutyrate dehydrogenase, bnp, urea nitrogen, hrcp I, myoglobin,age, d dimer, lymphocyte, cystatin c, igG, neutophils, albumin, creatinine kinase isozyme, creatinine, % eosinophil RR, total platelet, x blood glucose, eosinophil count, platelet distribution width, average platelet volume, hsc reactive protien, alkaline phosphate, basophil count, thrombin time, x platelet hematocrit, temperature, lipoprotien a, hbeab, phospherous, aptt
Gao et al. [67]	14	0.9186	2160	116	Consciousness, male sex, sputum, blood urea nitrogen [BUN], respiratory rate [RR], D—dimer, number of comorbidities, age, platelet count [PLT], fever, albumin [ALB], SpO2, lymphocyte, and chronic kidney disease
Bertsimas et al. [68]	7	0.9019	2755	307	IL-2R, IL-6 , IL-8, TNF-α, B cells, CD4+ T cells, CD8+ T cells, NK cells
Abdulaal et al.[69]	22	0.9012	398	40	Consciousness, male sex, sputum, blood urea nitrogen [BUN], respiratory rate [RR], D—dimer, number of comorbidities, age, platelet count [PLT], fever, albumin [ALB], SpO2, lymphocyte, and chronic kidney disease
Hu et al. [70]	4	0.8810	183	64	Consciousness, male sex, sputum, blood urea nitrogen [BUN], respiratory rate [RR], D—dimer, number of comorbidities, age, platelet count [PLT], fever, albumin [ALB], SpO2, lymphocyte, and chronic kidney disease
Pan et al. [71]	8	0.8600	98	25	LYM%, PT, lactate dehydrogenase (LDH), total bilirubin (T-Bil) , eosinophil percentage (EOS%), creatinine (Cr), NEUT%, and ALB.

Table 6 cont:

Parchure et al. [72]	55	0.8550	396	170	Age,Gender ,Length of stay , Admission type, Admission Source ,Respiratory rate Pulse, Diastolic blood pressure, Percutaneous oxygen saturation, Systolic blood pressure Temperature, Blood urea nitrogen , Serum Creatinine, Platelet count, Serum chloride, Anion gap, Serum sodium, Corrected WBC count, C-reactive protein, Red blood cell count, Partial pressure of carbon dioxide in arterial blood, (PACO2), Partial pressure of oxygen in arterial blood (PAO2), Partial pressure of carbon dioxide in venous blood (PVCO2), Partial pressure of oxygen in venous blood (PVO2), Serum potassium Activated partial thromboplastin time, Serum lactate, pH of arterial blood Serum total protein, Hemoglobin Complement C3 Complement C4 Interleukin 1 beta Interleukin 6 Interleukin 17 D-dimer, Aspartate aminotransferase Alanine, aminotransferase Serum calcium, Serum ferritin Lymphocyte count, Lactate dehydrogenase Serum albumin, NT-pro hormone B-type natriuretic peptide, pH of venous blood, Bicarbonates by arterial blood gas analysis, Serum direct bilirubin Serum total bilirubin T wave axis, P wave axis R wave axis Atrial rate Ventricular rate PR interval QRS duration
Vaid et al. [73]	73	0.8400	1514	2201	Not reported
Yu et al.[66]	9	0.8060	172	74	age, BNP, urea nitrogen, total platelet count, average platelet volume, D-dimer, high-sensitivity troponin I, LDH and creatinine kinase isoenzyme

Table 7- Deep Learning models that are used to predict patient mortality in patients admitted to hospital from COVID-19, with the training set being the number of people used to create the model and the test set being the number of people used when validating the model, sorted by highest AUROC (n=3)

Author	Number of incorporated parameters	AUROC	Training set	Test Set	Parameters looked at
Zhu et al.[74]	5	0.9540	187	33	D-dimer, oxygen index, neutrophil to lymphocyte ratio (NE:LY), C-reactive protein (CRP), and lactate dehydrogenase (LDH).
Meng et al.[75]	5	0.9430	246	120	sex, age, severity grade, and with/without chronic disease) and image features
Li et al.[76]	6	0.8480	997	111	age, LDH, procalcitonin, troponin, CRP and SpO2

References

1- Wang L, Lv Q, Zhang X, Jiang B, Liu E, Xiao C, et al. The utility of MEWS for predicting the mortality in the elderly adults with COVID-19: A retrospective cohort study with comparison to other predictive clinical scores. *PeerJ*. [Online] 2020; Available from: doi:10.7717/peerj.10018
2- Zou X, Li S, Fang M, Hu M, Bian Y, Ling J, et al. Acute Physiology and Chronic Health Evaluation II Score as a Predictor of Hospital Mortality in Patients of Coronavirus Disease 2019. *Critical Care Medicine*. [Online] 2020; Available from: doi:10.1097/CCM.0000000000004411
3- de Giorgi A, Fabbian F, Greco S, Di Simone E, de Giorgio R, Passaro A, et al. *Prediction of in-hospital mortality of patients with SARS-CoV-2 infection by comorbidity indexes: An Italian internal medicine single center study*. [Online] European Review for Medical and Pharmacological Sciences. 2020. Available from: doi:10.26355/eurrev_202010_23250
4- Liu S, Yao N, Qiu Y, He C. Predictive performance of SOFA and qSOFA for in-hospital mortality in severe novel coronavirus disease. *American Journal of Emergency Medicine*. [Online] 2020; Available from: doi:10.1016/j.ajem.2020.07.019
5- Ji D, Zhang D, Xu J, Chen Z, Yang T, Zhao P, et al. Prediction for progression risk in patients with COVID-19 pneumonia: The CALL score. *Clinical Infectious Diseases*. [Online] 2020; Available from: doi:10.1093/cid/ciaa414
6- Tang X, Du RH, Wang R, Cao TZ, Guan LL, Yang CQ, et al. Comparison of Hospitalized Patients With ARDS Caused by COVID-19 and H1N1. *Chest*. [Online] 2020; Available from: doi:10.1016/j.chest.2020.03.032
7- Satici C, Demirkol MA, Sargin Altunok E, Gursoy B, Alkan M, Kamat S, et al. Performance of pneumonia severity index and CURB-65 in predicting 30-day mortality in patients with COVID-19. *International Journal of Infectious Diseases*. [Online] 2020; Available from: doi:10.1016/j.ijid.2020.06.038
8- Liu FY, Sun XL, Zhang Y, Ge L, Wang J, Liang X, et al. Evaluation of the risk prediction tools for patients with coronavirus disease 2019 in Wuhan, China: A single-centered, retrospective, observational study. *Critical Care Medicine*. [Online] 2020; Available from: doi:10.1097/CCM.0000000000004549
9- Hu H, Yao N, Qiu Y. Comparing Rapid Scoring Systems in Mortality Prediction of Critically Ill Patients With Novel Coronavirus Disease. *Academic Emergency Medicine*. [Online] 2020; Available from: doi:10.1111/acem.13992
10- Bradley P, Frost F, Tharmaratnam K, Wootton DG, Ahmad M, Aigbirior J, et al. *The utility of established prognostic scores in COVID-19 hospital admissions: A multi-centre prospective evaluation of CURB-65, NEWS2, and qSOFA*. [Online] medRxiv. 2020. Available from: doi:10.1101/2020.07.15.20154815

11- Ortiz D, Diaz A, Almasary A, Rafique Z. 223 Evaluation of Pneumonia Scores in Patients Hospitalized for COVID-19-Related Dyspnea. *Annals of Emergency Medicine*. [Online] 2020; Available from: doi:10.1016/j.annemergmed.2020.09.236
12- Gupta RK, Marks M, Samuels THA, Luintel A, Rampling T, Chowdhury H, et al. Systematic evaluation and external validation of 22 prognostic models among hospitalised adults with COVID-19: an observational cohort study. *European Respiratory Journal*. [Online] 2020; Available from: doi:10.1183/13993003.03498-2020
13- Halalau A, Imam Z, Karabon P, Mankuzhy N, Shaheen A, Tu J, et al. External validation of a clinical risk score to predict hospital admission and in-hospital mortality in COVID-19 patients. *Annals of Medicine*. [Online] 2021; Available from: doi:10.1080/07853890.2020.1828616
14- Cetinkal G, Kocas BB, Ser OS, Kilci H, Keskin K, Ozcan SN, et al. Assessment of the Modified CHA2DS2VASc Risk Score in Predicting Mortality in Patients Hospitalized With COVID-19. *American Journal of Cardiology*. [Online] 2020; Available from: doi:10.1016/j.amjcard.2020.08.040
15- Liu Q, Song NC, Zheng ZK, Li JS, Li SK. Laboratory findings and a combined multifactorial approach to predict death in critically ill patients with COVID-19: A retrospective study. *Epidemiology and Infection*. [Online] 2020; Available from: doi:10.1017/S0950268820001442
16- Qin ZJ, Liu L, Sun Q, Li X, Luo JF, Liu JS, et al. Impaired immune and coagulation systems may be early risk factors for COVID-19 patients: A retrospective study of 118 inpatients from Wuhan, China. *Medicine*. [Online] 2020;99(35): e21700. Available from: doi:10.1097/MD.0000000000021700
17- Wang J, Yu H, Hua Q, Jing S, Liu Z, Peng X, et al. A descriptive study of random forest algorithm for predicting COVID-19 patients outcome. *PeerJ*. [Online] 2020;8: 1–19. Available from: doi:10.7717/peerj.9945
18- Weng Z, Chen Q, Li S, Li H, Zhang Q, Lu S, et al. ANDC: An early warning score to predict mortality risk for patients with Coronavirus Disease 2019. *Journal of Translational Medicine*. [Online] 2020;18(1): 1–10. Available from: doi:10.1186/s12967-020-02505-7
19- Soto-Mota A, Marfil-Garza BA, Martínez Rodríguez E, Barreto Rodríguez JO, López Romo AE, Alberti Minutti P, et al. The low-harm score for predicting mortality in patients diagnosed with COVID-19: A multicentric validation study. *Journal of the American College of Emergency Physicians Open*. [Online] 2020;1(6): 1436–1443. Available from: doi:10.1002/emp2.12259
20- Mei J, Hu W, Chen Q, Li C, Chen Z, Fan Y, et al. Development and external validation of a COVID-19 mortality risk prediction algorithm: A multicentre retrospective cohort study. *BMJ Open*. [Online] 2020;10(12). Available from: doi:10.1136/bmjopen-2020-044028
21- Luo Y, Mao L, Yuan X, Xue Y, Lin Q, Tang G, et al. Prediction Model Based on the Combination of Cytokines and Lymphocyte Subsets for Prognosis of SARS-CoV-2 Infection. *Journal of Clinical Immunology*. [Online] Journal of Clinical Immunology; 2020;40(7): 960–969. Available from: doi:10.1007/s10875-020-00821-7
22- Luo Y, Xue Y, Mao L, Yuan X, Lin Q, Tang G, et al. Prealbumin as a Predictor of Prognosis in Patients With Coronavirus Disease 2019. *Frontiers in Medicine*. [Online] 2020;7(June): 1–9. Available from: doi:10.3389/fmed.2020.00374
23- Zhou J, Huang L, Chen J, Yuan X, Shen Q, Dong S, et al. Clinical features predicting mortality risk in older patients with COVID-19. *Current Medical Research and Opinion*. [Online] Taylor & Francis; 2020;36(11): 1753–1759. Available from: doi:10.1080/03007995.2020.1825365
24- Cheng A, Hu L, Wang Y, Huang L, Zhao L, Zhang C, et al. Diagnostic performance of initial blood urea nitrogen combined with D-dimer levels for predicting in-hospital mortality in COVID-19 patients. *International Journal of Antimicrobial Agents*. [Online] Elsevier Ltd; 2020;56(3). Available from: doi:10.1016/j.ijantimicag.2020.106110
25- Laguna-goya R, Utrero-rico A, Talayero P, Lasa-lazaro M, Aguado JM, Martinez-lopez J. Since January 2020 Elsevier has created a COVID-19 resource centre with free information in English and Mandarin on the novel coronavirus COVID- 19 . The COVID-19 resource centre is hosted on Elsevier Connect , the company ' s public news and information . 2020;(January).
26- El-Solh AA, Lawson Y, Carter M, El-Solh DA, Mergenhagen KA. Comparison of in-hospital mortality risk prediction models from COVID-19. *Plos One*. [Online] 2020;15(12): e0244629. Available from: doi:10.1371/journal.pone.0244629

27- Shang Y, Liu T, Wei Y, Li J, Shao L, Liu M, et al. Scoring systems for predicting mortality for severe patients with COVID-19. *EClinicalMedicine*. [Online] Elsevier Ltd; 2020;24(December 2019): 100426. Available from: doi:10.1016/j.eclinm.2020.100426

28- Mei Q, Wang AY, Bryant A, Yang Y, Li M, Wang F, et al. Development and validation of prognostic model for predicting mortality of COVID-19 patients in Wuhan, China. *Scientific Reports*. [Online] 2020;10(1): 1–12. Available from: doi:10.1038/s41598-020-78870-6
29- Fumagalli C, Rozzini R, Vannini M, Coccia F, Cesaroni G, Mazzeo F, et al. Clinical risk score to predict in-hospital mortality in COVID-19 patients: a retrospective cohort study. *BMJ open*. [Online] 2020;10(9): e040729. Available from: doi:10.1136/bmjopen-2020-040729
30- Gude-Sampedro F, Fernández-Merino C, Ferreiro L, Lado-Baleato Ó, Espasandín-Domínguez J, Hervada X, et al. Development and validation of a prognostic model based on comorbidities to predict Covid-19 severity. A population-based study. *International Journal of Epidemiology*. [Online] 2020; 1–11. Available from: doi:10.1093/ije/dyaa209
31- Torres-Macho J, Ryan P, Valencia J, Pérez-Butragueño M, Jiménez E, Fontán-Vela M, et al. The PANDEMYC Score. An Easily Applicable and Interpretable Model for Predicting Mortality Associated With COVID-19. *Journal of Clinical Medicine*. [Online] 2020;9(10): 3066. Available from: doi:10.3390/jcm9103066
32- Li J, Chen Y, Chen S, Wang S, Zhang D, Wang J, et al. Derivation and validation of a prognostic model for predicting in-hospital mortality in patients admitted with COVID-19 in Wuhan, China: the PLANS (platelet lymphocyte age neutrophil sex) model. *BMC Infectious Diseases*. [Online] BMC Infectious Diseases; 2020;20(1): 1–10. Available from: doi:10.1186/s12879-020-05688-y
33- Hajifathalian K, Sharaiha RZ, Kumar S, Krisko T, Skaf D, Ang B, et al. Development and external validation of a prediction risk model for short-term mortality among hospitalized U.S. COVID-19 patients: A proposal for the COVID-AID risk tool. *PLoS ONE*. [Online] 2020;15(9 September): 1–15. Available from: doi:10.1371/journal.pone.0239536
34- Manocha KK, Kirzner J, Ying X, Yeo I, Peltzer B, Ang B, et al. Troponin and Other Biomarker Levels and Outcomes Among Patients Hospitalized with COVID-19: Derivation and Validation of the HA 2 T 2 COVID-19 Mortality Risk Score . *Journal of the American Heart Association*. [Online] 2020; Available from: doi:10.1161/jaha.120.018477
35- Tusha J, Khanam V, Tegeltija V, Kumar S. the Mulbsta Score: Predicting Risk of Mortality and Disease Severity in Patients With Covid-19 Pneumonia. *Chest*. [Online] American College of Chest Physicians; 2020;158(4): A300. Available from: doi:10.1016/j.chest.2020.08.299
36- Fernandez A, Obiechina N, Koh J, Hong A, Nandi A, Reynolds TM. Survival Prediction Algorithms for Covid-19 Patients Admitted to a UK District General Hospital. *International Journal of Clinical Practice*. [Online] 2020; 0–2. Available from: doi:10.1111/ijcp.13974
37- Cai L, Zhou X, Wang M, Mei H, Ai L, Mu S, et al. Predictive Nomogram for Severe COVID-19 and Identification of Mortality-Related Immune Features. *Journal of Allergy and Clinical Immunology: In Practice*. [Online] 2021;9(1): 177-184.e3. Available from: doi:10.1016/j.jaip.2020.10.043
38- Núñez-Gil IJ, Fernández-Pérez C, Estrada V, Becerra-Muñoz VM, El-Battrawy I, Uribarri A, et al. Mortality risk assessment in Spain and Italy, insights of the HOPE COVID-19 registry. *Internal and Emergency Medicine*. [Online] Springer International Publishing; 2020;(0123456789). Available from: doi:10.1007/s11739-020-02543-5
39- Varol Y, Hakoglu B, Kadri Cirak A, Polat G, Komurcuoglu B, Akkol B, et al. The impact of charlson comorbidity index on mortality from SARS-CoV-2 virus infection and A novel COVID-19 mortality index: CoLACD. *International Journal of Clinical Practice*. [Online] 2020;(November): 1–7. Available from: doi:10.1111/ijcp.13858
40- Mancilla-Galindo J, Vera-Zertuche JM, Navarro-Cruz AR, Segura-Badilla O, Reyes-Velázquez G, Tepepa-López FJ, et al. Development and Validation of the Patient History COVID-19 (PH-Covid19) Scoring System: A Multivariable Prediction Model of Death in Mexican Patients with COVID-19. *Epidemiology and Infection*. [Online] 2020;19. Available from: doi:10.1017/S0950268820002903
41- Altschul DJ, Unda SR, Benton J, de la Garza Ramos R, Cezayirli P, Mehler M, et al. A novel severity score to predict inpatient mortality in COVID-19 patients. *Scientific Reports*. [Online]

Nature Publishing Group UK; 2020;10(1): 1–8. Available from: doi:10.1038/s41598-020-73962-9

42- Gue YX, Tennyson M, Gao J, Ren S, Kanji R, Gorog DA. Development of a novel risk score to predict mortality in patients admitted to hospital with COVID-19. *Scientific Reports*. [Online] Nature Publishing Group UK; 2020;10(1): 1–8. Available from: doi:10.1038/s41598-020-78505-w

43- Knight SR, Ho A, Pius R, Buchan I, Carson G, Drake TM, et al. Risk stratification of patients admitted to hospital with covid-19 using the ISARIC WHO Clinical Characterisation Protocol: Development and validation of the 4C Mortality Score. *The BMJ*. [Online] 2020;370(September): 1–13. Available from: doi:10.1136/bmj.m3339

44- Lorente-Ros A, Monteagudo Ruiz JM, Rincón LM, Pérez RO, Rivas S, Martínez-Moya R, et al. Myocardial injury determination improves risk stratification and predicts mortality in covid-19 patients. *Cardiology Journal*. [Online] 2020;27(5): 489–496. Available from: doi:10.5603/CJ.a2020.0089

45- Shi Y, Pandita A, Hardesty A, McCarthy M, Aridi J, Weiss ZF, et al. Validation of pneumonia prognostic scores in a statewide cohort of hospitalised patients with COVID-19. *International Journal of Clinical Practice*. [Online] 2020;(December): 3–7. Available from: doi:10.1111/ijcp.13926

46- Rodriguez-Nava G, Yanez-Bello MA, Trelles-Garcia DP, Chung CW, Friedman HJ, Hines DW. Performance of the quick COVID-19 severity index and the Brescia-COVID respiratory severity scale in hospitalized patients with COVID-19 in a community hospital setting. *International Journal of Infectious Diseases*. [Online] International Society for Infectious Diseases; 2021;102: 571–576. Available from: doi:10.1016/j.ijid.2020.11.003

47- Fu L, Fei J, Xu S, Xiang HX, Xiang Y, Hu B, Li MD, Liu FF, Li Y, Li XY, Zhao H. Liver Dysfunction and Its Association with the Risk of Death in COVID-19 Patients: A Prospective Cohort Study. *Journal of clinical and translational hepatology*. 2020 Sep 28;8(3):246.

48- Garcia PD, Fumeaux T, Guerci P, Heuberger DM, Montomoli J, Roche-Campo F, Schuepbach RA, Hilty MP, RISC-19-ICU Investigators. Prognostic factors associated with mortality risk and disease progression in 639 critically ill patients with COVID-19 in Europe: Initial report of the international RISC-19-ICU prospective observational cohort. *EClinicalMedicine*. 2020 Aug 1;25:100449.

49- Bellmann-Weiler R, Lanser L, Barket R, Rangger L, Schapfl A, Schaber M, Fritsche G, Wöll E, Weiss G. Prevalence and predictive value of anemia and dysregulated iron homeostasis in patients with COVID-19 infection. *Journal of clinical medicine*. 2020 Aug;9(8):2429.

50- Liu ZM, Li JP, Wang SP, Chen DY, Zeng W, Chen SC, Huang YH, Huang JL, Long W, Li M, Gao RF. Association of procalcitonin levels with the progression and prognosis of hospitalized patients with COVID-19. *International journal of medical sciences*. 2020;17(16):2468.

51- Wang S, Ma P, Zhang S, Song S, Wang Z, Ma Y, Xu J, Wu F, Duan L, Yin Z, Luo H. Fasting blood glucose at admission is an independent predictor for 28-day mortality in patients with COVID-19 without previous diagnosis of diabetes: a multi-centre retrospective study. *Diabetologia*. 2020 Oct;63(10):2102-11.

52- Singh N, Anchan RK, Besser SA, Belkin MN, Cruz MD, Lee L, Yu D, Mehta N, Nguyen AB, Alenghat FJ. High sensitivity Troponin-T for prediction of adverse events in patients with COVID-19. *Biomarkers*. 2020 Nov 16;25(8):626-33.

53- Fois AG, Paliogiannis P, Scano V, Cau S, Babudieri S, Perra R, Ruzzittu G, Zinellu E, Pirina P, Carru C, Arru LB. The systemic inflammation index on admission predicts in-hospital mortality in COVID-19 patients. *Molecules*. 2020 Jan;25(23):5725.

54- Aloisio E, Chibireva M, Serafini L, Pasqualetti S, Falvella FS, Dolci A, Panteghini M. A comprehensive appraisal of laboratory biochemistry tests as major predictors of COVID-19 severity. *Archives of pathology & laboratory medicine*. 2020 Dec;144(12):1457-64.

55- Foy BH, Carlson JC, Reinertsen E, Valls RP, Lopez RP, Palanques-Tost E, Mow C, Westover MB, Aguirre AD, Higgins JM. Association of red blood cell distribution width with mortality risk in hospitalized adults with SARS-CoV-2 infection. *JAMA Network Open*. 2020 Sep 1;3(9):e2022058-.

56- Stefanini GG, Chiarito M, Ferrante G, Cannata F, Azzolini E, Viggiani G, De Marco A, Briani M, Bocciolone M, Bragato R, Corrada E. Early detection of elevated cardiac biomarkers to optimise risk stratification in patients with COVID-19. *Heart*. 2020 Oct 1;106(19):1512-8.

57- Trabulus S, Karaca C, Balkan II, Dincer MT, Murt A, Ozcan SG, Karaali R, Mete B, Bakir A, Kuskucu MA, Altiparmak MR. Kidney function on admission predicts in-hospital mortality in COVID-19. *Plos one*. 2020 Sep 3;15(9):e0238680.
58- Cao J, Zheng Y, Luo Z, Mei Z, Yao Y, Liu Z, Liang C, Yang H, Song Y, Yu K, Gao Y. Myocardial injury and COVID-19: Serum hs-cTnI level in risk stratification and the prediction of 30-day fatality in COVID-19 patients with no prior cardiovascular disease. *Theranostics*. 2020;10(21):9663.

59- Esposito A, Palmisano A, Toselli M, Vignale D, Cereda A, Rancoita PM, Leone R, Nicoletti V, Gnasso C, Monello A, Biagi A. Chest CT–derived pulmonary artery enlargement at the admission predicts overall survival in COVID-19 patients: insight from 1461 consecutive patients in Italy. *European radiology*. 2020 Dec 23:1-1.
60- Francone M, Iafrate F, Masci GM, Coco S, Cilia F, Manganaro L, Panebianco V, Andreoli C, Colaiacomo MC, Zingaropoli MA, Ciardi MR. Chest CT score in COVID-19 patients: correlation with disease severity and short-term prognosis. *European radiology*. 2020 Dec;30(12):6808-17.
61- Lichter Y, Topilsky Y, Taieb P, Banai A, Hochstadt A, Merdler I, Oz AG, Vine J, Goren O, Cohen B, Sapir O. Lung ultrasound predicts clinical course and outcomes in COVID-19 patients. *Intensive care medicine*. 2020 Oct;46(10):1873-83.
62- Xu PP, Tian RH, Luo S, Zu ZY, Fan B, Wang XM, Xu K, Wang JT, Zhu J, Shi JC, Chen F. Risk factors for adverse clinical outcomes with COVID-19 in China: a multicenter, retrospective, observational study. *Theranostics*. 2020;10(14):6372.
63- An C, Lim H, Kim D, Chang JH, Choi YJ, Kim SW. Machine learning prediction for mortality of patients diagnosed with COVID-19: a nationwide Korean cohort study. *Scientific Reports*. 2020; 10 (1): 1-11. Available from: doi: 10.1038/s41598-020-75767-2 [Accessed Jan 12, 2021].
64- Yuan Y, Sun C, Tang X, Cheng C, Mombaerts L, Wang M, et al. Development and Validation of a Prognostic Risk Score System for COVID-19 Inpatients: A Multi-Center Retrospective Study in China. *Engineering*. 2020; Available from: doi: 10.1016/j.eng.2020.10.013 [Accessed Jan 12, 2021].
65- Booth AL, Abels E, McCaffrey P. Development of a prognostic model for mortality in COVID-19 infection using machine learning. *Modern pathology*. 2020; 1-10. Available from: doi: 10.1038/s41379-020-00700-x [Accessed Jan 12, 2021].
66- Yu Y, Zhu C, Yang L, Dong H, Wang R, Ni H, et al. Identification of risk factors for mortality associated with COVID-19. PeerJ. 2020; 8 e9885. Available from: doi: 10.7717/peerj.9885 9885 [Accessed Jan 12, 2021].
67- Gao Y, Cai G, Fang W, Li H, Wang S, Chen L, et al. Machine learning based early warning system enables accurate mortality risk prediction for COVID-19. *Nature Communications*. 2020; 11 (1): 1-10. Available from: doi: 10.1038/s41467-020-18684-2 [Accessed Jan 12, 2021].
68- Bertsimas D, Lukin G, Mingardi L, Nohadani O, Orfanoudaki A, Stellato B, et al. COVID-19 mortality risk assessment: An international multi-center study. *PLOS ONE*. 2020; 15 (12): e0243262. Available from: doi: 10.1371/journal.pone.0243262 [Accessed Jan 12, 2021].
69- Abdulaal A, Patel A, Charani E, Denny S, Mughal N, Moore L. Prognostic Modeling of COVID-19 Using Artificial Intelligence in the United Kingdom: Model Development and Validation. *Journal of Medical Internet Research*. 2020; 22 (8): e20259. Available from: doi: 10.2196/20259 [Accessed Jan 12, 2021].
70- Hu C, Liu Z, Jiang Y, Shi O, Zhang X, Xu K, et al. Early prediction of mortality risk among patients with severe COVID-19, using machine learning. *International Journal of Epidemiology*. 2020; Available from: doi: 10.1093/ije/dyaa171 [Accessed Jan 12, 2021].
71- Pan P, Li Y, Xiao Y, Han B, Su L, Su M, et al. Prognostic Assessment of COVID-19 in the Intensive Care Unit by Machine Learning Methods: Model Development and Validation. *Journal of Medical Internet Research*. 2020; 22 (11): Available from: doi: 10.2196/23128 [Accessed Jan 12, 2021].
72- Parchure P, Joshi H, Dharmarajan K, Freeman R, Reich DL, Mazumdar M, et al. Development and validation of a machine learning-based prediction model for near-term in-hospital mortality among patients with COVID-19. *BMJ Supportive & Palliative Care*. 2020; Available from: doi: 10.1136/bmjspcare-2020-002602 [Accessed Jan 12, 2021].

73- Vaid A, Somani S, Russak AJ, De Freitas JK, Chaudhry FF, Paranjpe I, et al. Machine Learning to Predict Mortality and Critical Events in a Cohort of Patients With COVID-19 in New York City: Model Development and Validation. *Journal of Medical Internet Research*. 2020; 22 (11): Available from: doi: 10.2196/24018 [Accessed Jan 12, 2021]
74- Zhu JS, Ge P, Jiang C, Zhang Y, Li X, Zhao Z, et al. Deep-learning artificial intelligence analysis of clinical variables predicts mortality in COVID-19 patients. *Journal of the American College of Emergency Physicians Open. 2020*; 1 (6): 1364-1373. Available from: doi: https://doi.org/10.1002/emp2.12205 [Accessed Jan 12, 2021].
75- Meng L, Dong D, Li L, Niu M, Bai Y, Wang M, et al. A Deep Learning Prognosis Model Help Alert for COVID-19 Patients at High-Risk of Death: A Multi-Center Study. *IEEE Journal of Biomedical and Health Informatics*. 2020; 24 (12): 3576-3584. Available from: doi: 10.1109/JBHI.2020.3034296 [Accessed Jan 12, 2021]
76- Li X, Ge P, Zhu J, Li H, Graham J, Singer A, et al. Deep learning prediction of likelihood of ICU admission and mortality in COVID-19 patients using clinical variables. *PeerJ*. 2020; 8 Available from: doi: 10.7717/peerj.10337 [Accessed Jan 12, 2021].