COVID-19 Scientific Advisory Group Rapid Response Report

Key Research Question: Are there demographic, clinical, basic lab or radiologic features that predict testing positive for COVID-19 infection?

Context

- Results from previous research have identified patient factors that are associated with a positive COVID-19 test result.
- This question was initially posed to determine if the more easily derived demographic and clinical predictor variables could potentially be used by Alberta Health Services (AHS) clinicians to help prioritize patients for COVID-19 testing, particularly if testing resources are limited.
- Overreliance on negative COVID-19 testing can lead to inappropriate cessation of isolation and PPE in the face of a false negative result despite clinical indicators suggesting a significant COVID-19 risk.
- There are various sources of possible error in the collection and processing of swabs taken for COVID-19 RT-PCR testing which affect test sensitivity, raising questions about whether patients with a moderate or high pretest probability for COVID-19 should still be considered as possible COVID-19 despite a negative RT-PCR swab.
- AHS has expanded the HCW screening tool to include additional milder symptoms to increase sensitivity of testing and reduce transmission of COVID in acute care, subacute care, congregate living and ambulatory settings and it is not yet clear how these symptoms perform in predicting risk of COVID-19 infection or how they should impact Fitness to Work assessments.
- Prior risk assessment tools focused on travel exposure history and advanced diagnostic or laboratory testing algorithms which are less relevant in context of later stages of pandemic and when rates of community and nosocomial transmission are lower.
- Transition to a maintenance phase in this pandemic requires reconsideration of ways to capture predictive symptoms in different patient populations and to maximize the yield of initial laboratory and diagnostic imaging testing.

Key Messages from the Evidence Summary

- There is a lack of scientifically rigorous evidence to support the use of patient demographic, environmental or clinical factors as a means to stratify pre-test probability for a positive COVID-19 RT-PCR test result. Although research studies have identified various predictive factors with a suitable level of statistical significance, the quality of these studies is low due to small sample sizes, lack of control groups, methodologic shortcomings, risk of bias, risk of model overfitting, and study participants not being representative of the predictive models' targeted populations.
- Those predictive factors that are statistically significant in more than one study, and are biologically plausible as well as clinically rational, might be considered (with suitable caution) by clinicians to very estimate a potentially increased risk of COVID-19 infection in patients presenting with respiratory symptoms. These factors include elevated temperature/fever, low lymphocyte count, advanced age, fatigue, and shortness of breath, as well as ground glass opacification and/or bilateral lung involvement on chest imaging among patients who present to the emergency department or are already admitted to hospital.
- For those patients presenting to community assessment centres for testing, and for healthcare workers, subjective reporting of fever and new loss of smell or taste may be more predictive of a positive test result than ILI symptoms (cough and fever).
- More recent predictive models have been developed using exposure history, demographic, clinical, lab and radiographic variables which perform well in initial derivation datasets. These studies, while more methodologically sound and demonstrating statistically and clinically reliable performance on Area under

the receiver operating characteristic (AUROC) metrics, require further validation in other settings and more representative populations. The variables which have the strongest performance and validity includes: exposure to a COVID-19 positive case, fever, respiratory symptoms, evidence of pneumonia on CXR or CT and either an increased neutrophil lymphocyte ratio (NLR – calculated by dividing the neutrophils by lymphocytes) (> 3.53) or lymphopenia both of which can be assessed on CBC with differential.

- Simpler predictive tools, such as the COVID Early Warning System or the PARIS score have been developed which incorporate exposure history, demographic, symptom and simple lab or diagnostic imaging criteria can identify a high or low pretest probability of COVID infection. While these require external validation, documenting this level of risk will be helpful to support ongoing isolation needs and viral testing priority as well as Fitness to Work status.
- As we establish ongoing pandemic health care processes consistent monitoring, and documentation of indicators of COVID-19 infection risk is important. Optimal protective interventions including contact and droplet isolation, PPE including mask, eye protection and hand hygiene as well as other social distancing strategies, should be maintained in the presence of patients with any exposure history, or symptom / sign associated with increased risk of COVID-19 infection, supported by implementation of COVID risk assessment tools. Use of tools should be tracked and assessed and research monitored.

Committee Discussion

There was general agreement with the review. It was suggested that because none of the models, regardless of population of interest, have been externally validated, a separate Research Gaps section should be included. This section outlines the further recommendation that data from the Alberta population be longitudinally collected, analyzed and monitored in order to support development of models that could more confidently be applied in the local setting. It was further suggested that risk factors be clearly defined as demographic, clinical and exposure-related in nature. One committee member suggested that “loss of smell” be further defined as reduction versus total loss, and to determine the possible temporary or permanent nature of this change. Finally it was agreed that control populations used in model development should optimally include patients with ILI symptoms and include age- and sex-matching, as it was noted, for example, that loss of smell is age-related.

Recommendations

1. Clinical and exposure risk factors for predicting a higher pretest probability of COVID-19 positive RT-PCR testing can be identified and should be documented at admission, in addition to consideration for transitions in care. The presence of recent travel to a high risk country or area with increased community transmission, or direct contact with a COVID-19 positive person in addition to the presence of fever and or cough, clinical evidence of pneumonia on imaging and the presence of lab abnormalities such as lymphopenia or an elevated NLR (>3.5) can be currently considered as clinical features with suggestive evidence of predictive weight in multiple studies.
2. Clinical and exposure risk factors for predicting a higher pretest probability of COVID-19 positive RT-PCR testing in community settings (people presenting to assessment centres or via symptom tracker apps) have been identified and perform differently than those presenting to hospital with acute respiratory symptoms. These include loss of smell or taste, severe or significant persistent cough, severe fatigue and reduced appetite. These factors are predictors in univariate analyses (i.e., stand alone predictors) and as part of multi-factor models. Fever and shortness of breath are less likely to be strong predictors in this population. These symptoms should be included in community and assessment centre tracking systems in addition to age, exposure to a COVID-19 positive persons or outbreak locations and to inform access to testing and to support community level needs for future public health interventions. The Alberta Health Services list of COVID-19 symptoms can be found here: https://www.albertahealthservices.ca/topics/Page16997.aspx#sign
3. Risk assessment tools cannot replace the need for RT-PCR testing, and repeated testing may be required in patients initially testing negative who had a high pre-test probability based on clinical assessment and the factors noted above.

Research Gaps

1. The identified factors, from all populations of interest, which are associated with a positive COVID-19 test result are derived from models that lack external validation, particularly in a North American population.
2. The control groups used to develop and internally validate these models optimally should ensure age- and sex-matching of controls.
3. It is important to ensure that "loss of smell" is new and to qualify "loss of smell" (as it is reported in the cited studies included in this review) as partial versus complete loss, in addition to document whether it is temporary or permanent if possible.
4. Further development and external validation of the presented models using local datasets should be prioritized and consistently documented for ongoing development of risk stratification tools.

Summary of Evidence

Hospital Setting (Inpatients and ED) – Demographic, Clinical and Laboratory Predictors

Nine (9) publications were identified which developed diagnosis models to predict a positive test result for COVID-19 infection among patients who presented to emergency departments (EDs), specialty fever clinics or were admitted to hospital. The identified models included demographic, clinical and laboratory features. One publication used data from patients in France, while the remainder developed models from patient data derived in China. Those models that included exposure history used a variable that was specific to travel in Wuhan, China. All models included some component of hematological parameters, with variable inclusion of demographic and exposure data elements. The most frequently reported predictors were elevated temperature/fever, lymphocyte count or percent, age, fatigue, and shortness of breath. The models, with their included variables and performance results, are described in the table below. No model was externally validated and all were at high risk for model-overfitting. Reported model performance may therefore be inflated.

Summary of prediction models for a positive COVID-19 test result among patients in the hospital setting.

Study Population Description	Total Sample Size (n; % positive cases)	Predictor Variables Included in the Model	Model Performance	Comments
Outpatients presenting to a single centre in China with COVID-19 symptoms[1]	276 (181; 66%)	Age Lymphocyte percentage Monocyte count (x10^9/L)	AUC=.91 (95%CI 0.88-0.94)	https://bjdth.shinyapps.io/COVID-19/ Not validated
Admitted patients with confirmed COVID-19 from 5 hospitals in 4 cities in China[2] Admitted patients with pneumonia (COVID-19 negative) at 1 hospital in China	Development Cohort: 98 (51; 52%) Validation Cohort: 38 (19; 50%)	RR (bpm) HR Temp WBC count Cough (yes/no) Fatigue (yes/no) Lymphocyte count (low, normal, high)	AUC=0.95 (95%CI 0.92-0.97) AUC=0.97 (95%CI 0.91-1.0)	Not externally validated
Patients presenting to an infectious diseases	788 (54; 6.9%)	Sex Exposure (contact with positive case, travel to Wuhan, travel to China)	AUC=0.91 (95%CI 0.86-0.96)	Not validated.

treatment facility in Singapore with COVID-19 symptoms[3]		Temp HR RR Systolic BP Diastolic BP Sore throat Sputum production Shortness of breath GI symptoms CXR/CT suggestive of pneumonia Lymphocyte count Neutrophil count Eosinophil count Creatinine Sodium		Travel to Wuhan was the strongest predictor for a positive test result: OR=23.1 (1.54-2.76). When exposure variables are removed from the model, temperature becomes the strongest predictor for a positive test result: OR=2.55 (1.32-5.21)
Patients who presented to a single centre hospital in China with COVID-19 symptoms.[4]	Development cohort: 711 (73; 10%) Validation cohort: 600 (20; 3%)	Signs of pneumonia on CT Exposure hx Fever Age Sex Max temp NLR	AUC=0.96 (95%CI 0.93-0.98) AUC=0.97 (95%CI 0.93-1.0)	Pre-print Known as the **COVID-19 Early Warning Score (EWS)** Not externally validated
Patients presenting to an ED or infectious disease department at 3 hospitals in France[5]	Development cohort: 100 (50; 50%) Validation cohort: 300 (208; 69%)	Eosinophils <0.06 G/L Lymphocytes <1.3 G/L Neutrophils <5 G/L Basophils <0.04 G/L	AUC=0.92 (95%CI 0.87-0.97) AUC=0.89 (95%CI 0.85-0.93)	Pre-print Known as the **PARIS score** Not externally validated
Patients admitted with COVID-19 symptoms to 18 hospitals in China[6]	Development cohort: 729 (293; 0%) Validation cohort: 183 (69; 37%)	Exposure hx (relationship with cluster outbreak, travel to Wuhan, exposure to patients with resp symptoms who travelled to Wuhan, exposure to patients with resp symptoms who travelled to other outbreak areas) Muscle soreness Dyspnea Fatigue Lymphocyte count WBC count CXR/CT changes	AUC=0.95 (95%CI not provided) AUC=0.97 (95%CI not provided)	Pre-print Authors note that removal of exposure variables reduces the performance of the model. Not externally validated
Patients admitted with COVID-19 symptoms to a fever clinic/ED at a single centre in China[7]	Development cohort: 132 (26; 20%) Validation cohort: 33 (6; 18%)	Age Max temp HR Diastolic BP Systolic BP Fatigue Headache Sore throat Shiver Shortness of breath PLT count MCH Basophil count	AUC=0.84 (95%CI not provided) AUC=0.67 (95%CI not provided)	Pre-print https://intensivecare.shinyapps.io/COVID19/ Not externally validated

		Eosinophil count Monocyte ratio IL-6		
Patients presenting with COVID-19 symptoms to various hospitals in China[8]	Development cohort: 431 (211; 49%) Validation cohort: 189 (91; 48%)	Age RDW aPTT TG A/G Uric acid Serum potassium Serum calcium 3-Hydroxybutyrate	AUC=0.89 (95%CI no provided) AUC=0.87 (95%CI not provided)	Pre-print Known as the COVID-19 Diagnosis AID APP Not externally validated
Patients presenting with COVID-19 symptoms to 5 hospitals in China[9]	Development cohort: 146 (50; 34%) Validation cohort: 74 (40; 54%)	Total protein Total bilirubin Glucose Creatinine Calcium LDH Creatine kinase isoenzyme Potassium Magnesium Platelet distribution width Basophil count	AUC=1.0 (95%CI not provided) AUC=0.99 (95%CI not provided)	Pre-print http://lishuyan.lzu.edu.cn/COVID2019_2/. Not externally validated

Hospital Setting (Inpatients and ED) – Diagnostic Imaging Predictors

A recently updated systematic review[10] identified and critically appraised twenty-six (26) publications and pre-prints describing thirty-four (34) diagnosis models which predicted COVID-19 infection using diagnostic imaging results. Most incorporated computed tomography (CT) images, while others evaluated chest radiographs. The authors applied the PROBAST (Prediction Model Risk of Bias Assessment Tool) and determined that all 34 models had a high overall risk of bias. All were scored as unclear regarding the predictor domain, indicating that the predictors were not clearly defined. Specifically, the authors noted that these studies inadequately described the image pre-processing steps (i.e., image cropping) and applied machine learning algorithms that transformed images into predictors in a complex manner. This reduces the transparency and reproducibility of the models. The authors did not recommend that any of these models be used in practice.

Publications which have pooled the results of multiple descriptive studies have reported the presence of certain chest imaging features in patients with COVID-19. These features include bilateral lung lesions[11-15], ground glass shadows/opacity[11-15], peripheral distribution[11 14], and multilobar involvement[11 14]. However none of these studies compared the presence of these features between patients who were COVID-19 positive with those patients who were COVID-negative. Therefore caution must be applied in the interpretation and application of these results.

Community Assessment Setting

Four publications were identified which compared clinical symptoms among patients who tested positive and negative for infection with COVID-19 and who presented to a community assessment centre or a virtual care program for testing. Three papers examined various demographic and clinical symptoms[16-18], while one paper exclusively examined taste perception[19].

Residents of South Carolina who were symptomatic for COVID-19 were encouraged to access a free virtual care consultation and screening service established by the Medical University of South Carolina. Screened and prioritized patients were then tested via a drive-through testing facility. The virtual care consultation included patient-entered text information regarding their symptoms. With the intention of creating a model for test prioritization screening, Obeid et al. applied text analytics and machine learning techniques to data from 6,813 patients who underwent testing (498 tested positive).[17] Their analysis determined that words such as “smell”, “taste” “sense”, “lost” and “temperature” were used with much higher frequency in those who tested positive for COVID-19 compared to those who tested negative. Words such as “cough”, “fever” and “difficulty breathing”, however, were not as prominent. The AUCs from the development and training cohorts for their screening model

was 0.96 and 0.73 respectively. The authors noted that their results highlight the importance of loss of smell or taste as predictive symptom for a positive test, yet this symptom is often not included in screening tools.

Menni et al. analyzed data collected from residents of the United Kingdom (n=15,638; 6,452 tested positive) and the United States (n=2,763; 726 tested positive) who voluntarily used a COVID-19 symptom tracking, smartphone-based app.[16] The app collected information regarding symptoms, testing outcomes, demographic information and pre-existing medical conditions. From these collected data, the authors created a model to predict a positive COVID-19 test which included age, sex, loss of smell, severe or significant persistent cough, severe fatigue and skipped meals. The development cohort had an AUC=0.76 (95%CI 0.74-0.78) while the validation AUC was 0.75 (95%CI 0.74-0.76). Validation using the US data resulted in an AUC=0.76 (95%CI 0.74-0.78). Loss of smell or taste was the strongest predictor for a positive test result.

Zoabi and Shomron analyzed population-based data which detailed the age, gender, presence and severity of clinical symptoms, exposure to confirmed patients, geographical area and risk of complications among all individuals in Israel who were tested for COVID-19 (development cohort = 51,831 with 4,769 positive cases; validation cohort = 47,401 with 3,624 positive cases).[18] A model was created using gender, age (binary variable as 60 and younger or older than 60), known contact with an infected person, and five clinical symptoms (cough, fever, sore throat, shortness of breath, headache). The development cohort AUC was 0.93 (95% CI not provided), while the validation cohort AUC was 0.90 (95%CI 0.89-0.91). Fever and cough combined was the strongest predictor for a positive test result. Anosmia was not assessed in this study.

As loss of taste and smell was increasing reported as a potential symptom of COVID-19, researchers in Poland investigated if the reported ageusia was related to specific tastes.[19] An outbreak was detected at a university in Warsaw, which resulted in testing of those students who resided in the dormitories. Eighty-eight students (52 who tested positive) participated in this study which assessed their abilities to taste pre-formed and concentrated tablets of sweet, sour, salty and bitter tastes. Subjective taste loss was reported in 65% of those students who tested positive and 8% of those who tested negative. Using the taste-specific tablets, taste disturbances were detected in 50% of students who tested positive, compared to 22% who tested negative. This taste disturbance difference was most notable, and statistically significant, for the sweet flavour. A model that combined the sweet taste test and self-reported presence of fever, smell disorders and taste disorders produced an AUC=0.75 (95%CI 0.64-0.86). This model was not validated.

Healthcare Workers

Three publications were identified in which clinical and demographic features of healthcare workers (HCWs) were compared between those who were confirmed positive for COVID-19 with those who were confirmed negative. Two papers described predictive models [20] [21] and one provided descriptive analyses[22].

Clemency et al. tested 961 HCWs from a health care system in western New York with 225 (23%) testing positive.[20] At the time of testing, HCWs were asked to identify the presence or absence of symptoms from a standardized list. Loss of taste or smell had the largest positive likelihood ratio (PLR) of 3.3 (95% CI 2.6-4.1), indicating that this symptom in HCWs increased the probability for a positive COVID test by approximately 20%.[23] The PLR for fever was 1.45 (95% CI 1.26-1.63). A testing criteria model was developed using the symptoms of fever (measured or subjective), difficulty breathing, dry cough and loss of taste or smell, where a HCW could have any combination of one or more of these symptoms. This model produced an AUC=0.77 (95% CI .73-0.80) and demonstrated superior performance compared to models with fever/loss of taste or smell, and fever/difficulty breathing/cough. Validation of this model, however, was not performed.

Tostmann et al. developed a diagnostic model to predict COVID infection among HCWs in the Netherlands, where 627 HCWs (56 positives) and 176 HCWs (34 positives) comprised the development and testing cohorts respectively.[21] Within 24 hours of testing, HCWs responded to an online questionnaire in which they identified the presence or absence of symptoms (which included respiratory and non-respiratory symptoms) from a standardized list. On univariate analysis, loss of smell was strongly associated with a positive COVID test (OR 23.0 95%CI 8.2-64.8). The OR for fever was 2.7 (95% CI 1.7-4.2). The authors created a diagnostic model that used those symptoms which on univariate analysis were most strongly associated with a positive COVID test, and weighted the symptoms based on their association: anosmia, muscle ache, extreme tiredness, headache, ocular

pain, fever and general malaise (respiratory symptoms such as cough and shortness of breath were not significant on univariate analysis in this study population). The AUC for this model was 0.78 (95% CI 0.70-0.88).

Using descriptive statistics, Yombi et al., reported on symptoms at the time of COVID testing among HCWs in Belgium.[22] Testing conducted before March 30, 2020 (n=158; 81 positive) was limited to those HCWs who had fever and respiratory symptoms, although some HCW without fever were tested. After March 30th, testing was performed on HCWs with respiratory symptoms, with or without fever (n=378; 94 positive). During the first period of testing 75% of COVID positive HCWs and 62% of COVID negative HCWs had fever. During the second period of testing, 52% and 20% of COVID positive and negative HCWs respectively had a fever at the time of testing. The authors conclude that, although fever is associated with a positive COVID test among HCWs, many cases will be missed if fever is a required symptom for testing. This study did not assess anosmia.

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Authorship & Committee Members

This review was written by Susan Jelinski and Elizabeth Mackay, and scientifically reviewed by Elizabeth Mackay, Nathan Zelyas, and Melissa Potestio (external reviewer). The full Scientific Advisory Group was involved in discussion and revision of the document: Lynora Saxinger (co-chair), Braden Manns (co-chair), John Conly, Alexander Doroshenko, Shelley Duggan, Nelson Lee, Andrew McRae, Jeremy Slobodan, James Talbot, Brandie Walker, and Nathan Zelyas.

Appendix

List of Abbreviations

A/G	Albumin/globulin
AHS	Alberta Health Services
AP	Antero-posterior
aPTT	Activated partial thromboplastin time
AUC	Area under the curve
AUROC	Area under the receiver operating characteristic
BP	Blood pressure
CBC	Complete blood count
CHARMS	Checklist for critical appraisal and data extraction for systematic reviews of prediction modelling studies
CI	Confidence interval
CRP	C-reactive protein
CXR	Chest x-ray
CT	Computed tomography
ED	Emergency department
EWS	Early warning score
GI	Gastro-intestinal
HCW	Healthcare worker
HR	Heart rate
Hx	History
ILI	Influenza-like illness
IL-6	Interleukin-6
LDH	Lactate dehydrogenase
Max	Maximum
MCH	Mean corpuscular hemoglobin
NLR	Neutrophil lymphocyte ratio
NP	Naso-pharyngeal
OR	Odds ratio
PA	Postero-anterior

PCR	Polymerase chain reaction
PLT	Platelet
PPE	Personal protective equipment
PRISMA	Preferred reporting items for systematic reviews and meta-analyses
PROBAST	Prediction model risk of bias assessment tool
RDW	Red blood cell distribution width
Resp	Respiratory
RR (bpm)	Respiration Rate (breaths per minute)
RT-PCR	Reverse-transcriptase – polymerase chain reaction assay
SR	Systematic review
Temp	Temperature
TG	Triglyceride
TRIPOD	Transparent reporting of a multivariable prediction model for individual prognosis or diagnosis
WBC	White blood cell

Literature Search Details

The literature search was performed by Lauren Seal from the AHS Knowledge Resource Service.

Medline/PubMed

1 exp Coronavirus/ or Coronavirus Infections/ or coronaviru*.mp. or corona viru*.mp. or ncov*.mp. or n-cov*.mp. or novel cov*.mp. or COVID-19.mp. or COVID19.mp. or COVID-2019.mp. or COVID2019.mp. or SARS-CoV-2.mp. or SARSCoV-2.mp. or SARSCoV2.mp. or SARSCoV19.mp. or SARS-Cov-19.mp. or SARSCov-19.mp. or SARSCoV2019.mp. or SARS-Cov-2019.mp. or SARSCov-2019.mp. or severe acute respiratory syndrome coronaviru*.mp. or severe acute respiratory syndrome cov 2.mp. or 2019 ncov.mp. or 2019ncov.mp. (24646)

2 exp Forecasting/ (84841)

3 (predict* adj1 model*).mp. (65289)

4 predict*.mp. (1619375)

5 pre-test*.mp. (9561)

6 pretest*.mp. (16719)

7 presumptive.mp. (17928)

8 probabilit*.mp. (239574)

9 diagnostic model {Including Related Terms} (17515)

10 presumed.mp. (50975)

11 "predict* model*".mp. (35637)

12 "early warning tool*".mp. (96)
13 "early warning score*".mp. (909)
14 2 or 3 or 4 or 5 or 6 or 7 or 8 or 9 or 10 or 11 or 12 or 13 (1967087)
15 exp "Signs and Symptoms"/ (2057868)
16 symptom.mp. (202252)
17 "clinical feature*".mp. (103699)
18 "clinical manifestation*".mp. (65757)
19 exp Demography/ (1522516)
20 demographic*.mp. (330060)
21 exp Environmental Exposure/ (299162)
22 exp Diagnostic Imaging/ (2625965)
23 CT.mp. (334164)
24 radiology.mp. (71330)
25 laboratory.mp. (539167)
26 exp Clinical Laboratory Techniques/ (2576289)
27 "exposure history".mp. (1344)
28 15 or 16 or 17 or 18 or 19 or 20 or 21 or 22 or 23 or 24 or 25 or 26 or 27 (8884357)
29 exp Patients/ (64650)
30 exp Emergency Service, Hospital/ (77630)
31 "emergency department".mp. (79832)
32 "emergency room".mp. (17436)
33 ED.mp. (76543)
34 ER.mp. (90353)
35 "assessment center*".mp. (240)
36 "assessment centre*".mp. (210)
37 exp Health Personnel/ (510691)
38 "healthcare worker*".mp. (9450)
39 "health care worker*".mp. (12588)
40 doctor*.mp. (124960)
41 nurse*.mp. (351498)
42 physician*.mp. (558883)

43 "healthcare professional*".mp. (21224)

44 "health care professional*".mp. (23352)

45 "health professional*".mp. (52169)

46 29 or 30 or 31 or 32 or 33 or 34 or 35 or 36 or 37 or 38 or 39 or 40 or 41 or 42 or 43 or 44 or 45 (1516017)

47 1 and 14 and 28 and 46 (30)

48 limit 47 to dt=20191201-20200608 (13)

CINAHL

S1 (MH "Coronavirus+")

S2 (MH "Coronavirus Infections+")

S3 coronaviru*

S4 "corona virus"

S5 ncov*

S6 n-cov*

S7 COVID-19 OR COVID19 OR COVID-2019 OR COVID2019

S8 SARS-COV-2 OR SARSCOV-2 OR SARSCOV2 OR SARSCOV19 OR SARS-COV-19 OR SARSCOV-19 OR SARSCOV2019 OR SARS-COV-2019 OR SARSCOV-2019

S9 "severe acute respiratory syndrome cov 2" OR "severe acute respiratory syndrome coronavirus*"

S10 "2019 ncov" OR 2019ncov OR Hcov*

S11 S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10

8,114

S12 (MH "Forecasting") 15,939

S13 (MH "Predictive Validity") OR (MH "Predictive Value of Tests")

58,584

S14 predict* OR "predict* model*" OR pre-test OR pretest OR presumptive OR presumed OR probabilit* OR "diagnostic model*" OR "early warning tool*" OR "early warning score*"
512,633

S15 S12 OR S13 OR S14 522,872

S16 (MH "Signs and Symptoms+") 703,836

S17 symptom* OR "clinical feature" OR manifestation* 431,510

S18 (MH "Demography+") 554,455

S19 demograph* 169,843

S20	(MH "Environmental Exposure+")	48,873
S21	"exposure histor*"	493
S22	(MH "Diagnostic Imaging+")	458,361
S23	CT OR x-ray OR radiology OR laborator*	304,115
S24	(MH "Diagnosis, Laboratory+")	278,925
S25	S16 OR S17 OR S18 OR S19 OR S20 OR S21 OR S22 OR S23 OR S24	2,217,390
S26	(MH "Patients+") OR (MH "Health Personnel as Patients+")	297,813
S27	"emergency department*" OR "emergency room*" OR ED OR ER	103,297
S28	"assessment center*" OR "assessment centre*"	310
S29	(MH "Health Personnel+")	601,507
S30	"healthcare worker*" OR "health care worker*" OR "health worker*" OR "healthcare professional*" OR "health care professional*" OR "health professional*" OR "health care personnel*" OR "healthcare personnel*" OR "health personnel*" OR doctor* OR nurse* OR physician*	933,761
S31	S26 OR S27 OR S28 OR S29 OR S30	1,431,417
S32	S11 AND S15 AND S25 AND S31	40
S33	S11 AND S15 AND S25 AND S31	7

TRIP PRO/Google Scholar/Google Advanced

(COVID-19 OR coronavirus OR “corona virus” OR sars-cov-1) AND (“prediction model” OR “predictive model” OR predict OR prediction OR presumptive OR presumed OR probability OR pre-test OR pretest OR “diagnostic model” OR “early warning score” OR “early warning tool”) AND (patient OR “health care worker” OR “healthcare worker” OR doctor or nurse or physician) from:2020

LitCovid/WHO COVID-19 Database/CEBM/Medrxiv

(“prediction model” OR “predictive model” OR predict OR prediction OR presumptive OR presumed OR probability OR pre-test OR pretest OR “diagnostic model” OR “early warning score” OR “early warning tool”) AND (patient OR “health care worker” OR “healthcare worker” OR doctor or nurse or physician)

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